David and Goliath: small banks in an era of consolidation. Evidence from Italy

by

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Abstract

Consolidation in the banking industry has caused concern about the survival of small banks. However, empirical evidence shows that often small banks are performing better than larger banks in terms of loan growth and profitability. This paper addresses the main question of "how David can be successful in a Goliath's world" analysing two broad sets of issues, tested on a sample of Italian small banks. We first address the question of whether peculiarities of small banks are good explanatory variables of their loan growth. In particular, we demonstrate that, in terms of loan growth, best performers in the small banking group are those banks who are most able t o ripen the hypothesized small bank advantages, e.g. their ability to process and use soft-information. Second, we also investigate the relationship between loan growth and profitability and credit risk to point out which small banks can continue to be viable competitors of larger banks.

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1. Introduction

Several trends in the financial industry have threatened the survival of small banks in recent years.

Economies of scale in the production of financial services, sophisticated (and costly) risk management techniques, customers' preference for one-stop-shopping, and the related bank's need to diversify into different lines of business (and sources of revenues), the consolidation process in the bank sector,…..all are evidence of an economic arena where only large banks are seemingly fit to operate and survive. In a world made for Goliath, David might be at such a disadvantage that he will no longer survive.

Despite these challenges, empirical evidence from the US and Italy shows that small banks not only survive, but also have been growing more rapidly than their larger competitors over the recent period, conquering new loan and deposit market shares at the expenses of large banks, while maintaining high profitability standards.

Italy may represent a natural case-study. The process of consolidation among large banks has been impressive; however, large Italian banks are still national champions which concentrate more than 80% of their activities in national boundaries where, given the typical small size of Italian firms, they naturally operate in the same credit markets of small banks. Despite their size, small banks seem to better off large banks in terms of loan and deposit market shares and in terms of profitability (Bank of Italy, 2005, p. 298).

A recent study of the drivers of the increased importance of Italian small banks suggests that their loan growth is to be mainly attributed to organizational diseconomies at large banks (Bonaccorsi di Patti *et al.*,2005). Indeed, large Italian banks are facing restructuring and re-organizing problems after their numerous M&A operations and the introduction of more advanced risk management techniques, stimulated by the new capital adequacy regulatory rules (Basle 2). As a consequence, Italian small banks might be successful because large banks are retreating, making room to them. One possible conclusion is that the better performance of small banks appears to be a transitory phenomenon. As soon as large banks are back in action, small banks will lose their advantage.

However, in our judgement, this conclusion was drawn before exploring the wide literature on peculiarities of small local banks. Our paper levers on this literature and addresses the main question of "how David can be successful in Goliath's world". Two broad sets of issues will be investigated.

The first question is whether peculiarities of small banks are good explanatory variables of their loan growth. In particular, we posit that, in terms of loan growth, best performer in the small banking group are those banks who are good at ripening the hypothesized small bank advantages, such as their ability to process and use soft-information (Banerjee *et al.*, 1994; Besley and Coate, 1995; Stiglitz, 1990), their natural attitude towards relationship lending given their skills in producing soft-information and their (lean) organisational structure (Ferri, 1997; Berger and Udell, 2002; Berger *et al.*, 2002; Stein, 2002; Alessandrini *et al.*, 2005).

Second, the relationship between loan growth and profitability and credit risk is analysed. Possible combinations of "*Non Performing Loans over Gross Loans*" and "*ROE*" associated with a higher or lower probability of high loan growth are here explored.

We address this question via a segmentation methodology that splits our sample of banks into relevant and homogeneous clusters that exhibit significant differences in their risk and profitability patterns with respect to the likelihood of being fast banks. A classification and regression tree (CART) is used as developed by Breiman *et. al.* (1984). CART is particularly well suited for our purposes because it enables us to highlight the characteristics that better represent high performing/high growth banks (fit and fast), high performing/low growth banks (fit but slow), low performing/high growth banks (fat yet fast), low performing/low growth banks (fat and slow).

Our main contribution consists in shedding light on what constitutes a fit shape for a small bank in an era of consolidation. Combining our analysis with the results achieved by Bonaccorsi di Patti *et al.* (2005), we can construct a strategic matrix which to identify which small banks are likely to continue to be viable competitors of larger banks, e.g. those able to combine structural advantages with a favourable situation in which large banks face difficulties in maintaining their loan market share.

The rest of the paper is organized as follows: Section 2 provides the motivation of research and reviews the relevant literature; Section 3 discusses our methodology and data; Section 4 presents our results and Section 5 our conclusions.

2. Motivation of research and review of the empirical literature

In recent years, in most developed countries, the survival of small banks has been threatened by various challenges: advances in IT, economies of scale in the production of new and more sophisticated financial instruments, innovations in bank production processes, e.g. the introduction of innovative (yet costly) risk management techniques, customers' preference for one-stop-shopping and the bank's need to diversify into different lines of business (and sources of revenues). Last, but not least, worldwide, the banking sector has undergone a substantial consolidation. All these trends appear to favour large banks at the expense of small banking institutions. All in all, in a world designed for Goliath, David might be at a disadvantage and find it particularly difficult to survive. As a matter of fact, the number of small banks has shrunk in most countries. This holds true for all types of banks, as a natural consequence of the process of consolidation which indistinguishably concerned all banking institutions. However, since small banks are a primary source of financing for small firms, the decline in the number of small banks has raised the concern that the access of small businesses to credit may be restricted. Therefore a fair amount of (mainly empirical) literature has been produced on the effect of bank consolidation on small business lending. In this specific area of study, an interest is cast on the potential differences in the way large and small banks approach small businesses. The real focus of these studies is on the availability of credit for small businesses after M&As. What emerges is that the general picture differs according to the point of view undertaken.

In particular, empirical evidence at bank-level suggests that when banks become larger, they considerably reduce the supply of loans to small borrowers. One possible explanation is that large banks have access to a larger pool of potential borrowers and can supply a greater variety of products as opposed to small banks; therefore it is likely that small borrowers are supplied with less credit given their higher risk profile and the larger costs associated in supplying small business loans. Organizational complexity may represent a further obstacle to the propensity of banks to provide credit to small borrowers: theory suggests that small business lending is characterized by soft information and that monitoring and control by loan officers can be more difficult in larger and complex organizations (Peek and Rosengren, 1998; Petersen and Rajan, 1995; Bonaccorsi di Patti and Gobbi, 2001; Sapienza, 2002; Berger and Udell, 2002; Focarelli, Panetta and Salleo, 2002).

At the market-level, the relationship between consolidation and small business lending suggests that consolidation activity is either unrelated to small business loan growth or associated with higher loan growth; in particular, the share of small business lending funded by local banks tends to rise in those markets undergoing consolidation (Berger *et al.*, 1998; Avery and Samolyk, 2004). Two distinctly different – though not mutually exclusive – explanations stand out.

One explanation contends that other lenders (in particular *de novo* entrants) appear to fill in the gaps in lending and tend to offset some, if not all, of the negative effects of M&A participants (Berger *et al.*, 1998). In this regard, *de novo* banks play an important role as they tend to lend more to small businesses as a percentage of their assets than other small banks of comparable size and that this percentage lasts for a number of years, consistent with a (aggregate) positive effect of M&As on small business lending (Goldberg and White, 1998; DeYoung *et al.*, 1999; Gobbi and Lotti, 2004).

The other explanation contends that small banks are better equipped at processing credit information than large banks: their high-touch, locally focused, relationship-based approach should make them more effective at underwriting and monitoring loans to informationally opaque firms. Small banks enjoy an advantage in lending to small business, and such an advantage relies on their ability to develop what is known as "relationship lending".

A substantial literature suggests that the development of strong bank-firm relationship helps the intermediation process via reduced information asymmetries and agency problems (Diamond, 1984; Boot, 2000).

Small banks are apter than large banks to develop relationship lending because they generally operate in a small community and are owned and/or managed by community members. Two hypothesis are at work: "the long-term interaction hypothesis" (Banerjee *et al.*, 1994; Besley and Coate, 1995) and the "peer monitoring hypothesis" (Stiglitz, 1990; Hoff and Stiglitz, 1990). In the first case, taking active part in the life of a community, the bank shares relations of various kind, not only economic, through which relevant (and not necessarily hard) information can be acquired and used in its lending activity. Focusing on a different mechanism, the peer monitoring hypothesis considers a contract for which each member may continue to benefit from her loan only if all the others' projects are successful, so members have an incentive to control each other. Making loans mainly to its members, a credit cooperative levers on the control incentive that neighbours face, thus contributing to a high loan repayment record. Effective peer monitoring is facilitated by the small size and the small area of operations of most credit cooperatives.

As Berger and Udell (2002, p.1) state, "relationship lending is one of the most powerful technologies available to reduce information problems in small firms finance […]. Under relationship lending, banks acquire information over time through contact with the firm, its owner, its local community on a variety of dimensions and use this information in their decisions about the availability and terms of credit to the firm". Therefore relationship lending is nested with the use of "soft information", i.e. information that cannot be easily observed, verified and credibly transmitted from one agent to another. As before, their nature of local banks helps small banks to capture and process "soft information" and use it in developing relationship lending.

Finally, organizational structure matters. As soft information is difficult to transmit and relationship lending is mainly based on "soft data", relationship lending need to be associated with a fundamentally different lending process – than transaction-based lending - and therefore it requires a different organizational form (Ferri, 1997; Berger and Udell, 2002; Berger *et al.*, 2002; Stein, 2002; Scott, 2004). This stream of literature argues that large hierarchical firms (banks) may be at a disadvantage in transmitting the type of soft information associated with relationship lending, while there is a strong incentive for soft-information production in small organizations. However, small size may not be a sufficient condition; the *functional proximity* between the local system where the bank operates and the decisional centre of the same bank might be relevant, as shown by Keeton (1995) and Alessandrini *et al.* (2005). Functional proximity concerns all banks that, given the localization of their decisional centre and strategic functions, are close to the areas where they operate. Being a small local bank is not a sufficient condition for being functionally proximate to its territory: if the bank belongs to a banking group, whose decisional centre and strategic functions are far from the bank's territory, intrabank governance mechanisms may affect the credit process of the local affiliate up to the point that soft-information is no longer captured and used, with the final effect that credit to small, young, opaque firms is dampened.

The above peculiarities may provide small banks with enough ammunitions to survive in a more competitive and inhospitable environment. To the best of our knowledge, the issue of survival (and the future) of small banks has been directly investigated by few studies.

For the U.S. banking system, Basset and Brady (2002) document that, during the period 1985-2001, small bank assets have grown at rates exceeding their large bank competitors while maintaining their historically high levels of profitability, even if their average cost of deposits increased. The persistent competitiveness of small banks is related to their aggressive and apparently more profitable loan growth.

More recently, DeYoung and Hunter (2002) and DeYoung *et al.* (2003) examine the comparative strengths and weaknesses of large and small banks (in the new more competitive and technological world) and outline a stylized "strategic map" of the banking industry that summarizes the past, present and potential future impact of environmental changes on the structure of the banking industry. Such a strategic framework supports the idea that well-managed community banks can financially outperform large commercial banks. The authors conclude that the community business model is financially viable and that well-managed community banks are likely to survive in the future.

Outside the US, Pastré (2001) describes how "small is beautiful", while Bonaccorsi di Patti *et al.* (2005) empirically study the determinants of Italian small banks' out-performance in loan growth withy respect to larger banks.

The former study is a simple list of what Pastré calls the "six commandments" for small banks' survival: 1) avoid businesses where economies of scales are predominant; 2) be specialized; 3) be flexible; 4) avoid taking too much risk; 5) develop banking networks; 6) price risk correctly.

The latter is an empirical investigation of what drives the rising loan and deposit market share of Italian small banks. The authors examine multiple demand and supply factors seemingly correlated to the different loan growths experienced by small and large banks and conclude that small banks' out-performance mainly depends on large banks' loss of market grip. This group of banks is indeed facing restructuring and re-organizing problems after their M&A operations and the introduction of more advanced risk management techniques encouraged by the new regulatory rules for capital adequacy (Basle 2). Therefore, Italian small banks' best performance appear to be a transitory phenomenon. As soon as large banks are back in action, small banks will lose their advantage.

Indeed, Italy is an interesting testing arena: on the one hand, the size of the consolidation process has been impressive: between 1990 and 2001 more than 500 M&A occurred among banks accounting for 50% of total funds intermediated by the entire banking system (Panetta, 2005); on the other hand, somehow unexpectedly, small Italian banks have been increasing their loan and deposit market shares. Despite their well-known risk-aversion, small co-operative banks were particularly keen to make loans to non-financial firms (Banca d'Italia, Annual Report, 2005), while *de novo* entry has thrived, driven by persistent extra profits in local credit markets (Gobbi and Lotti, 2004).

As the Italian small banking group is extremely heterogeneous, comprising credit cooperatives or joint-stock banks, specialized or universal banks, independent banks or banks affiliated to large groups, it is useful to investigate the drivers of their increased loan market share. Although small banks have taken advantage from their large competitors' retreat, as highlighted by Bonaccorsi di Patti *et al.* (2005), our analysis can help to underline the specific features that can provide small banking institutions with a viable and successful survival strategy in an era of consolidation.

In the following section, we discuss our hypothesis and data sources used in this investigation.

3. Data and methodology

3.1 Data sources

According to the Bank of Italy, the demarcation line between small and medium banks is set at € 7 millions total assets. Banks whose total assets fall below such a threshold are defined "small and minor" banks, amounting respectively to 126 and 599 in 2004. Minor banks are mainly credit cooperatives operating in just one province with few branches; small banks are a more diversified group comprising local banks, branches of foreign banks and banks specialized in private banking or leasing/factoring, consumer credit and investment banking.

We investigate the drivers of loan growth and the effect of growth on bank risk and return for a sample of 221 banks. We gathered financial statement information for these 221 intermediaries from Bankscope, while ownership and legal form information is taken from the Bank of Italy web site.

Coverage of our sample in terms of total loans is 16% with respect to the national loan figures and 47% with respect to the total loans lent by "small and minor banks".

Our sample period is 1998-2004.

3.2 Methodology

Given the prior discussion, we first address the question of whether peculiarities of small banks are good explanatory variables of their loan growth. In particular, we posit that, in terms of loan growth, best performer in the small banking group are those banks who are good at ripening the hypothesized small bank advantages discussed in the prior section.

Therefore we estimate the following logit model using bank-level data from Bankscope:

Probability (Bank *j* enjoys loan growth higher than sample median loan growth)

= *f* (Cooperative, Thinking Head, Relationship Lending, Strategy, Control Variables)

The dummy variable "*Cooperative*" – which takes the value 1 if a small bank is a credit cooperative and zero otherwise - represents a proxy for both the "long-term interaction hypothesis" and the "peer monitoring hypothesis" (Angelini *et al*., 1998).

Second, we posit that being independent, i.e. not belonging to a group, increases a bank's ability to capture and use soft-information in lending decisions. Following Alessandrini *et al.*(2005) "*Thinking Head*" is a dummy variable that takes the value 1 if a bank is independent or head of a group and zero if it belongs to a group.

Finding a proxy for "*Relationship Lending*" is not an easy task. Prior empirical research has in fact studied relationship lending via field surveys addressed to samples of non-financial firms; in such studies, information on the number of bank relations in force and the duration of the bank-firm relationship were deemed good proxies for relationship lending. Absent such a set of information on banks' customers, defining whether a bank specializes in relationship banking or focuses on transaction-based activity becomes harder. Relationship lending generally requires a high touch, value added service supplied by the bank to its customers. Therefore we can expect that relationship loans require more attention and time by loan officers; as a reward, relationship loans should be priced higher than transaction-based loans (the price includes the value of services offered). In this respect, two proxies for relationship lending practices can be used: the "*Net Interest Margin",* i.e. the ratio of net interest income on total assets, and the ratio of "*Loans to the Number of Bank's Employees*". All else being equal, high interest margins should be consistent with a high value added personalized banking strategy while low interest margins should be consistent with high volumes-low cost transactional banking strategies (deYoung, Hunter and Udell, 2003 p.32). A drawback is represented by the fact that high margins could reflect low competition in markets where the bank operates. A bank with a high degree of market power operates as price setter, irrespective to the chosen lending strategy. Therefore a control variable capturing the degree of market power enjoyed by our sample banks is added to the equation. "*Degree of Market Power*" is constructed, for each bank, as follows:

$$(\text{Market Power})_i = \frac{\text{Number of branches in non provincial capitals}}{\text{Total number of branches}}$$

We assume that branches in provincial capitals operate in a competitive market, given that the number of banks operating in these markets is quite high; the same does not always hold true when considering small municipalities and villages, where banks may enjoy local monopoly power.

The ratio of "*Loans to the Number of Bank's Employees*" represents the second variable used to proxy "Relationship Lending": our expectation is that the lower the ratio, the more intense the relationship lending, given that this tends to be more time consuming, in the bank's view, as opposed to transaction-based lending. Even in this case, a drawback exists, since a low ratio may reflect a bank's inefficiencies or even the presence of diseconomies of scale. The "*Cost Income*" ratio is therefore added to the equation in order to control bank's efficiency, while diseconomies of scale are controlled by the natural logarithm of Total Assets. Apart from specific peculiarities of small banks, their high loan growth could be explained by strategic patterns followed by this group of banks in order to strengthen their position in the loan market. For instance, they might have levered on lending activity, thus showing a higher share of total assets invested in loans. As a consequence, such a strategy should negatively affect the potential for revenue diversification, as captured by a higher ratio of net interest revenue to total revenue.

The choice to invest more in lending activity can be detected by the fact that the bank is more capitalized: we expect a higher equity to total assets ratio at fast banks as they use capital to expand and absorb the greater risks that such a strategy may imply.

Finally, a dummy variable that takes the value 1, 2 and 3 respectively if a bank operates in Northern regions, in the Centre or in the South of Italy is added in order to capture potential differences in regional macroeconomic conditions that can influence a bank's loan supply.

Variable definitions are summarized in Table 1.

Table 2 reports summary statistics for the explanatory variables over the years 1998-2004. We also break up our sample into "fast" and "slow" banks according to whether their average loan growth over the sample period was higher or lower the sample median. A t-test for differences in means is reported for the above bi-partition. With reference to low growth banks, fast small banks are more likely to be better capitalized, less risky and more profitable in terms of ROE, making relatively more loans, as a percentage of total assets, be more likely independent and credit cooperative banks.

A second step of our analysis investigates the relationship between loan growth and profitability and credit risk. We explore possible combinations of "*Non Performing Loans over Gross Loans*" and "*ROE*" associated with a higher or lower probability of high loan growth.

A classification and regression tree (CART) is used for this purpose. CART, a nonparametric regression and classification method originally introduced by Breiman *et al.* (1984), has a number of advantages over traditional parametric regression methods because it allows the relaxation of underlying assumptions, revealing interactions of covariates, and using them to improve the quality of the model (see Appendix A for further details on the methodology).

CART is particularly well suited for our purposes because, by simultaneously identifying significant clusters that exhibit relevant differences with respect to the dependent variable, it provides us with a unique insight into profitability and risk patterns that can be identified in the data. In other words, we are able to split our dataset into relevant and homogeneous clusters that exhibit significant differences in their NPL/Gross Loans ratio and ROE with respect to the likelihood of being fast banks.

4. Empirical Results

4.1 Logit results

Table 3 presents the results of the logit estimation. Standard errors are in parentheses. From our sample of 221 banks we excluded firms that clearly presented outlying values and end up with 210 banks.

Column 2 shows the results of our model specification as detailed in Section 3: the dependent variable, a dummy that takes the value 1 if a bank's loan growth is greater than the sample median and zero otherwise, is regressed against proxies for localism, relationship lending activities, strategic patterns, control variables and dummies for geographic location.

The logit model shows a good predictive power: 73% of banks are correctly classified, while Nagelkerke R-squared is equal to 37%. All the variables in the equation show the expected sign with the exception of the ratio of Net Interest Revenue to Total Revenue; most of the proxies for structural peculiarities of small banking institutions are also statistically significant. In particular, high loan growth is more likely to characterize those banks that are credit cooperatives, invest in relationship lending, specialize in lending and are more capitalized. For instance, the estimated coefficient of the variable "cooperative" means that being a credit cooperative increases the odds of being a bank with high loan growth by a factor of 14.[1] Being independent does not add to a bank's ability in using soft-information in its lending activity and loan growth: "Thinking Head" is in fact not statistically significant. On the contrary, geography, i.e. the proxy for differences in macro-regional conditions, appears to positively influence a bank's loan growth: bank's operating in Central regions are in fact better off with respect to banks located in the North. The same does not attain when a bank is located in Southern regions.

The negative sign of the ratio of Net Interest Revenue to Total Revenue stands out with respect to our a-priori. One possible explanation may reside in the fact that our sample of banks includes financial institutions specialized in retail asset management and private banking. Indeed, these banks experienced high loan growth in the years under study for two main reasons. First, most of these institutions are *de novo* banks: therefore their initial level of loans was low if not null. Second, some of these banks entered the residential housing mortgage sector which was experiencing a fast expansion in the years under study. If we subsequently discard these banks, the

[1] The logistic coefficients can be interpreted as the change in the log odds associated with a 1 unit change in the independent variable. Since its easier to think of odds rather than log odds, the *e* raised to the power of B_i is the factor by which the odds change when its independent variable increases by 1 unit.

coefficient of Net Interest Revenue to Total Revenue is no longer statistically significant (columns 4 and 5), while all the other results are confirmed.

Our model I presents a second problem: in fact, the large standard error of the estimated coefficient of "Loans/ N. of Employees" may embody a potential problem of multicollinearity. Among the many warning signal that a researcher could consider, two are the most commonly used: the bivariate correlation among variables and the VIF (variance influence factor. Both tests confirm the presence of multicollinearity. In fact, a big "value" correlation is found (0.83) among "Loans/ N. of Employees" and "Loans/Total Assets"; indeed, the result was not unexpected as the two variables share the same numerator. At the same time, the VIF for our offending variable is quite high, and equal to 7[2]. Therefore, we decided to substitute the ratio of Loans to the Number of Employees with a new variable capturing a similar meaning, i.e. the ratio of Net Interest Revenue to the Number of Employees. Results of the new model are reported in column 3. Previous results are confirmed and the newly inserted proxy for relationship lending presents the expected sign, while being statistically significant with no signs of multicollinearity. Besides, the control variable for efficiency (the Cost Income ratio) is now significant at 10% level and exhibits the negative expected sign: more efficient banks are more likely to experience higher loan growth. Finally, in order to check for the robustness of our estimates with respect to their power of capturing the extent of relationship lending net of banks' market power, we decided to estimate a fourth model. This is a two-stage model, where in the first-stage we regress "Net Interest Margin" on "Market Power"; in the subsequent, second-stage, the estimated residuals are included as an explanatory variable (proxy for relationship banking, net of market power) for estimating the probability of being a bank with high loan growth. Results of this model are reported in column 5. Relationship banking is confirmed as a relevant variable for loan growth: both proxies are significant at the 1% level; any other results are confirmed.

4.2 Classification tree results

From our sample of 210 we exclude 15 banks for which the required data were missing as the ratio of NPL/Gross Loans was not available for all the banks.

CART tree is shown in graph 1 and the results are summarized in table 4. Our sample is partitioned into five groups, according to their profitability and risk patterns with respect to the likelihood of being fast growing banks. Therefore, we end up with five clusters of banks exhibiting the following strategies with respect to loan growth, profitability and credit risk (table 4):

Group 1: *fat and slow*: the cluster exhibits a low loan growth and a high level of NPL to gross loans;

Group 2: *semi-fit and fast*: the cluster exhibits high loan growth, combined with the highest ROE (> 7%) and a medium level of NPL to gross loans (laying in the interval 4%-14%, with a mean of 5,22%);

Group 3: *fat yet fast*: the cluster exhibits high loan growth combined with a low performance in both ROE and NPL to gross loans;

Group 4: *semi-fit and fast*: the cluster exhibits high loan growth, combined with a medium ROE and the lowest level of NPL to gross loans;

Group 5: *semi-fat and slow:* the cluster exhibits a low loan growth, combined with a medium ROE and a medium level of NPL to gross loans.

[2] A commonly given rule of thumb is that VIFs of 10 or higher may be reason for concern; however, in logistic regression a lower level (at 2.5) is considered a warning signal for multicollinearity.

Each cluster's further characteristics are reported in table 5.

The two best performer clusters (G-2 and G-4) differ in their choice of profitability (ROE) and risk (NPL/Loans). G-4 banks show a more prudent strategy: they target a lower risk-return combination and maintain a higher capital ratio. This result is obtained notwithstanding the lower presence of credit cooperatives in the cluster, i.e. banks which are well known for their low appetite for risk and are not subject to the constraint of maximizing shareholders' value. An alternative explanation of the different strategies adopted by G-2 and G-4 may reside in the fact that G-2 comprises a higher percentage of banks affiliated to groups (24% and 13% respectively): a parent bank may be prone to short-termism in the trade-off between profitability and risk.

G-3 comprises few banks (7), most of which belong to large bank groups and tend to be specialized in corporate or private banking. All the banks in the cluster are characterized by very low ROE (mean value 0.35%, standard deviation 1.8%).

G-1 and G-5 clusters consist of banks with a low loan growth. They share similar value for ROE, while G-1 banks exhibit the highest level of NPL on gross loans (20.02%), which is in part due to the fact that the group comprises the highest percentage of banks located in the South and a lower percentage of credit cooperative.

A further step of our analysis combines the results of the logit exercise with those of the CART analysis: our aim is to verify how the various small banks' peculiarities and strategic patterns in lending activity, that proved to be significant in explaining small banks' high loan growth, are allocated among our clusters. For this purpose, Table 6 reports the mean value for "Net Interest Margin", "Net Interest Revenue/N. of Employees", "Loans/ Total assets", "Leverage". These values are reported only for the three most numerous clusters (G-2; G-1 and G-5) since a t-test for differences in means loses its statistical significance when applied to small samples. If all the above mentioned characteristics hold true for each cluster, potential differences in means should show no statistical significance. This is mainly true for almost all the variables reported in table 6; although two exceptions stand out, both having to do with relationship lending. In fact, G-2 exhibits a statistically significant higher value of "Net Interest Margin": the result may imply that this group of banks lever particularly on this proxy of relationship banking. Interestingly, G-5 seems to invest in relationship banking; but lacking other strategic levers they fail to obtain higher loan growth.

5. Conclusions

This study provides a two-step evaluation of the potential for survival of small banks in a Goliath world.

In the first step, we demonstrate that most of the peculiarities of small banks, i.e. localism and relationship lending, are good explanatory variables of their recent high loan growth. Exhibiting strategies focusing on lending activity and being more capitalized matters as well.

The second step explores the relationship between loan growth and profitability and credit risk. We end up with five groups of banks that exhibit the following strategies: a) two *semiFit & Fast* clusters: high performing banks – in terms of low NLP/Loans and high ROE- with high loan growth; b) one *Fat and Fast* cluster - low performing banks with high loan growth; c) two *Fat and Slow* clusters - low performing banks with low loan growth.

In sum, the small banks' group is not homogeneous in its loan growth which, for best performer, is driven by structural factors, such as the ability to lever on their local status, on relationship lending and to control credit risk while pursuing a good level of profitability as well.

As such, their growth is not a transitory phenomenon, depending on the fact that large Italian banks are facing difficulties in maintaining their market share due to transitory organizational diseconomies combined with a reconsideration of their lending policies, more centred on the use of credit scoring techniques.

Making use of a "strategic matrix" (see table7), our study provides a criterion to highlight which small bank business model is still economically viable. In fact, it appears that 44% of our sample of small banks will be able to survive and prosper even when the causes of large banks' difficulties will disappear.

Tables and figures

Table 1 Independent variables: definition of the variables and expected sign of coefficients

	Variable name	Definition	Expected effect on loan growth	
LOCALISM	Cooperative	Dummy variable that takes the value 1 if a bank is a cooperative and 0 otherwise	+	Proxy for the positive effects of "peer monitoring" and "long term" hypotheses on banks' lending patterns
	Thinking Head	Dummy variable that takes the value 1 if a bank is independent and 0 if it belongs to a group	+	Decision-making autonomy can foster bank's ability to use soft information in its lending activity
	Geography	Dummy variable that takes the value 1, 2 and 3 respectively if a bank operates in Northern regions, in the Centre or in the South of Italy	?	Differences in regional macroeconomic conditions can influence a bank's loan supply
relationship lending	Net Interest Margin	The ratio of net interest revenue on total assets	+	Greater attention to relationship lending is the driver of high loan growth: the higher the interest margins the most probable a high value added personalized banking strategy is at work with positive effects on loan growth
	Loans / Number of employees	The ratio of Loans to the number of bank's personnel (in natural logarithms)	-	Greater attention to relationship lending is the driver of high loan growth: the lower the number of loans per personnel the most probable a high value added personalized banking strategy is at work with positive effects on loan growth
STRATEGY	Loans/Total Assets	The ratio of Loans to Total assets	+	A strategy that focus on lending activity reflects positively on loan growth
	Net Interest Revenue/ Total Revenue	The ratio of net interest revenue on total revenue	-	Higher values are signs of a strategy that focuses on lending activity and a minor attention to revenue diversification potential
	Equity /Total Assets	The ratio of bank's equity on total assets	+	Faster banks need more capital to fund their (riskier) strategy
control variables	Total Assets	Total assets (in natural logarithms)	?	Dimension matters?
	Cost / Income	Cost income ratio	-	More efficient banks are deemed to grow faster
	Market Power	The ratio of the number of branches in non provincial capitals over total number of branches	+	Greater market power influence pricing

Table 2 Summary Statistics

The following table presents medians for the explanatory variables over the sample period 1998-2004. Column 2 refers to the whole sample of 221 small banks. Columns 3 and 4 present means for the bi-partition "fast growth" and "slow growth" : specifically, banks are grouped within "fast growth" and "slow growth" according to whether their loan growth is greater than the sample median or not. A t-test for differences in means is applied across the bi-partition. Columns 5 and 6 present medians for the same bi-partition. A Mann-Whitney test for differences in medians is applied across the bi-partition: Statistical significance for the test at the 10%, 5% or 1% level are indicated by *, **; *** respectively.

variable	median	mean when fast growth	mean when slow growth	median when fast growth	median when slow growth
Loan Growth 98-04	13.58	20.96***	8.40	17.86***	10.25
ROE	6.81	7.63**	6.45	7.70***	6.04
NPL/Gross Loans	6.71	6.73***	10.66	5.57***	8.05
Total Capital ratio	16.30	19.91	19.41	16.03	16.98
Net Interest Margin	3.56	3.55	3.47	3.64**	3.47
Cost Income	72.74	73.71	73.05	72.38	72.97
Operating Costs/ Total Earning Assets	3.27	3.43	3.19	3.19	3.29
Personnel Costs/ N. of employees	55.12	55.94	58.29	55.03	55.57
Personnel Costs / Total Assets	1.65	1.66	1.60	1.67	1.62
Loans/ N. of employees	2,036	2,426	2,595	2,101	1,953
ROA	0.79	0.85	0.75	0.88**	0.74
Service Income/Net Interest Revenue	21.36	23.80	22.31	21.19	21.44
Net Interest Revenue /Total Revenue	78.81	76.83	77.68	78.83	78.56
Loans/Total Assets	66.83	67.76**	62.54	70.84**	62.93
Equity/Total Assets	12.72	15.14**	12.78	13.48**	12.20
Loans/Funding	77.15	88.25	94.19	77.87	75.78
Total Assets	391,486	794,555	1,053,863	324,486	522,186
N. of employees	100	291	274	93	148
Cooperative (dummy)	119	72***	41		
Thinking Head (dummy)	164	89**	75		
Specialized (dummy)	20	8	12		
North	111	57	54		
Centre	64	37	27		
South	44	16	28		
Market Power	28.57	28.57	26.97		

Table 3 Logit results for loan growth.

The dependent variable takes the value 1 when a bank experiences a loan growth higher than the sample median and zero otherwise. In model I explanatory variables are proxies for localism, relationship lending activities, strategic patterns, control variables and dummies for geographic position as reported in table 2. In model II, a new variable, "net interest revenue/ n. of employees", is inserted, substituting "loans/n. of employees" Models III differs from Model II in the number of observations: it is, in fact, estimated on a sample of 204 banks, excluding banks specialized in retail asset management and private banking. Model IV is a robustness check of our estimates to capture the extent of relationship lending net of banks' market power; it includes the residuals of a regression where "net interest margin" is the dependent variable and "market power" its explanatory variable. Standard errors in parenthesis; statistical significance at the 10%, 5% or 1% level are indicated by *, **; *** respectively.

	Model I	Model II	Model III	Model IV
	(B)	(B)	(B)	(B)
Cooperative	2.68 (.65) ***	2.84 (.68)***	2.62 (.70)***	2.60 (.70)***
Thinking Head	.44 (.53)	.16 (.54)	.25 (.56)	.25 (.56)
Net Interest Margin	.79 (.43)*	1.43*** (.45)	1.63 (.48)***	
Residuals (Relationship lending net of Market Power)	-	-	-	1.64 (.47)***
Loans/ n. of Employees (in log)	-2.66 (1.17)**	-	-	-
Net Interest Revenue/ n. of Employees		-.03 (.01)***	-.04 (.02)***	-.04 (.02)***
Loans/Total Assets	.08 (.03)***	.03 (.014)**	.04 (.02)**	.04 (.02)**
Equity/ Total Assets	.06 (.03)**	.08 (.04)**	.08 (.03)**	.08 (.03)**
Net Interest Revenue /Total Revenue	-.06 (.03)*	-.05 (.03)*	-.02 (.04)	-.02 (.04)
Total Assets (in log)	.14 (.22)	.13 (.23)	.14 (.25)	.15 (.24)
Cost income	-.02 (.02)	-.030 (.02)*	-.05 (.03)*	-.05 (.03)*
North	*	*		*
Centre	1.10 (.46)**	.97 (.46)**	.98 (.48)**	1.00 (.47)**
South	.26 (.53)	.20 (.55)	.20 (.58)	.22 (.57)
Market Power	-.01 (.01)	-.02 (.010)	-.02 (.01)	-
Constant	13.77 (8.45)*	-1.44 (4.82)*	-2.66 (5.95)	1.67 (5.45)
N. of observations	210	210	204	204
Negelkerke R squared	37.2%	39.2%	39.3%	39.3%
Overall classification ability	72.9%	74.8%	74.5%	74.5%

Table 4 Clusters' characteristics with respect to profitability and credit risk and their likelihood of being fast or slow banks. Banks are defined as fast when their loan growth is higher than the sample median.

ROE \ NPL/grossLoans	> 14%	]4, 14%]	<=4%
<=1,7%		G3- fast banks	
]1,7%-7%]	G1-slow banks	G5-slow banks	G4- banks
>7%		G2 - fast banks	

Table 5 Clusters' summary statistics.

The following table reports mean values for a set of explanatory variables that help further characterize the five clusters identified via CART analysis. Columns 2 and 6 report mean values for the bi-partition of fast and slow banks: banks are defined as fast when their loan growth is higher than the sample median (see Table 2).

	Mean when fast	G-2 *semi-fit and fast*	G-4 *semi-fit and fast*	G-3 *fat yet fast*	Mean when slow	G-1 *fat and slow*	G-5 *semi-fat and slow*
Number of banks in cluster	111	69	16	7	110	33	70
% of fast banks	100	68%	62.5%	71.4%	0	15.2%	35.7%
NPL to Gross loan (mean value)	6.7%	5.75%	3.19%	6.37%	10.66%	20.02%	8.07%
ROE (mean value)	7.6%	9.64%	6.07%	0.35%	6.45%	5.22%	5.6%
Total capital ratio (mean value)	19.91%	18.06%	24.11%	17.08%	19.41%	24.23%	19.38%
% of cooperatives	65%	62%	56%	14.3%	37%	48.5%	54.3%
% of specialized banks	7%	2.89%	0%	42.9%	11%	12.1%	4.3%
% of thinking heads	80%	76%	87%	57.1%	68%	69.7%	81.4%
% in Southern regions	14%	7.25%	0%	0%	25%	72.7%	15.7%

Table 6 Small banks' peculiarities and strategic patterns leading to higher loan growth, mean values. A t-test for differences in means is applied for each group. In particular G-2 means are compared to the sample mean of fast banks, while G-1 and G-5 means are compared to the sample mean of slow banks. Statistical significance at the 5% level is indicated by **.

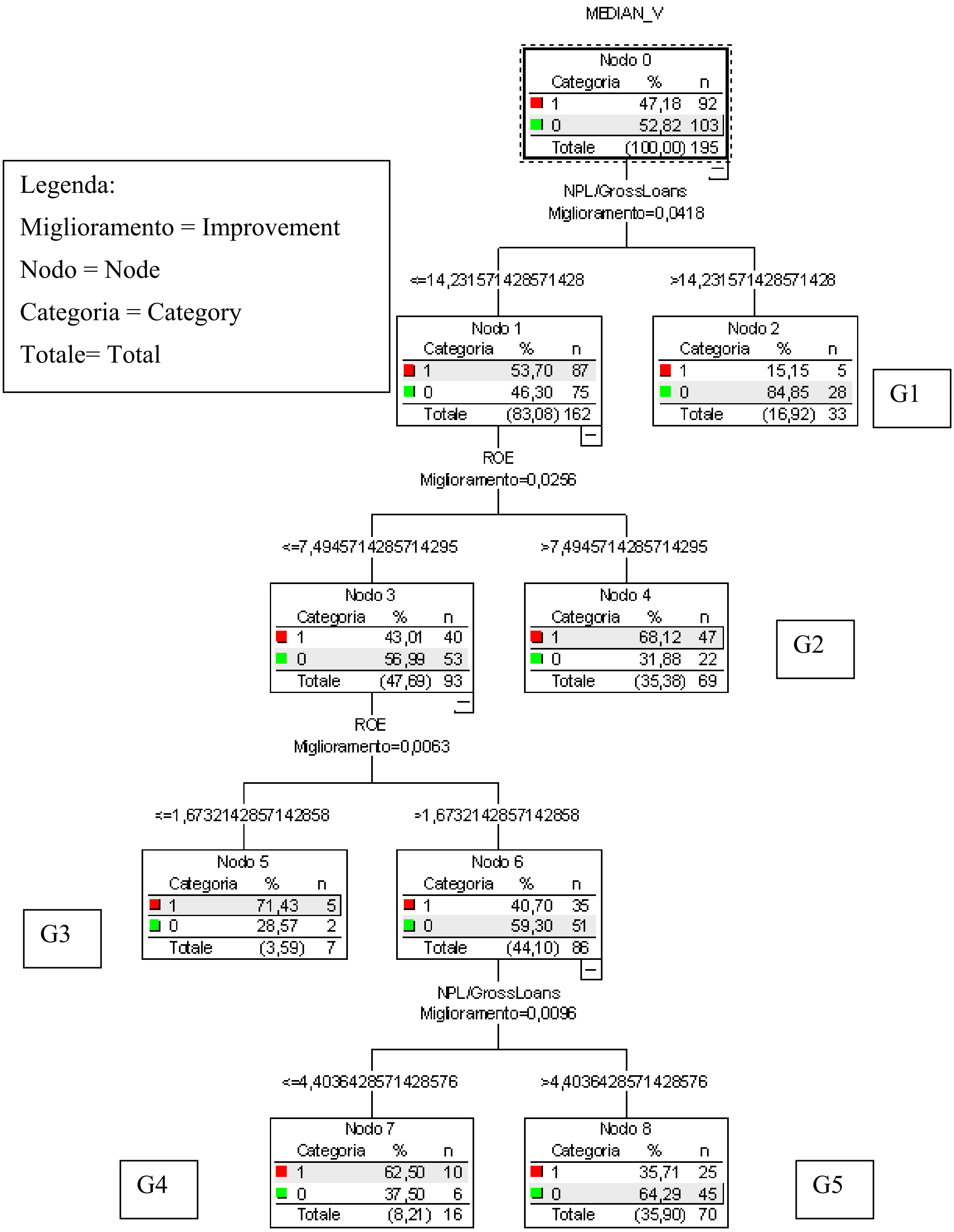
	G-2 *semi-fit and fast*	G-1 *fat and slow*	G-5 *semi-fat and slow*
Net interest margin	3.66%**	3.47%	3.42%
Net interest revenue/ n. of employees	103.66	132.04	111.57**
Loans/ TA	71.13%	55.53%	64.56%
Leverage	13.93%	13.37%	13.56%

Table 7 A strategic map

<table>
<tr><td colspan="2" rowspan="2">Growth</td><td colspan="2">Driven by transitory factors
(e.g. transitory large banks organizational problems)</td></tr>
<tr><td>Yes</td><td>No</td></tr>
<tr><td rowspan="2">Driven by structural factors
(e.g. localism, relationship lending, focus on lending activity, high capital)</td><td>Yes</td><td>G2-G4
(44% of sample)</td><td></td></tr>
<tr><td>No</td><td>G3
(3% of sample)</td><td>G1-G5
(53%)</td></tr>
</table>

Graph 1 Classification Tree.

The dependent variable is a dummy variable that takes the value 1 if a bank's loan growth is greater than the sample median, and zero otherwise. Independent variables are NPL/Gross Loans and ROE. Overall classification ability is equal to 70%.



APPENDIX A

In CART, the sample of subjects is systematically sorted into completely homogeneous subsets until a saturated tree is found. For each split, CART considers the entire set of available predictor variables to determine which one maximizes the homogeneity of the following two daughter nodes. This is a hierarchical process that reveals interdependencies between covariates. The process is continued until the nodes are completely homogeneous and cannot be split any further. Breiman *et al.* (1984) describe a number of possible splitting methods. Among them, the entropy impurity criterion is identified as the best method for the identification of the predictors of a dependent variable with low frequency. Consider the splitting of a parent node, where *a, b, c,* and *d* denote the number of subjects in the two daughter nodes:

	Predictor	Bank> median value	Bank<median value	
Left node (t_L)	s_i=1	A	B	a+b
Right node (t_R)	s_i=0	C	D	c+d
	a+c	B+d	*n*= a+b+	c+d

Source Breiman et al. (1984)

The entropy impurity in the left daughter node is

$$i(t_L) = -\frac{a}{a+b}\log\left(\frac{a}{a+b}\right) - \frac{b}{a+b}\log\left(\frac{b}{a+b}\right)$$

Similarly, the entropy impurity in the right daughter node is

$$i(t_R) = -\frac{c}{c+d}\log\left(\frac{c}{c+d}\right) - \frac{d}{c+d}\log\left(\frac{d}{c+d}\right)$$

Consequently, the impurity of the parent node is

$$(3) \quad i(t) = -\frac{a+c}{n}\log\left(\frac{a+c}{n}\right) - \frac{b+d}{n}\log\left(\frac{b+d}{n}\right)$$

The goodness of a split, *s*, is then measured by

$$\Delta I(s,t) = i(t) - P\{t_L\}i\{t_L\} - P\{t_R\}i\{t_R\}$$

where P{t} is the probability associated with the occurrence of the each daughter node. The goodness of a split is calculated for all available predictor variables. The split characterized by the highest $\Delta I(s,t)$ allows the identification of the best predictor. This recursive partitioning process continues until the tree is saturated. That is, nodes cannot be split any further because the subjects they contain are perfectly homogeneous. T_0 is the saturated tree. The saturated tree is usually too large to be useful. And, in the worst case, it is trivial because each terminal node could consist of just one case. Of course, the resulting model is also subject to severe over-fitting problems. As a result, it is necessary to find a nested subtree of the saturated tree that exhibits the best "true" classification performance and satisfies statistical inference measures.

Pruning

The purpose of pruning is to find the right-sized tree, which should be a sub-tree of T_0. We use the cost-complexity pruning algorithm suggested by Breiman et. al. (1984), which ensures that a unique best sub-tree can be found for any given tree complexity. The right sized tree should not be subject to over-fitting and insignificant splits, but detailed enough to exhibit a good classification performance. Recall that CART predicts the outcome (e.g. Bank> median value and Bank<median value) based on the group membership of a case in the sample. In the tree, each subject falls into exactly one terminal node. We choose a class assignment rule that assigns a class to every terminal node $t \in \tilde{T}$,. In our application, node *t* is assigned "Bank> median value" $\{Y = 1\}$ if $P\{P = 1|t\} \geq 0.5$ and vice versa. In this simple case, the expected cost resulting from any subject within a node is given by

$$r(t) = 1 - P(i|t)$$

where $P(i|t)$ is the percentage of misclassified subjects in a node.[1] The classification performance of the entire tree is given by the quality of its terminal nodes

$$R(T) = \sum_{t \in \tilde{T}} P(t) r(t)$$

where R(T) is the misclassification cost of all terminal nodes in the tree. $\tilde{T}$ the set of terminal nodes, and P(T) the probability of a subject to fall into the terminal node t.

We are now ready to turn to the main idea of cost-complexity pruning (Breiman *et al.*, 1984, pp. 66-71): For any subtree $T \leq t_0$, define its complexity as $|\tilde{T}|$, the number of terminal nodes in T. Let $\alpha \geq 0$ be a real number called the complexity parameter and define the cost complexity of the entire tree as

$$R_\alpha(T) = R(T) + \alpha|\tilde{T}|$$

For any value of $\alpha \geq 0$, there is a unique smallest subtree of t_0 that minimizes $R_\alpha(T)$.

Thus, by gradually increasing α, a sequence of nested essential subtrees of T_0 can be constructed by pruning off the weakest branches at each threshold level of α. Note that T_0 minimizes $R_\alpha(T)$ if $\alpha = 0$. If α be-comes large enough, the root node becomes the optimal solution.

Selection of the best pruned tree using cross-validation

The classification performance R(T) is obviously biased and results in severe over-fitting. To select the best pruned tree, we need a more honest estimate of the true misclassification cost of the tree. This is usually done with an independent test sample, e.g., boot-strapping or cross-validation. However, we choose a 20-fold cross validation procedure because it makes better use of the information contained in the original dataset than the independent test sample method and, in addition, it outperforms bootstrapping in terms of reduced bias (Breiman *et al.*, 1984, pp. 72-78, 311-313). We estimate $\hat{R}(t)$ by growing a series of V auxiliary trees together with the main tree grown on the learning sample . The V auxiliary trees are grown on randomly divided, same sized subsets, Λ_v $v = 1,\ldots,V$ with the v-th learning sample being $\Lambda^{(v)} = \Lambda - \Lambda_v$ so that $\Lambda^{(v)}$ contains the fraction $(V-1)/V$ of the total data cases. For each v, the trees and their pruning sequence are constructed without ever seeing the cases in Λ_v . Thus, they can serve as an independent test sample for the tree $T^{(v)}(\alpha)$. The idea now is that for V large, $T^{(v)}(\alpha)$ should have about the same classification accuracy as $T(\alpha)$. The estimated misclassification costs $\hat{R}(t)$ equal the proportion of misclassified test set cases in the V auxiliary trees at the α complexity levels. The best pruned tree is the one with the smallest $\hat{R}(t)$.

Significance of splits

Finally, the significance of each individual split in the selected tree can be tested following Sheskin (2000). Recall that we calculate the resubstitution risk as

$$r = \frac{\frac{a}{a+b}}{\frac{c}{c+d}}$$

The calculation of the confidence interval of r requires to compute the standard error of the two daughter nodes, which is given by

$$SE_r = \sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}$$

Since the sampling distribution of the re-substitution risk is positively skewed, a logarithmic scale transformation is employed in computing the confidence interval. The α confidence level is obtained by

$$\left\{e^{[\ln(r) - SEz_\alpha]}; e^{[\ln(r) + SEz_\alpha]}\right\}$$

where z_α is the tabled two-tailed z value for the (1- α) confidence level. For the 95% confidence level, the relevant .05 value is $z_{.05}$=1.96. This test is computed for all splits in the tree that was selected from the pruning sequence after the cross-validation procedure.

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