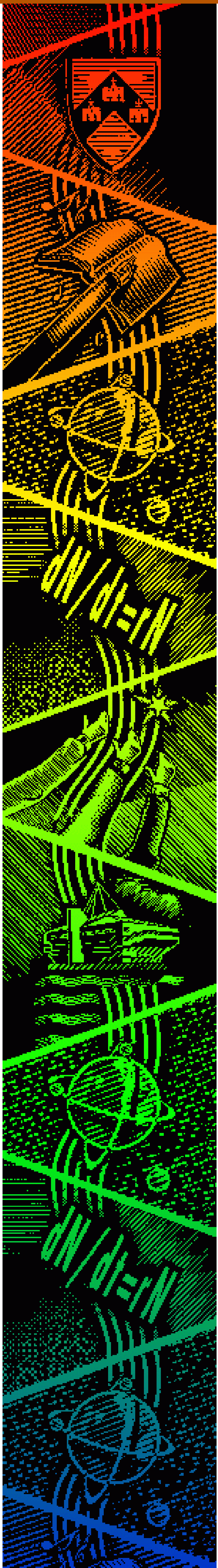

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Market and Supervisory Information: Some Evidence from Italian Banks

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MARKET AND SUPERVISORY INFORMATION:

SOME EVIDENCE FROM ITALIAN BANKS

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ABSTRACT

There is an increasing debate on the potential use of the signals arising from financial markets as a complement to the information set available to supervisors. Following this stream of research, this paper provides for the first time some empirical evidence on Italian banks, using a unique dataset matching accounting ratios, equity-market variables and supervisory judgements. More specifically, we analyse the behaviour of four well-used equity-based indicators for the Italian banks whose shares were listed on the Milan stock exchange between 1995 and 2002 and look at the correlation across banks and across indicators, verifying what type of signal (if any) different variables are able to convey. Moreover, we investigate whether equity-based indicators provide additional information for supervisors with respect to the set of data they usually rely on, assuming the supervisory ratings as a benchmark.

JEL classification numbers: G14, G21, G28, E58

Key-words: bank, supervision, market discipline, early warning

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MARKET AND SUPERVISORY INFORMATION: SOME EVIDENCE FROM ITALIAN BANKS [•]

INTRODUCTION

Banking supervision is based on a wide range of information, typically acquired through the periodic statistics due to supervisors by banks and the inspections that are carried out with a lower frequency on the main premises of the intermediaries. On the one hand, off-site analyses provide the supervisors with a continuous and systematic picture of intermediaries' activity, on the other hand on-site examinations enable supervisors to acquire detailed information on specific aspects of the banks' operating framework, such organisations or IT systems. Therefore, these two instruments are complementary, providing supervisory authorities with a deep knowledge of single banks and, indirectly, of the banking system as a whole.

In recent years an intense debate has developed among academics and supervisors about the potential use of the signals coming from financial markets as a complement to the information already available to supervisors, the main idea being that "market participants have an incentive to look through reported accounting figures to the real financial condition of a bank and to price a bank's securities based on their best estimates of the distribution of the security's future cash flows"[1]. For this reason the picture supervisors are able to draw on the risk profile of banks could (in theory) be integrated with the information that financial markets, if efficient, tend to promptly reflect in prices. In other words, even though supervisors do have a big amount of insider information, financial markets might be more rapid in updating their evaluations.

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[1] Flannery (2001).

Thus, what is under discussion is not the supremacy of one information with respect to the other, but understanding whether the signals coming from financial markets can represent for supervisors an additional tool to identify weak banks.

This issue seems to be relevant mainly for large banks, whose portfolios are considered to be more "opaque" and therefore more difficult to be evaluated, and represents only one of the several points of view from which "market discipline" can be studied. Indeed, it is possible to distinguish between "market monitoring", regarding the hypothesis that investors (able to perceive the true risk profile of the intermediaries) promptly incorporate in prices the new information coming from the market, and "market influence", which reflects the ability of outside claimants (such as investors) to induce managers to effectively modify their actions (Bliss and Flannery, 2002)[2].

According to the former definition ("market monitoring"), the first stream of research has widely concentrated on bond spreads, particularly on subordinated notes and debentures (SND). In effect, economic theory suggests that subordinated bondholders have a strong incentive to monitor the evolution of the bank's riskiness, given that – when a crisis occurs – their exposure is not covered by deposit insurance and the reimbursement of their capital is subordinated to that of all the other creditors. For this reason bondholders are considered to have an objective – the limitation of risk – which is broadly similar to supervisors' one; in other words, bondholders care more about the downside risk of the bank's performance than the upside one. On the contrary, shareholders – given their limited responsibility – have no limits to the potential gain and, at the same time, a predefined limit to the loss; therefore, they can be willing to increase the risk profile of their investment with no negative effects on share prices. Based on this argument, in recent years mandatory subordinated debt issuance by banks has also been recommended as a new tool for supervisors to discipline banks (e.g. Calomiris, 1997).

More recently the attention has shifted on equity markets. First, there is broad consensus that they are more efficient in elaborating and incorporating new available information; second, equity-based data are more frequent and easier to be collected, as there are more

[2] The relevance of these issues is confirmed by the reform of the Capital Accord for banks proposed by the Basle Committee on Banking Supervision. The new regulation will be based on minimum capital requirements (pillar 1), a supervisory review process (pillar 2) and specific disclosure requirements aiming at enhancing market discipline (pillar 3).

banks whose shares are listed on stock exchanges than banks issuing SNDs on regulated markets; third, recent studies have provided evidence on the fact that bondholders do not have strong incentive to run a costly monitoring activity if they perceive supervisory authorities adopted a too-big-too-fail policy; finally, although conceptually simple, the implementation of bond spreads is not straightforward, i.e. different bonds issued by the same bank may yield different estimates of the spread.

This paper contributes to the second stream of research, by providing for the first time empirical evidence on Italian banks based on a unique dataset matching accounting, market and supervisory information. We believe that such an analysis is particularly noteworthy given the relatively recent development of the Italian financial market. More specifically, the research addresses two main questions:

I. *What kind of information does the Italian stock market provide on the financial condition of intermediaries?*

II. *Given their higher frequency with respect to quantitative data, can equity-based indicators provide supplementary information for supervisors?*

In order to answer these questions, we analyse the behaviour of four well-used equity-based indicators for the Italian banks whose shares were listed on the Milan stock exchange from 1995 to 2002. In particular, we look at the correlation across banks (for the same indicator) and across indicators (for the same bank), verifying what type of signal (if any) different variables are able to convey. Furthermore, following the methodology adopted in the recent literature, we test for Italy the ability of market variables to add informative value to quantitative supervisory data, thus reflecting, at least to a certain extent, the qualitative information employed by the Bank of Italy in assigning supervisory ratings (PATROL). Our main goal is therefore to identify some source of information that, even if less precise, is available on a timelier basis.

The paper is structured as follows. Section 1 contains a survey of the literature, focussing on the research that provides empirical evidence on the equity market. In section 2 the behaviour of four well-used equity-based indicators is described, paying particular attention to the correlation analysis. In section 3 a logistic model is estimated, where the dependent variable is the level of PATROL ratings and the explanatory variables are – in addition to the balance-sheet ratios – some of the selected market indicators.

1. A SURVEY OF THE LITERATURE

There is an extensive academic literature regarding the complementarity of supervisory and market information. The bulk of this stream of research has focused on the U.S. secondary bond markets, in order to analyse the ability of subordinated bond spreads to signal banks' soundness (for a detailed review see, among the others, Flannery, 1998). The main findings are that bond spreads tend to increase when firm's riskiness increases. To our knowledge, there is only one paper (Sironi, 2003) which looks at the European market of subordinated notes and debentures (SND); studying the characteristics of over 1,800 bond issues performed by European banks between 1988 and 2000, it confirms that bond spreads reflect the different risk profiles of the issuers.

More recently, the attention has been focused also on the signals arising from equity markets and several studies have been dealing with the usefulness of equity-based information and its contribution in improving the supervisors' knowledge of intermediaries' financial condition. Given the focus of our paper, some of the main empirical literature belonging to this stream of research is surveyed below.

Berger, Davies and Flannery (1998) compare the supervisory judgements on Bank Holding Companies (BHCs) – represented by the rating assigned after the inspections (BOPEC[3]) – with the evaluations incorporated in some market variables (e.g. Moody's ratings on subordinated bonds, equity abnormal returns); the goal of the exercise is to understand the timeliness and accuracy of different kinds of information. Their results suggest that supervisory data and those incorporated in the agencies' ratings are complementary, to the extent that the latter help improve BOPEC forecast; by contrast, the relationship between

[3] In the U.S., the Federal Reserve is the supervisory body of the bank holding companies. The general inspections are usually carried out yearly and they mainly focus on the analysis of credit quality, internal audit, business plan After the inspection, the FED assigns its rating (BOPEC, Banks Subsidiaries, Other non bank subsidiaries, Parent company, Earnings and Capital adequacy) that reflects intermediary's overall soundness. It shifts from 1 to 5 as the overall performance of the BHC worsens; the supervisory rating is strictly confidential. Conversely, the CAMELS (Capital adequacy, Asset quality, Management, Earnings, Liquidity, Sensitivity to risk) is the on-site rating assigned once a year on a solo basis.

supervisory and market variables is weak. The authors explain the inconsistencies in the results with the different incentives of the various players involved in banks' monitoring. Supervisory authorities and rating agencies would be mainly concerned on preventing the default risk, since they somehow protect debtors' interests; by contrast, shareholders would primarily care of the rise in bank's value, even if achieved by an increase in risk taking.

Similarly, Krainer and Lopez (2001) examine whether market variables such as equity returns and probabilities of default (KMV's expected default frequencies, EDF™[4]) can be used by supervisors for assessing the soundness of BHCs. In particular, they analyse the ability of equity-based indicators to anticipate BOPEC's downgrading, thus improving the performance of the early warning system already in use, which is based exclusively on balance-sheet and supervisory data[5].

The exercise is divided into several steps. From the behaviour of equity abnormal returns they infer that, in the quarters preceding an upgrading, the indicator is significantly different from zero; by contrast, it is negative before BOPEC's downgradings and not significantly different from zero when supervisors don't modify their evaluations on the banking group. This result is confirmed also when the one-year EDF is considered as the explanatory variable.

In order to evaluate the insights that market information may provide, they start estimating an ordered logit model in which the BOPEC rating is firstly predicted by the balance-sheet variables that proxy the main profiles of banking operations; the model is then extended by including equity-based indicators (i.e. abnormal return, EDFs, volatility) in order to test their significance and the potential improvement in forecasting accuracy. Econometric results reveal that volatilities and abnormal returns are both significant, however their inclusion do not appreciably improve the performance of the model.

Gunther et al. (2001) estimate an ordered probit model for determining the ability of EDFs in forecasting the level of BOPEC assignments, after supervisory data are included. Results

[4] The EDF (expected default frequency) represents the default probability of a firm in a specified time horizon.

[5] The model (System for Estimating Examiner Ratings, SEER) allows forecasting the failure of a bank two years ahead and the CAMELS rating one quarter ahead. In particular, the model used to predict CAMELS rating is estimated quarterly in order to select troublesome banks in the interval between two inspections and possibly strengthen supervisory activity.

show that, notwithstanding the significance of EDF's coefficient, the explanatory power of the model is not higher than that of the regression that only considers balance-sheet variables. The econometric exercise is then repeated using the downgrading of the BOPEC rating as the dependent variable, rather than its level; unlike the previous specification, the model including both balance-sheet and market variables shows a better forecast accuracy.

Similarly, the exercise performed by Curry et al. (2003) aims at assessing the contribution of some equity-based indicators in forecasting future BOPEC's changes as against balance-sheet and supervisory data. Using a logit model, three different specifications are estimated (including respectively balance-sheet variables, market data and finally the entire set of regressors). Furthermore, in order to capture the impact of the business cycle the sample is divided into three sub-periods: 1988-1992 (slowdown), 1993-1995 (recovery), 1996-2000 (boom).

Results are different in the three sub-samples. In expansionary and recessionary phases several balance-sheet and market variables (primarily the volatility, the abnormal return, the market leverage and turnover) are significant and their sign is correct. The specification including only market-based indicators shows a lower performance with respect to the model that considers balance-sheet and supervisory data; however, when both the subsets of variables are included the explanatory power of the regression increases. The empirical evidence is not equally clear-cut for the period 1993-1995. In a nutshell, the main findings do not allow concluding that market operators are able to catch BOPEC's changes before the supervisory authorities; nonetheless, market information seems to make the forecast more precise, at least in certain phases of the business cycle.

In order to sort out if market variables can be considered as leading indicators of banks' distress, Gropp et al. (2002) consider as a proxy of banks' fragility the rating assigned by the agencies rather than the BOPEC; given that in Europe very few banks formally declared bankruptcy, they used the downgrading of a bank to below C in the Fitch/Ibca individual rating. Unlike previous papers, they don't include control variables, since they assume that balance-sheet indicators are already incorporated in market information. By contrast, a dummy variable is considered in order to test if the likelihood of public bailouts represents an incentive for reducing market discipline.

Two equity-based indicators are used: an equity-based "distance-to-default" (*à la* Merton) and subordinated bond spreads. The main findings – based on European banks for the period 1991-2001 – show that both variables have a predictive power for bank fragility. More particularly, the distance-to-default has got good predictive power in the 6-18 months preceding the downgrading by the agencies; conversely, in the quarter prior the rating change, coefficients result significant only for the banks characterised by a low likelihood of public bailouts. On the contrary, bond spreads are able to convey some signal only when the time horizon is more limited. Again, market perception of a likely public intervention is relevant: indeed the variable is significant only for those banks, generally small sized ones, with a low probability of bailout.

Finally, the informative content of several market variables is thoroughly assessed by Baumann et al. (2003), looking specifically at the behaviour of six equity- and bond-based indicators: bond spreads, credit default swap (CDS) prices[6], equity prices (returns), implied volatilities and implied probabilities of default (PDs) – both derived from option-pricing theory – and the interest rate spread of deposit held by other financial companies over a risk free rate. The sample is made by seven major UK-owned banks, representing on a consolidated basis for more than 90 per cent of the total assets of UK banks.

Unlike equity-based measures, bond spreads and CDS prices are highly positively correlated across banks, suggesting that they are presumably more sensitive to systematic shocks and that many of the events that influence bank riskiness are common to all banks; on the contrary, real equity prices and implied PDs may be more sensitive to bank specific factors or noisier than the debt-based variables. Moreover, they find that the selected indicators rarely provide unambiguous signals during periods of stress; the provided explanation is that either the variables are sensitive to different type of information or there are some data problems, such as illiquid markets or the influence of noise trading. Finally, the econometric evidence show that market indicators move in the expected direction with contemporaneous movements in balance-sheet measures of bank risk; furthermore, bond

[6] In a CDS, debt holders pay insurance to a third party for protection in case the issuer defaults (because of his failure to repay or, alternatively, because of any other credit event as specified in the contract); the CDS price indicates the value of the swap, determined by the probability of failure of the bank and the recovery rate. With respect to bond spreads, CDs prices are easier to observe directly and to be collected.

spreads are more sensitive to macroeconomic risk than bank specific ones, whereas the reverse is for equity-based indicators.

All in all, the main findings of the recent literature are not completely unambiguous: the usefulness of different variables turns out to be strongly dependent on the specifications of the model, the hypotheses assumed on their behaviour, the width of the event window. Nonetheless, the market seems to provide a correct signal, possibly anticipating supervisors' perception, on the changes in the soundness of banks. Besides, it is worth mentioning that the empirical evidence is primarily focused on the US and UK markets; to our knowledge, there are no analyses carried out on relatively less developed markets, where the role of equity-market information might be less evident.

2. DO DIFFERENT INDICATORS PROVIDE DIFFERENT SIGNALS?

In this section we analyse the behaviour of a set of equity-based indicators for the Italian banks listed on the Milan stock exchange between 1995 and 2002; we focussed on this period mainly because until the half of the Nineties only a limited number of banks was listed on the Italian stock exchange.

In line with the pattern observed in the main industrial countries, in the last decade the Italian banking system experienced an impressive process of consolidation. Between 1990 and 2000 there were 513 concentrations, involving intermediaries representing 45 per cent of total assets. The degree of concentration of the banking system, as measured by the market share of the five largest groups, grew from about one-third up to 54 per cent; accordingly, the number of banks declined from 1,100 to 841. This process was accompanied by the privatisation of the major banks and their listing on the stock exchange; the market share of intermediaries controlled by the state or foundations fell from 68 per cent at the end of 1992 to 12 per cent in 2000.

In the same period, the Italian stock exchange has significantly developed. At the end of 2000 the capitalisation of the Italian stock market represented 70 per cent of gross domestic product, with respect to 18 per cent at the end of 1994. The capitalisation of the banking sector increased as well: its weight on total market capitalisation rose from 16.5 to 24.6 per cent. This is the result of the bullish trend observed in the financial markets of major countries in the second half of the decade and of the increased number of Italian listed banks, passed from 31 to 40. At the end of 2002 they represented about 80 per cent of the consolidated assets of the banking system[7].

Following some previous research on the Italian market, banks are classified as "big caps", "small caps", "co-operative banks" and "asset managers", according to their market value, legal status and specialisation in specific business areas[8]. Collecting the data from Datastream, we computed the following variables:

1. Equity prices; the main advantage of this variable derives from its easy availability; on the other hand, economic theory suggests that the movement of stock prices only provides with an outlook on the interest of investors to the single companies and not necessarily with a proxy of the issuer's risk profile. In other words, as mentioned in Baumann et al. (2003), "the relationship between equity prices and bank default is not clear cut; (…) this implies share prices might rise rather than fall as the riskiness of assets increase".

2. Daily returns and abnormal returns (computed as the difference between the former and the return of the index of the banking sector).

3. Historical volatility, computed as exponential moving average following the methodology suggested by RiskMetrics[9]. On a general basis, the volatility results to be higher for big caps and asset managers. On the contrary, around specific events (such as the Russian crisis in summer 1998 and the 9/11 terroristic attack) it is quite similar across all the banks and higher than the average.

4. Distance-to-default (DTD), derived from Merton's option-pricing model (1974) and widely used in the financial community to compute the probability of default of single companies within a predetermined time horizon[10]. The main idea is that equity can be

[7] Market variables, collected from Datastream, are adjusted to take into account M&A operations; balance-sheet data, derived from supervisory reports, are not adjusted except in the case of major operations.

[8] See, for instance, the semi-annual Reports on the Italian listed banks' shares by Prometeia.

[9] This volatility measure is different from the simple moving average because different weights are used in computing the standard deviation. The volatility is therefore more sensitive to recent shocks: the higher the value given to the decay factor (between 0 and 1; equal to 0.94 in this paper, as suggested by RiskMetrics), the higher the weight of past observations and, therefore, the less prompt the adjustment to more recent conditions.

[10] From an economic point of view, a company is in default when its own funds go to zero and therefore the market value of the assets is not sufficient to repay the liabilities. Therefore, the probability of default depends,

modelled as a call option on the firm with a strike price equal to the book value of the debt; therefore, option-pricing theory can be used to derive the market value and volatility of assets from the observable equity value and volatility. Given these values and defining the Default Point (DP) as the asset value below which the company is assumed to become insolvent, DTD is computed as the difference between the market value of the assets and DP with respect to the volatility of the assets (which reflects the volatility of the business of the company)[11].

A first type of signal we can derive from equity-based data is the exposure of the banking system to common risk factors, as proxied by the degree of correlation of each of the four indicators across banks: i.e. a positive and high correlation coefficient might reflect the sensitivity of all banks to risk factors of the same nature. Tab. 1 contains all the pairs of inter-bank correlation coefficients, averaged across banks.

Tab. 1

The sign of the coefficients is positive in all cases whereas the magnitude of the correlation is quite different across the variables. It is equal to 0.51 for equity prices, much lower (0.22) for returns. Unlike returns, the correlation coefficient for equity prices is presumably driven also by the long-term pattern of the stock market and the trend of consumer price index. The low value shown by the distance-to-default seems to reflect the specific characteristics of the single banks, such as leverage and the riskiness of the assets, which play a big role in the construction of the variable itself. This result is consistent with the evidence found by Baumann et al (2003).

given the stock of debts, on the future level of firm's assets, which in turn reflects the actual and perspective profitability, and its volatility. Assets' riskiness is affected by different types of risks: credit, market and operational risk. Option pricing theory enables to get the firm's value. For details, see Crosbie (1999).

[11] Gropp et al (2002) show that equity-based distance-to-default, together with subordinated bond spreads, have two desirable properties to be leading indicators of bank fragility: they are *complete* (they reflect the three main drivers of default risk: earnings expectations, leverage and asset risk) and *unbiased* (they reflect these risks correctly).

In order to assess the stability of correlation coefficients over time, we divided the whole sample in three different sub-periods, which can be broadly associated with three different phases of the Italian stock market: boom (January 1995 - June 1998), stability (July 1998 – June 2000), decrease (July 2000 – December 2002). Tab. 1 shows that daily returns and volatilities have a quite stable correlation coefficient across banks, whereas prices and DTDs show a more differentiated pattern. More specifically, equity prices of all the listed banks in our sample result very much correlated in the boom phase, unlike the decrease phase and, even more, the stability phase. Intuitively, this seems to be consistent with the idea that in presence of financial "euphoria" the market pays greater attention to common factors (i.e. macroeconomic scenarios, industry trends) whereas in other phases investors tend to be more selective in their investment decisions.

Focussing on the different categories of banks (Tab. a1, in the Appendix), "big caps" show much higher correlation coefficients for all variables, mainly because of the larger market capitalisation and higher exposure to systemic factors. A peculiar pattern characterises the behaviour of market variables for "asset managers": i.e. very high coefficients for equity prices and volatility (mainly due to the common dependence on the performance of financial markets) and lower values for returns and, to a larger extent, DTDs.

Another type of information that can be derived from market variables is the different signal conveyed by each of them; in fact, even though they are all based on equity data, they are characterised by growing complexity. We therefore examined whether movements in the four variables described above are correlated for each bank with the expected sign. Tables 2 and a2 present the correlation between any of two variables, averaged across all banks.

Tab. 2

Correlation coefficients are quite low, restricted within a range of -0.1 and +0.1. This result is consistent with the findings of similar studies and provides a confirmation that the signals conveyed by the selected variables are significantly different from each other, even though market expectations are in all cases somehow captured.

The only coefficient which results significantly different from zero is that between DTD and volatility (-0.46), in line with the economic framework behind the DTD: the higher it is equity volatility the lower the distance of the company from the default point. Similar findings can be observed for the different categories of banks. On the contrary, only for "big caps" the correlation coefficient between prices and DTD is positive whereas the correlation analysis between volatility and equity prices does not provide with unique evidence.

Overall, equity-based indicators seem to convey some hints on banks' exposure to common risk factors, especially for "big caps" and when the stock market is in a bullish phase. However, the type and the magnitude of this signal depend to a large extent on the nature of the single indicators.

3. MARKET DATA AND SUPERVISORY EVALUATIONS: A STATISTICAL ANALYSIS

In this section we analyse the relationship of some of the indicators described above with the judgements that the Bank of Italy assigns on a yearly basis to single banks (PATROL ratings).

3.1 Data description

PATROL ratings. – They represent the synthetical judgements assigned yearly to banks by the Bank of Italy; they are strictly confidential. In assigning the supervisory rating, supervisors virtually use all the relevant available information according to standardised procedures; the output of the analysis is therefore a combination of quantitative scoring and human judgement. Similarly to U.S. CAMELS, the PATROL rating system focuses on five components of the bank performance: capital adequacy (PATrimonio), profitability (Redditività), credit risk (Rischiosità), management (Organizzazione) and liquidity (Liquidità). Following this approach, both the five profiles and the overall condition of the intermediary are rated. Ratings can vary from 1 (sound banks) to 5 (distressed banks)[12].

[12] For details on the PATROL rating system, see Serata (1997) .

In this paper, we consider the PATROL rating as a benchmark, under the hypothesis that it incorporates all the relevant aspects of banks' operations. Moreover, we determine the timing of the other indicators with respect to the instant (usually September) in which supervisory ratings are assigned[13].

Market variables. – Bearing in mind the results described in the previous section, we selected the following market indicators:

- Abnormal return (AR), which is calculated as the difference between the return on the bank's shares and that of the banking index; we consider four different time windows (1, 3, 6 and 12 months from the date in which the PATROL is assigned) in order to understand the pattern of market prices prior the "event";

- Distance-to-default (DTD), calculated at t, t-3, t-6 and t-9 with respect to the "event";

- Distance-to-default (MDTD), computed as the average of the monthly DTD in the 3, 6 and 9 months before the assignment of the PATROL.

Balance-sheet data. – We selected some of the balance-sheet variables more widely employed in off-site supervisory analyses. Since analysts rely on both annual and semi-annual reports, variables are lagged by 9 months (December) and 3 months (June). The selected variables, grouped by technical profile, are listed below:

- Riskiness: bad debts / total loans (RISKST), flow of new bad debts / performing loans (RISKFL), loan losses / operating profit (LLOSS). These ratios aim at capturing respectively the overall riskiness of bank's portfolio (stock credit risk indicator), the bank's ability to select new borrowers (flow of funds credit risk indicator) and the incidence of the worsening of debtors' financial conditions on the P/L account.

- Profitability: net income / capital and reserves (ROE), net income / gross income (NETINC), income stemming from financial services / gross income (FSERVIN), operating expenses / gross income (EFFIC). These variables measure the overall

[13] Since the data on annual profit-and-loss accounts become available at the end of April (quarterly information are already available at the end of February) and the banks submit the evidence referring to the first half of the year at the end of August, the PATROL model is run in Autumn.

profitability of the bank, the contribution of the different sources of earnings to the net income (diversification) and the weight of operating costs on profitability (efficiency).

- Capital adequacy: supervisory capital / risk-weighted assets (SOLVER), tier 1 capital / risk weighted assets (TIER1R). The former allows assessing bank's capability to comply with the minimum regulatory requirements; the latter, even if not provided for by the legislation, is an indicator widely used by market operators (such as rating agencies) and increasingly included in the supervisory analyses as well.
- Size: computed as the logarithm of total assets (SIZE). It is a control variable; the log-form takes into account the potential non-linear relationship between size and supervisory judgements.

Table 3 provides a summary of the variables we considered in the analysis and the data sources we used. Although we largely relied on supervisory statistics, most of the indicators can be built up using alternative and (very often) publicly available sources.

Tab. 3

3.2 The univariate analysis

Given the relatively small number of Italian listed banks, the analysis has been carried out cross-section in order to maintain a sufficiently large number of observations. Moreover, panel techniques would have been not fully reliable since many listed banks have been involved in M&A operations in the sample period. Therefore, the time perspective has been eliminated in the analysis: the reference date is not relevant, what actually matters is the lag structure of the variables. As a consequence, a single bank can be included in the dataset more than once, i.e. at different points in time.

Tables a3 and a4 show the mean and median values of the explanatory variables grouped by PATROL class; it is worth noting that the sample size for the extreme classes (1 and 5) is quite small.

It is not surprising that the balance-sheet variables are consistent with supervisory assessments; banks with higher rating show, on average, better credit quality, higher profitability and capital adequacy levels.

In particular, among the riskiness variables, the ratio of the stock of bad debts to total loans (RISKST) increases when the PATROL rating worsens; similar evidence arises from the flow of funds riskiness indicator (RISKFL), even in presence of an ambiguous behaviour for class 3.

With reference to profitability, the return on capital and reserves (ROE) and the incidence of operational costs on gross income (EFFIC) behave as expected. It is interesting to underline that the contribution of income from services to gross income is higher for banks with a better PATROL, confirming the benefits arising from diversification of earnings. Capital adequacy indicators (SOLVER and TIER1R) essentially reflect supervisory judgements, even if with a less clear-cut pattern.

Bank's size does not seem to be a relevant factor in the assignment of PATROL ratings; however, it is worth reminding that the sample is mainly formed by medium and large sized banks.

As regards market variables, findings are more complex. In general, distance-to-defaults reflect quite clearly PATROL levels (except for classes 1 and 5): on average, the worse the supervisory ratings the lower the DTD (i.e. the distance to the default point); no significant differences arise by considering different lags. The behaviour of the average DTD is instead less clear-cut, albeit the median values are consistent with PATROL levels.

The pattern of abnormal returns is consistent with PATROL ratings when narrower event windows are considered (1 and 3 months before the event): AR1 and AR3 decrease as supervisory assessment worsens. That may reveal that equity price performance tend to some extent to anticipate the information included in the PATROL rating. By contrast, signals deriving from the abnormal returns are less clear when wider intervals are considered (6 and 12 months); this is likely the result of the higher level of "noise" they incorporate.

3.3 The econometric results

In order to verify the ability of market variables to add information beyond that available to supervisors, we estimated an ordered logit model in which the PATROL rating is the dependent variable and the balance-sheet and market-based indicators are the regressors[14]. Since PATROL ratings are assigned on an annual basis, the exercise is aimed at investigating the possibility to exploit for supervisory purposes market-based data, which are generally more timely than supervisory statistics and quicker in incorporating news, even if (presumably) less precise.

We estimated the three following models:

- $Prob(Patrol_i=k) = \alpha + \mathbf{Sb}_i\,balance\text{-}sheet\ variable + \mathbf{m}_i$
- $Prob(Patrol_i=k) = \alpha + \mathbf{Sd}_i\,market\ variable + \mathbf{m}_i$
- $Prob(Patrol_i=k) = \alpha + \mathbf{Sb}_i\,balance\text{-}sheet\ variable + \mathbf{Sd}_i\,market\ variable + \mathbf{m}_i$

where $k=2,3,4;\ i=1, 2,\dots n$

Given the substantial stickiness of PATROL ratings in the sample, we decided to use as the dependent variable the level of PATROL ratings rather than their changes (downgrading/upgrading)[15]. Therefore, in the exercise we modelled the probability to obtain a positive judgement (low PATROL).

Since the two extreme classes have been excluded because of their small size, the dependent variable may assume three values (2, 3, 4)[16].

It is worth emphasising that our model is based on a static "contemporaneous" relationship between the dependent and the explanatory market variables. Indeed, we believe that at this

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[14] For details on the logistic models and, in general, on the discrete choice models see, among the others, Maddala (1983).

[15] In fact, having too many "no change" values for the dependent variable might affect the robustness of the results. In particular, a variable might turn out to be significant just because it explains few events of supervisory rating change.

[16] As a robustness check we also estimated the model including the extreme classes. Results are not substantially different.

stage it is better to sort out which are the most meaningful market variables rather than trying to distinguish between contemporaneous and leading indicators. In other words, the model is intended to explain PATROL level rather than to forecast it.

More specifically, we estimated five different specifications of the model: we started including only balance-sheet variables (lagged by 3 and 9 months), then we considered only market-based indicators and, finally, we added the whole set of variables[17]. The most parsimonious model has been chosen via general-to-simple approach, i.e. starting from a plausible general specification and eliminating insignificant regressors at successive stages; the estimation output is reported in table 4.

Tab. 4

In specifications 1 and 2, which only include balance-sheet indicators, the three riskiness variables (RISKST, RISKFL, LLOSS) and the return on equity (ROE) are significant; by contrast, the other profitability indicators and capital adequacy ratios are not significant at all conventional levels. All the significant variables show the expected sign, except RISKFL whose behaviour was not unequivocal in the univariate analysis as well. Consistently with the evidence from the descriptive statistics, bank's size (SIZE) does not seem to have any explanatory power in the assignment of PATROL level. This result is different from the findings contained in some previous research which, however, used supervisory rating downgrading as the dependent variable; therefore, it is not astonishing that bank's size is not significant in determining PATROL level even if it is a factor that may, in principle, reduce the probability of downgradings.

As mentioned above, the assessment of balance-sheet variables is very relevant in the assignment of PATROL ratings. It is therefore not surprising that both specifications are satisfactory in terms of goodness of fit: the adjusted R-square is equal to 47 per cent when the variables are lagged by 9 months (December) and to 41 per cent when they are lagged by 3

[17] It is worth pointing out that the meaning of the numeric index associated with each variable is different for the two sets of indicators. For balance-sheet variables it reflects the lag, for market indicators it represents the time-horizon over which they are computed.

months (June). Also the value of the Goodman and Kruskal's gamma indicator is satisfactory in both the specifications (0.70 and 0.65 respectively). They have been thus used as benchmarks in order to assess the performance of the models that also include market-based data.

With reference to specification 3, that only considers market variables, we found that the coefficient of the distance-to-default is statistically different from zero whereas the abnormal return is not. This confirms that the former reflects quite accurately the bank's risk profile while the latter is reasonably affected by shareholders' incentives. The signs of the coefficients are positive (except for the average DTD): the probability to obtain favourable PATROL ratings increases as the distance-to-default rises. The value of the adjusted R-square (13 per cent) and that of the gamma (0.32) confirm that equity-based data do provide information, even though they are – as expected – less powerful than balance-sheet indicators.

Once tested the explanatory power of market information, we re-estimated the model including the two sets of variables at the same time (specifications 4 and 5), in order to verify that market indicators are not redundant and their inclusion contributes to improve the fit of the model. We found no substantial differences in the selection of the significant variables and in the signs of the coefficients; the only remarkable change is that in specification 5 the proxy for bank's size (SIZE) becomes significant at 10 per cent level with a negative sign and the flow of funds riskiness indicator (RISKFL) turns out to be not significant. The joint use of both types of variables makes it possible to significantly improve the overall goodness of fit: in specification 4 and 5 the adjusted R-square is equal to 64 and 66 per cent respectively, in line with the results achieved in previous research focussed on other countries.

Most importantly, the number of concordant pairs of observations increases (to around 90 per cent in both the specifications) as well as the gamma statistics (around 0.8), reflecting higher predictive performance of the model that includes market variables.

Some further evidence of the contribution of market-based indicators is derived from the comparison of specifications 4 and 5 with specifications 1 and 2 respectively: different tests show that the former specifications do have an higher explanatory power than the latter ones. The model that uses, beyond market variables, balance-sheet indicators lagged by 9 months results the one that better fits the data; the Akaike information criterion (AIC) and the

Schwarz's criterion (SC) are more favourable, with values significantly lower than those of the other specifications.

As regards the economic significance of the regressors, we performed an *ad hoc* analysis, given that the marginal effects of the regressors on the probabilities are not equal to the coefficients in models with discrete dependent variables.

Specifically, in order to assess the effect of a change in the explanatory variables on the PATROL probabilities, we calculated the partial derivative of the estimated probability and assumed a 10 per cent increase of each of the regressors from its median value, *coeteris paribus*. Then, given that the logistic function provides a cumulative probability, i.e. in our case the probability to obtain a PATROL score lower or equal to a specific outcome, we computed the difference between two cumulative probabilities, in order to obtain a measure of the impact that a change in one of the regressors has on the probability of having a specific PATROL score. The regressors are those resulted to be significant in specification 4. We repeated the exercise using the 10^{th} and the 90^{th} percentile as alternative starting values of the regressors.

Looking at table 5 we observe that, for instance, a 10 per cent increase of DTD determines an absolute change of 3.3 percentage points of the probability of PATROL 2.

Tab. 5

It is worth noticing that the simulated shocks on the regressors do not have a significant impact on the probability of having a PATROL equal to 4; the main reasons being that only few banks reporting such a score are included in the sample and that for these banks, as shown in Tables a3 and a4 in the Appendix, the median values are not dramatically different from better quality classes.

4. CONCLUDING REMARKS

In recent years an intense debate has developed among academics and practitioners on the potential usefulness of market-based data in improving supervisory authorities' knowledge of the intermediaries' financial conditions. Given that the bulk of previous findings primarily refer to the U.S. market, we focused on the Italian equity market and selected the banks listed on the Milan stock exchange between 1995 and 2002; at this stage we did not analyse bond spreads.

In principle, it is possible to build up several market-based indicators according to the different availability and frequency of the data. They generally differ in complexity and result to provide different information on the market perception of the bank's riskiness: of course there is an understandable trade-off between timeliness and accuracy. In fact, the descriptive analysis clearly showed that different indicators do provide different information on bank's exposures to either idiosyncratic or common risks. On the one hand, consistently with economic theory stock prices are scarcely able to reflect the evolution of bank's riskiness, furthermore they are excessively affected by market trends and the evolution of consumer prices. On the other, the distance-to-default based on the option pricing theory seems to be a variable well suited for catching bank's specific riskiness.

This evidence has been confirmed by the comparison of equity-based variables with the supervisory ratings assigned each year by the Bank of Italy (PATROL ratings). DTD is basically consistent with supervisory ratings; on the contrary, equity returns provide reliable insights only when they refer to time windows close to the supervisory assignment while they are more "noisy" for wider time horizons, making their interpretation more difficult.

Econometric results confirmed the informative content of equity-based variables and their complementarity with supervisory information: they provide with a picture of the intermediary's soundness which, even if less accurate, is more easily and frequently available. In the various specifications we estimated to capture PATROL level, market indicators turned out to be highly significant and showed the expected sign; furthermore, they contributed to improve the performance of the model.

In sum, our analysis presents some first evidence for Italy of the usefulness of market information for supervisory purposes. Monitoring the evolution of equity markets may therefore represent a valuable tool for supervisors in order to acquire some preliminary data on the changes of the risk profile of listed banks, before the ordinary supervisory statistics become available. In a macro-prudential perspective, this might enrich the assessment of financial stability.

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Table 1

Correlation across banks

Pairs of inter-bank correlation coefficients, averaged across banks

Period	**Prices**	**Returns**	**Volatility**	**DTD**
1995 - 2002	0.51	0.22	0.43	0.28
1.1995 - 6.1998	0.83	0.22	0.47	0.1
7.1998 - 6.2000	0.21	0.21	0.46	0.17
7.2000 - 12.2002	0.38	0.23	0.43	0.3

Table 2

Correlation across indicators

Correlation between variables, averaged across banks

	DTD	Prices	Returns	Volatility
DTD	1	-0.06	-0.04	-0.46
Prices		1	0.13	0.11
Returns			1	0.08
Volatility				1

Table 3

SELECTED VARIABLES

VARIABLE	Description	Source	Publicly available?
AR	abnormal return (return over bank index)	Datastream	YES
DTD	distance-to-default	Datastream	YES
MDTD	average distance-to-default	Datastream	YES
RISKST	bad debts / total loans	Supervisory statistics	YES
RISKFL	flow of new bad debts / performing loans	Supervisory statistics	NO
LLOSS	loan losses / operating income	Supervisory statistics	YES
ROE	net income / (capital + reserves)	Supervisory statistics	YES
NETINC	net income / gross income	Supervisory statistics	YES
FSERVIN	financial services income / gross income	Supervisory statistics	YES
EFFIC	operating expenses / gross income	Supervisory statistics	YES
SOLVER	supervisory capital / risk weighted assets (including market risk)	Supervisory statistics	YES
TIER1R	tier1 capital / risk weighted assets (including market risk)	Supervisory statistics	YES
SIZE	natural logarithm of total assets	Supervisory statistics	YES

Table 4

Ordered Logistic Estimation

In all the specifications, the dependent variable (PATROL) may assume three values since we excluded the two extreme classes; we estimated the probability to get a positive evaluation (low PATROL). For each model, the most parsimonious specification has been choosen by the general-to-simple approach.

EXPLANATORY VARIABLES	EXPECTED SIGN	Specific. 1: Balance sheet t-9			Specific. 2: Balance sheet t-3			Specific. 3: Market			Specific. 4: Balance sheet t-9 and market			Specific. 5: Balance sheet t-3 and market		
		coeff.	Wald test	sign.	coeff.	Wald test	sign.	coeff.	Wald test	sign.	coeff.	Wald test	sign.	coeff.	Wald test	sign.
intercept 1		0.60	0.53		1.51	5.52	**	0.58	3.89	**	1.26	1.22		7.01	4.09	**
intercept 2		4.63	18.28	***	5.22	37.34	***	3.19	51.69	***	5.90	15.87	***	11.32	9.45	***
BALANCE SHEET VARIABLES																
RISKST9	-	-0.18	3.53	*							-0.47	7.95	***			
SOLVER9	+															
SIZE9	+/-															
RISKFL9	-	0.10	5.92	**							0.13	6.00	**			
EFFIC9	-															
LLOSS9	-	-0.05	10.47	***							-0.07	10.41	***			
ROE9	+	0.15	5.07	**							0.19	5.12	**			
FSERVIN9	+															
RISKST3	-				-0.32	16.41	***							-0.44	12.64	***
SOLVER3	+															
SIZE3	+/-													-0.39	3.16	*
RISKFL3	-				0.05	4.23	**									
EFFIC3	-															
LLOSS3	-				-0.05	6.64	***							-0.06	5.09	**
ROE3	+				0.06	3.00	*							0.22	12.06	***
FSERVIN3	+															
MARKET VARIABLES																
DTD	+							0.18	3.38	*	0.43	7.43	***	0.47	7.99	***
DTD3	+															
DTD6	+															
DTD9	+							0.43	10.92	***	0.69	5.98	**	0.56	8.91	***
MDTD3	+															
MDTD6	+													-0.83	13.16	***
MDTD9	+							-0.64	15.95	***	-0.81	7.62	***			
AR1	+															
AR3	+															
AR6	+															
AR12	+															
Nr. observations			128			153			160			110			126	
AIC			173.58			219.64			266.10			123.77			144.61	
SC			190.69			237.82			281.48			148.07			170.14	
-2 log max likelihood			161.58			207.64			256.10			105.77			126.61	
Adjusted R^2			0.47			0.41			0.13			0.66			0.64	
% Concordant			84.90			82.30			64.30			89.90			89.60	
% Discordant			14.90			17.50			33.30			10.10			10.30	
Gamma			0.70			0.65			0.32			0.80			0.79	

Notes:

*, **, *** significant at 10, 5 and 1 per cent level respectively.

Wald test has a Chi-square distribution.

A pair of observations with different values of the dependent variable is concordant if the observation with the lowest value (best PATROL rating) shows the highest event probability; otherwise, the pair of variables is discordant. A pair of observations may be neither concordant nor discordant. Goodman and Kruskal's gamma indicator measures ranks' correlation between the observed ratings and predicted probabilities.

Table 5

Sensitivity analysis

Effect of a 10% regressor increase on estimated probabilities. Absolute changes of the probability to be classified in a given PATROL class are reported (percentage values).

Variable	Starting value	PATROL class 2	3	4
RISKST9	*P10*	-1.6287	1.5968	0.0319
	P50	-4.6257	4.4842	0.1415
	P90	-7.1817	7.0533	0.1284
RISKFL9	*P10*	0.1115	-0.1094	-0.0022
	P50	0.3068	-0.2973	-0.0095
	P90	2.5129	-2.4680	-0.0449
LLOSS9	*P10*	-0.8677	0.8507	0.0170
	P50	-3.1329	3.0372	0.0958
	P90	-6.7858	6.6645	0.1213
ROE9	*P10*	1.4981	-1.4688	-0.0294
	P50	3.8779	-3.7593	-0.1186
	P90	6.0849	-5.9761	-0.1088
DTD	*P10*	0.0000	0.0000	0.0000
	P50	3.3384	-3.2363	-0.1021
	P90	6.6297	-6.5111	-0.1185
DTD9	*P10*	0.0000	0.0000	0.0000
	P50	5.1841	-5.0256	-0.1586
	P90	8.0370	-7.8934	-0.1437
MDTD9	*P10*	0.0000	0.0000	0.0000
	P50	-7.4937	7.2645	0.2292
	P90	-9.8009	9.6258	0.1752

APPENDIX

Table a1

Correlation across banks by different kinds of banks

Pairs of inter-bank correlation coefficients, averaged across banks

Period	Prices	Returns	Volatility	DTD
	BIG CAPS			
1995 - 2002	0.8	0.48	0.77	0.59
1.1995 - 6.1998	0.93	0.45	0.56	0.66
7.1998 - 6.2000	0.38	0.44	0.78	0.97
7.2000 - 12.2002	0.87	0.81	0.77	0.33
	ASSET MANAGERS			
1995 - 2002	0.82	0.32	0.77	0.03
1.1995 - 6.1998	0.85	0.12	0.71	0.09
7.1998 - 6.2000	0.84	0.17	0.67	0.08
7.2000 - 12.2002	0.85	0.46	0.76	0.01
	SMALL CAPS			
1995 - 2002	0.79	0.18	0.33	0.26
1.1995 - 6.1998	0.9	0.21	0.48	0.23
7.1998 - 6.2000	0.16	0.2	0.37	0.35
7.2000 - 12.2002	0.22	0.12	0.32	0.17
	COOPERATIVE BANKS			
1995 - 2002	0.63	0.24	0.5	0.45
1.1995 - 6.1998	0.78	0.29	0.65	0.6
7.1998 - 6.2000	0.38	0.25	0.42	0.32
7.2000 - 12.2002	0.64	0.25	0.48	0.41

Table a2

Correlation across indicators by different kinds of banks

Correlation between variables, averaged across banks

	DTD	Price	Return	Volatility
		BIG CAPS		
DTD	1	0.27	-0.01	-0.55
Price		1	0.12	-0.22
Return			1	0
Volatility				1
		ASSET MANAGERS		
DTD	*1*	*-0.03*	*0.017*	*-0.25*
Price		1	0.1	0.13
Return			1	0.23
Volatility				1
		SMALL CAPS		
DTD	1	-0.25	-0.11	-0.6
Price		1	0.11	0.37
Return			1	0.18
Volatility				1
		COOPERATIVE BANKS		
DTD	1	-0.25	-0.04	-0.38
Price		1	0.16	0.22
Return			1	0
Volatility				1

Table a3

BALANCE SHEET INDICATORS:
by PATROL rating classes

		PATROL				
VARIABLE		**1**	**2**	**3**	**4**	**5**
RISKST3	Mean	0.14	3.71	5.90	11.41	33.50
	Median	0.14	3.41	5.71	10.99	33.33
RISKST9	Mean	0.01	3.90	6.40	10.93	30.39
	Median	0.01	3.79	5.98	10.86	31.54
RISKFL3	Mean	0.17	3.72	2.78	5.21	10.88
	Median	0.17	0.95	1.29	1.72	4.18
RISKFL9	Mean	0.07	2.57	2.42	4.90	8.12
	Median	0.07	0.87	1.31	1.80	4.43
LLOSS3	Mean	1.74	11.90	22.29	36.15	22.28
	Median	1.74	11.17	19.95	29.36	0.00
LLOSS9	Mean	14.22	15.62	28.09	69.81	52.82
	Median	14.22	14.45	25.97	76.18	87.70
ROE3	Mean	20.67	15.10	7.85	3.32	0.00
	Median	20.67	11.07	6.09	2.32	0.00
ROE9	Mean	11.60	11.09	6.31	3.65	0.00
	Median	11.60	8.85	5.76	2.37	0.00
NETINC3	Mean	26.43	21.59	14.15	4.30	15.82
	Median	26.43	18.41	12.39	2.48	0.00
NETINC9	Mean	20.55	19.30	12.97	5.27	0.00
	Median	20.55	15.38	10.11	3.37	0.00
FSERVIN3	Mean	63.93	49.73	38.66	35.18	31.22
	Median	63.93	45.11	35.99	34.07	20.95
FSERVIN9	Mean	58.60	46.53	35.15	32.42	37.96
	Median	58.60	42.06	34.07	32.80	30.03
EFFIC3	Mean	35.46	52.82	59.68	67.50	65.48
	Median	35.46	55.51	62.67	62.53	81.30
EFFIC9	Mean	42.50	55.29	62.01	73.34	80.89
	Median	42.50	58.61	64.08	69.24	84.90
SOLVER3	Mean	14.82	16.18	14.89	8.93	9.12
	Median	14.82	13.13	13.09	7.95	8.85
SOLVER9	Mean	16.75	16.78	14.17	9.14	9.25
	Median	16.75	13.60	12.82	8.41	9.25
TIER1R3	Mean	11.30	13.00	11.74	6.18	5.78
	Median	11.30	10.44	9.15	5.12	6.05
TIER1R9	Mean	12.50	13.47	11.29	6.54	6.19
	Median	12.50	10.37	9.09	5.18	6.19
SIZE3	Mean	16.62	15.75	15.72	16.72	15.62
	Median	16.62	15.81	15.63	16.70	15.60
SIZE9	Mean	16.59	15.68	15.70	16.73	15.67
	Median	16.59	15.77	15.63	16.66	15.72
Nr. observations		***2***	***102***	***88***	***11***	***5***

Table a4

MARKET INDICATORS
by PATROL rating classes

		PATROL				
VARIABLE		**1**	**2**	**3**	**4**	**5**
AR1	Mean	0.34	2.01	2.20	-0.44	-4.78
	Median	0.34	0.98	0.21	1.23	-1.50
AR3	Mean	4.45	5.42	4.16	3.11	-8.05
	Median	4.45	5.53	2.03	4.35	-9.50
AR6	Mean	16.03	2.83	2.35	2.48	-25.48
	Median	16.03	2.57	2.03	0.04	-25.92
AR12	Mean	-7.96	7.31	-0.58	9.84	-2.79
	Median	-7.96	2.87	-3.97	13.97	8.98
DTD	Mean	1.99	3.00	2.75	2.42	1.25
	Median	1.99	2.79	2.12	2.15	1.19
DTD3	Mean	3.24	3.45	3.32	3.65	2.38
	Median	3.24	3.45	3.58	3.31	2.74
DTD6	Mean	2.51	2.75	2.63	2.26	1.58
	Median	2.51	2.91	2.26	1.78	1.49
DTD9	Mean	2.97	3.12	2.61	1.66	1.43
	Median	2.97	3.06	2.58	2.08	1.29
MDTD3	Mean	3.13	3.30	3.27	3.36	1.78
	Median	3.13	3.54	3.22	2.60	1.99
MDTD6	Mean	3.15	3.13	2.98	3.37	1.85
	Median	3.15	3.34	3.17	2.85	2.01
MDTD9	Mean	3.04	3.02	2.87	2.92	1.56
	Median	3.04	3.07	2.79	2.68	1.74
Nr. observations		***2***	***102***	***88***	***11***	***5***