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Abstract:

This paper conducts an empirical assessment of the theories stating that ownership concentration improves the quality of shareholders' monitoring. In contrast with other studies, we do not use regressions of risk/performance on ownership concentration. Instead, we build an early warning model of bank distress that includes a leading indicator derived from banks' share price, the Merton-KMV distance to default (DD). The significance of this indicator depends on the efficacy of shareholders' monitoring. On a sample of European banks, we show that the predictive power of the DD is satisfactory only when banks' shareholding is characterized by the presence of blockholders.

Key Words :

Monitoring
Ownership concentration
Block ownership
Bank distress
Early warning models
Distance to default

JEL : G21, G32, G34, E44, E58

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1. Introduction, literature review and theoretical foundations

The quality of the monitoring implemented by bank security holders has been seriously called into question by the recent financial turmoil. This apparent failure of market discipline to prevent the massive accumulation of bad assets in the banking system is a challenge for supervisory policies. Indeed, it brings into question the possibility of extracting accurate leading indicators of bank fragility from equity and bond prices. In theory, prudential supervisors can exploit market information if at least three conditions are fulfilled (see, e.g., Flannery 2001; Bliss and Flannery 2002; Borio et al 2004; Gropp et al 2006): 1) shareholders and debtholders spend resources in monitoring banks; 2) they transmit the information gathered to the securities market; 3) their influence on the board's decisions is imperfect, i.e. does not lead to an immediate correction of the strategy. Conditions 1) and 2) ensure that monitoring investors identify any excessive risk taken by a bank and that they consequently sell some of their claims or transmit the information to the financial market by any other possible channel (e.g. proxy fights revealing their disagreement in shareholders' meetings). Condition 3) implies that the bank's share and bond prices stay at a lower level as long as the excessive risk is not wiped out. Hence, supervisory authorities can observe banks' securities prices and use them as leading indicators to implement corrective actions.

Of course, it is widely acknowledged that this market-derived information remains incomplete and can only be used as a complement to other sources (such as accounting reports, ratings or in-site supervisory monitoring). Bank assets are partially opaque to outside shareholders and creditors, who therefore have an incentive to delegate the task of monitoring and screening to the bank staff (see, e.g., Diamond 1984; Freixas and Rochet 1999). Another possible shortcoming of market signals is that an increase in banks' share prices may not always indicate a reduction of their risks because shareholders sometimes benefit from higher risk-taking. Indeed, when the failure probability is already high, the option value outweighs the charter value and shareholders therefore prefer risky strategies (see, e.g., Merton 1977; Keeley 1990; Park 1997; Anderson and Fraser 2000; Park and Peristiani 2007). Hence, close to the default point, it is better to use subordinated debt spreads as leading indicators rather than potentially misleading share prices. Further away from the default point, the use of a share price-derived indicator is possible. However, it is more cautious to use indicators that do not rely purely on the price but also take into account the level of debt and the volatility of bank assets (e.g., the distance to default or the z-score). Finally, another well-known weakness of market discipline is that holders of bank claims may not invest enough in monitoring because of the moral hazard generated by the safety net, the "too big to fail" effect and the substitution of regulatory discipline to market discipline (see, e.g., Sironi 2003; Imaï 2006; Gropp et al 2006, DeYoung et al 2001).

These three possible shortcomings of market signals (opacity, option value effect and moral hazard due to the safety net) have been extensively discussed in the literature. The conclusion is generally that they do not impede the use of market signals as leading indicators of bank distress. Indeed, econometric early warning models can control for the opacity effect using accounting variables. They can also use non-ambiguous market indicators such as distances to default or bond spreads, and introduce control variables accounting for the "too big to fail" and the safety net effects (see, e.g., Gropp et al 2006; Distinguin et al 2006; Curry et al 2007[1]).

In the present paper, we focus on a fourth factor potentially affecting the accuracy of the share price signal as a leading indicator of bank fragility. Banks' ownership structures generate various incentive schemes that influence the quality of shareholders' monitoring and, consequently, the informational content of banks' security prices (see, e.g., Tirole 2006). We contend that it is necessary to consider this ownership effect in early warning models of bank distress using share price-derived indicators because the latter may lose much of their predictive power for certain ownership structures. Some recent empirical papers have addressed the impact of ownership structures on value creation[2] or bank risk-taking[3] but, as far as we know, this is the first paper to deal with the impact of banks' ownership concentration on the accuracy of leading indicators of bank distress derived from share prices.

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[1] Other studies showing the predictive power of market signals as leading indicators of bank distress can be found, e.g., in Berger et al (2000), Gunther et al (2001), Sironi (2003), and Krainer and Lopez (2004).

[2] Empirical studies on the impact of ownership concentration on corporate performance obtain divergent results. For example, Demsetz and Villalonga (2001) study a sample of 223 US firms and find no significant relation between ownership structure and performance. They explain this result and the contradictory findings of previous studies by the endogeneity of ownership (see also Demsetz, 1983). On the contrary, Chen et al (2007) do find that concentrated ownership has a positive influence on post-merger performance but they also show that it is true only when the large owner is an independent institution with long term investments. In the banking domain, the two empirical studies on ownership and banks' performance that we know of also obtain divergent results: Iannotta et al (2007) do not find any significant effect of ownership concentration on the profitability of European banks. Meanwhile, Caprio et al (2007) study a panel of 244 banks across 44 countries around the world and show that banks' valuation is positively influenced by the concentration of cash flow rights and, to a lesser extent, by the concentration of control rights.

[3] The impact of ownership structures on bank risk-taking is still controversial. For instance, Anderson and Fraser (2000) find that outside blockholders have limited influence on bank risk-taking. Iannotta et al (2007) show that ownership concentration has a negative impact on risk-taking in European banks. Similarly, in a study of US state-chartered banks, Sullivan and Spong (2007) find that risk falls when bank owners and managers have more of their wealth concentrated in the banks. On the contrary, Laeven and Levine (2009) find in their worldwide study that the presence of large shareholders increases the level of

There is real support for this idea in the theoretical literature. The ground-breaking work of Berle and Means (1932) and Jensen and Meckling (1976) has opened an important research area concerning the separation of ownership and control in the modern corporation. One of the most important questions in this field is whether dispersed rather than concentrated ownership leads to a better monitoring of managerial strategies and, consequently, to a higher level of value creation and to a superior informational content of securities prices. Fama (1980) and Fama and Jensen (1983), argue that dispersed ownership by well-diversified portfolio investors is the best disciplining structure because it facilitates the trading of shares in response to managerial strategic decisions and, thus, creates a market for outside takeovers providing "discipline of last resort". On the other hand, Grossman and Hart (1980) show that ownership dispersion can raise a free-rider problem preventing takeover threat from being an efficient disciplinary mechanism. In their model, shareholders are discouraged from devoting resources to monitoring because everybody will freely benefit from this informational public good. The informational content of stock prices tends to be lowered if this free-riding problem is not solved. Shleifer and Vishny (1986) demonstrate that large shareholders can overcome this difficulty because they internalize the benefits from monitoring in proportion to their own shares and because the monitoring costs are lower for them. Holmström and Tirole (1993) argue that ownership dispersion increases the liquidity of a firm's share. Thus, informed investors can more easily benefit from their monitoring effort since they are able to hide their transactions behind those of liquidity traders (see also Bolton and von Thadden 1998). Nevertheless, Holmstrom and Tirole (1993) and Tirole (2006) argue that the information extracted by these informed speculative traders is only retrospective because they do not interact enough with the board to gather strategic information about the future course of action to be followed by the firm. Prospective information can only be acquired by active investors holding a sufficient stake in the firm so that they can bear the cost of information, keep themselves informed of strategic adjustments and, if relevant, influence the course of managerial decisions[4].

bank risk-taking. More recently, Barry et al (2010) study a sample of European commercial banks and find that changes in ownership structure do not affect risk-taking for publicly held banks whereas they do for privately held banks.

[4] Kahn and Winton (1998) emphasize that large investors can be doubly rewarded for their active monitoring effort: if their intervention improves the corporate strategy, it will have a direct positive impact on the value of their equity stake; and if the market undervalues the future performance of the firm, they can buy additional shares and make a speculative profit from their prospective information. However, if the stock market already anticipates the higher performance of the firm, large shareholders are then tempted not to intervene and to sell their stake ("cut and run" strategies). Similarly, Burkart et al (1997) show that too strong a monitoring by large shareholders can have a negative impact on value creation because it reduces managerial initiative and non-contractible investments. Another reason why monitoring by large shareholders may not improve

To summarize, corporate governance theories predict that large shareholders have an informational advantage allowing them to collect prospective and strategic information. They also show that this prospective monitoring is value-enhancing. However, they acknowledge that various factors may counteract its positive effects: reduction of managerial initiative, “cut and run” strategies, and illiquidity discounts in the shares’ price. The only unequivocal empirical prediction is that large shareholders are better informed and that their information will have a more or less rapid influence on market prices. This suggests the desirability of testing whether a firm’s stock price contains more forward-looking and firm-specific information in the presence of large shareholders. As far as we know, there are only a few empirical studies dealing with this point in a general multi-industry context (see, e.g., Brockman and Yan 2009), and there are none applied to the banking sector. It is quite surprising if we consider the importance of the issue for prudential supervision: if banks’ ownership structures can alter the predictive power of leading indicators of bank distress derived from share prices, early warning models of bank distress may be misleading in some cases. Therefore, we propose to test the following prediction:

Prediction 1. Large shareowners are better than small shareowners at collecting prospective and strategic information about the firms they have invested in. Their superior information eventually has an influence on the share prices of these firms. Consequently: *i) share price-derived leading indicators of bank fragility will be more accurate in the context of concentrated ownership and will lose their predictive power for widely held banks; ii) early warning models of bank distress including such indicators will perform better when the banks under supervision have a concentrated rather than a dispersed ownership; iii) the ability to predict financial recovery rather than distress may also be impaired by ownership dispersion.*

If this prediction was validated with our banking sector data, this would provide evidence for the informational advantage of large shareowners and their ability to transmit superior information to the stock market. Conversely, small shareholders of banks with dispersed ownership would appear to be short of relevant information to evaluate the banks’ financial health accurately. Consequently, rating downgrades should be new information to them and the share prices of banks with dispersed ownership

corporate market valuation is the monitoring/liquidity trade-off stressed by Holmstrom and Tirole (1993) and evidenced by Gaspar and Massa (2007).

should react to these downgrades more strongly and more negatively, at least as long as this informational gap persists[5]. An event study addresses this issue in the section dedicated to robustness tests.

For reasons already outlined hereinbefore, the share price-derived leading indicator we opt for is the Merton-KMV distance to default. To test Prediction 1, this indicator is incorporated into an early warning model of bank distress similar to the one proposed by Gropp et al (2006). We use this model as a benchmark and then introduce various dummy variables to account for the impact of banks' ownership concentration on the predictive power of the distance to default. The regressions are implemented on quarterly data over the period 1997-2005 with a discrete time survival model using a complementary log-log function to estimate the hazard rate. The dependent variable is either the probability of a serious downgrade of banks' financial rating or the probability of an upgrade to a level signalling financial recovery. It is regressed on two types of predictors computed several quarters in advance of the event. The first one is a set of CAMEL accounting ratios[6]. The second one is the Merton-KMV distance to default (DD). We implement a full set of robustness tests and find that the predictive power of the distance to default is significantly lower in the case of dispersed ownership than in the case of concentrated ownership for both downgrades and upgrades. We then conduct an event study of rating downgrades and show that share prices of banks with dispersed ownership react much more strongly and more negatively than those of other banks.

Performing these tests requires the use of five data sources[7]. The main difficulty is to find reliable, detailed and frequently updated ownership data. The Thomson One Banker Ownership (TOBO) database provides such data for European banks. We prefer TOBO's ownership data to Bankscope's because the updating frequency is quarterly in the former while it is only yearly in the latter. We match these ownership data with others from Datastream and Bankscope, and obtain a sample of listed European banks on which we have sufficient information to estimate our early warning model. For the event study, we use the FitchRatings web site and the Dow Jones Factiva business news database to

[5] We thank the referees for this suggestion.

[6] The CAMEL acronym means Capital adequacy, Asset quality, Management soundness, Earnings and profitability, Liquidity. Econometric models of bank distress usually integrate various accounting ratios to estimate the impact of the level of capital, the quality of the assets, the performance of the management team, the profitability and the liquidity of the bank. An "S" is sometimes added (CAMELS) when the data contain a measure of sensitivity to market risks. For recent studies using such indicators see, e.g., Männasoo and Mayes (2009); Curry et al (2007); Gropp et al (2006); Distinguin et al (2006).

[7] We also extracted data from the World Federation of Exchanges' website to compute the annual capitalization and turnover velocity of the stock-markets where our banks have their shares listed.

identify the days of the downgrades and to detect the confusing events that happen in the estimation and event windows.

The paper is organized as follows: in section 2 we describe our database, the construction of variables and the empirical methodology. The results are presented and discussed in section 3. Econometric robustness is assessed in section 4. Section 5 concludes the paper.

2. Data and empirical testing issues

2.1. Sample construction

We first collect in the BankScope database European banks for which accounting ratios are available at list four years between 1997 and 2005. We then select those for which a stock price is available in Datastream and a Fitch credit rating can be found in BankScope. At this stage, we obtain a sample of 84 banks. In order to compute reliable distances to default, we delete three banks whose stocks are not sufficiently traded[8]. We merge this data set with the Thomson One Banker ownership (TOBO) database where we find reliable ownership indicators updated quarterly over the period 1997-2005. The ownership information is available for 76 of these 81 banks. This number of banks is very similar to other comparable studies on European listed banks: Iannotta et al (2007) work on a sample of 181 large European banks from which they make a subsample of 74 listed banks. Gropp et al (2006) use a sample of 86 listed banks and Distinguin et al (2006) work with a sample of 64 listed banks. In fact, the lists of banks are very similar in all these studies, including ours.

Our final sample is an unbalanced panel of 36 quarters over the period 1997-2005, with a maximum of 2736 banks/quarters observations. The banks are localized in 18 European countries (Table 1) and eleven among them belong to the Euro Zone. The Bankscope and Datastream databases are well known and widely used. From Bankscope, we mainly use consolidated accounts except in a few cases in which they are not available. As far as we know, the TOBO database is the best source for European ownership structures. TOBO includes Worldscope, which is used in most international studies (see, e.g., La Porta et al 1999; Claessens et al 2000; Faccio and Lang 2002; Kho et al 2009), and is completed by Thomson's team with other specific local databases, annual reports, company-issued statements, legal schedules and so on. We carefully checked data consistency using banks' annual reports.

[8] Less than one thousand of their stocks are exchanged per day in more than 25% of the trading days.

Table 1 shows the bank types of our sample: there are 52 commercial banks, ten bank holding companies, six savings banks, three investment banks & securities houses, two cooperative banks, two real estate & mortgage banks and one medium & long term credit bank. Nevertheless, bank types are to be considered cautiously for European banks since commercial banks are in fact universal banks in many cases (see, e.g., Vander Vennet 2002).

PLEASE INSERT TABLE 1

Obviously, the stock-listed and Fitch-rated banks we study are bigger than most of the European banks present in Bankscope since they have an average market capitalization of 15 billion euros by the end of 2005, and an average total asset of 150 billion euros by the end of 2005. Therefore, our sample only represents the biggest and most actively traded European banks. Nonetheless, this is not a major limitation since we focus on the prevention of systemic risk, which is mainly located in this kind of bank. Furthermore, it is extremely difficult to build an early warning model of bank fragility without any rating, and impossible to introduce a stock price-derived leading indicator with non-listed banks.

2.2. Variables and descriptive statistics

Since bank bankruptcies are very rare events in Europe over the period under study, we consider a downgrade of the Fitch/IBCA Individual Rating to C or below as a proxy for bank distress, and an upgrade to B/C or above as a proxy for recovery. The Fitch agency provides several types of ratings ("Long-term", "Short term", "Individual" and "Support" ratings) for each monitored bank. We use the Individual Rating because it reflects the intrinsic situation of the bank, regardless of the financial profile of the holding it may be related to and without consideration for the potential support of supervisory authorities. The notation ranges from A (the best mark) to E (the worst) and can be revised at any moment. We build a dependent variable equal to 1 when the Fitch/IBCA Individual Rating of the bank becomes C or below, and equal to 0 otherwise. We test the same early warning model for upgrades, with a dependent variable equal to 1 when the Fitch/IBCA Individual Rating of the bank becomes B/C or above. We also consider the 'Support Rating' describing the intensity of the public support a bank can benefit from. This rating is used to control for Too-Supported-To-Fail effects. Gropp et al (2006) provide convincing arguments to support the use of such rating-based proxies. They show that all the rating downgrades in Europe are followed by injection of public or private funds, by a public or parent guarantee or by a major restructuring of the bank's operations. As far as we could see from the Dow Jones Factiva business news database, similar events happen to our downgraded banks. Table 2 beneath reveals that, in our sample, usable downgrades to C are fairly rare events (15 usable downgrades to C or below). Indeed, since we use lagged independent variables as leading indicators of future downgrades, it implies that banks already downgraded when entering the sample in 1997 are excluded from the estimations. In addition, severely downgraded banks do not get out of the Bankscope database because formal bankruptcy never happens. This may lead to overestimate the predictive power of the covariates since, when they are used as leading indicators, we correlate a downgraded rating of a given date with covariates known at an earlier date when the bank was already downgraded. It is therefore necessary to drop the severely downgraded banks immediately after the rating change, and to reintroduce them if they are upgraded in the sequel. The resulting distribution of the dependent variable is therefore highly asymmetrical. That is why we choose a complementary log-log function as the functional form for the hazard rate and compare the results with simple logit and probit models.

PLEASE INSERT TABLE 2

Upgrades to B/C or above are more frequent events since there are 31 usable upgrades to B/C or above in our sample (Table 2). We construct the early warning model for upgrades with exactly the same methodology and variables. It is a good robustness test and it is interesting in itself to assess the predictive power of the DD for upgrades. The prediction of good news is also an important issue for supervisors because it may allow scarce examination resources to be re-allocated away from banks that are recovering[9].

To implement the test of Prediction 1, we need to build an early warning model in which the probability of a severe downgrade is predicted by a share price-derived leading indicator. We also need to integrate the accounting information to give a picture of the financial situation of the bank. Moreover, we have to introduce numerous control variables accounting for the size of the bank, the potential public support in case of distress, the duration dependence of the rating change probabilities, the liquidity of stock markets, and the identity of block shareholders.

Concerning the stock price-derived indicator, we have already explained in the introduction why it is better to use a measure that takes into account the leverage of the bank and the volatility of its assets.

[9] We thank the editor for suggesting this test.

The distance to default (DD) appears to be particularly relevant for this purpose because it is computed with the implied asset value and volatility. It is defined as the number of standard deviations of the implied asset volatility that separate the firm from its default point in which the (implied) asset value equals the debt value[10]. This indicator reflects the three major determinants of default risk (value of assets, indebtedness, and volatility of assets). Moreover, the default probability is unambiguously decreasing in the DD while it can be increasing in the value of equity when the option value outweighs the charter value (see, e.g., Park and Peristiani 2007). The DD is computed monthly and converted to a quarterly frequency afterwards, using the mean of the monthly DD. The inputs used to compute the distance to default are the total market capitalization taken from Datastream, the level and maturity of the debt from Bankscope, and the historical volatility of the stock price. The latter is computed with the daily returns on a moving window of six months. We use the KMV standard for the definition of debt, i.e. the sum of the short-term debt and half the long-term debt. The debt available in Bankscope is updated yearly, semi-yearly or quarterly but we do not interpolate it because this would lead us to use the future level of debt in the computation of the current DD, which could possibly generate overestimation of its predictive power (Distinguin et al 2006).

To describe the financial situation of each bank, we use accounting ratios from Bankscope. In this database, several competing ratios are proposed for each of the six C.A.M.E.L. indicators (Capital adequacy, Asset quality, Management soundness, Earnings, and Liquidity). For each indicator, we retain the ratios with the largest number of observations over the period under study. The ratios selected are: capital funds over assets (C), loan loss provisions over net interest revenue (A), costs over income before provisions (M), return on average equity (E) and liquid assets over deposits and short term borrowings (L). Capital funds means equity + hybrid capital + subordinated debt. The return on average equity is preferred to a classic return on equity in order to minimize the volatility of this indicator. It is

[10] Several studies have shown that this indicator provides additional information to traditional financial ratios. Many are applied to the US banking system, for instance Gunther et al (2001), Krainer and Lopez (2003), Curry et al (2007). In the European case, Gropp et al (2006) show that the distance-to-default has predictive power for bank fragility up to 18 months before the "failure" event, even when they control for the safety net effect and include a synthetic measure of the CAMEL indicators. Nevertheless, Distinguin et al (2006), who also worked on European banks but with a different definition of the downgrade event, found that a stepwise regression procedure always conduct to prefer a stock price indicator (the difference between the natural logarithm of the stock price and its moving average on 261 days) to the DD.

calculated over a period of two years. The liquidity ratio is interpolated or extrapolated to replace 122 missing values (an average of 1.6 missing quarters per bank)[11].

The size of a bank can affect directly its distress probability because a bigger bank is stronger in front of adverse shocks and can finance itself more easily. Similarly, a bank with explicit or implicit public support can benefit from better financing conditions and thus have a lower distress probability. Moreover, moral hazard may induce shareholders to lower their monitoring effort if they think that the bank will be supported by public authorities in case of financial distress. We have to account for these effects in the regressions. We measure the size of each bank with the total asset at book value (TOTASSET) and also use as an interaction term a dummy DBIG equal to one when a bank's total asset is greater than the median. To measure the intensity of public support, we use the 'support ratings' provided by the Fitch Ratings agency[12]. We create a dummy variable DSUPP equal to one when the Fitch/IBCA Support Rating is one or two (highly supported banks) and equal to zero when the Fitch/IBCA Support Rating is three, four or five. Table 3 shows that 62% of the banks are highly supported, which is not surprising since we are studying large quoted banks. Moreover, in our sample, 30% of 'highly supported' banks are 'small' banks with assets below 630 million euros, whereas more than 14% of 'weakly supported' banks are 'big' banks. Consequently, the probability of distress may be affected by size for certain banks and by degree of public support for others.

We now come to our measures of ownership concentration. The TOBO database offers a good amount of ownership information such as the percentage of outstanding shares held by the investors, and the investors' type, country, size and identification. We build concentration ratios that give the percentage of outstanding shares held by the main shareholders[13]. The C1 ratio is the percentage of shares held by the most important shareholder. The C5 ratio is the percentage of shares held by the five main shareholders altogether. We create dummies depending on whether these important shareholders

[11] We obtained from Bankscope 2151 observations of this liquidity ratio while we had 2273 for the other accounting ratios. We have tried four replacement methods: interpolation-extrapolation with and without time dependence; replacement by mean; replacement by the nearest value. The results are not affected by this choice.

[12] These ratings express Fitch's assessment of a potential supporter's propensity to support a bank and of its ability to support it. Support Ratings communicate the agency's judgment on whether the bank would receive support should this become necessary. The rating ranges from "1" for a bank for which there is an extremely high probability of external support to "5" for a bank for which there is a possibility of external support, but it cannot be relied upon.

[13] It would have been very useful to complement these ownership concentration measures with wealth concentration indicators based on the percentage of an owner's personal wealth that is invested in the bank. This approach is used for instance in DeYoung (2007) and Sullivan and Spong (2007). Unfortunately, it was impossible for us to build such measures with the data we had access to. Nevertheless, we think that ownership concentration remains a relevant measure in our study because most block holders are strategic entities (see tables 3 and 4) who have portfolios much less diversified than those of institutional investors.

hold more than a certain percentage of total outstanding shares. Our main result is obtained by using the dummy variable DU5C1, which is equal to 1 if the bank's first stockholder holds at least 5% of the shares. Empirical papers dealing with ownership concentration generally view this cutoff value as the smallest relevant threshold to identify blockholders[14] (e.g. Barca and Becht 2001; Dlugosz et al 2006, Li et al 2006). Other studies about control rights consider that a threshold at 10% or 20% of the voting rights is the minimum percentage for shareholders to influence the management of the firm[15] (La Porta et al 1999; Facio and Lang 2002). Nevertheless, since monitoring probably starts at lower ownership levels than control, we consider this 5% threshold as meaningful for the purpose of studying the relationship between ownership dispersion, monitoring and the predictive power of the DD. We could not track ultimate owners because of data limitation. However, the average C1 of our sample is 24.2% with a 25% standard error: Laeven and Levine (2009) display exactly the same figures in their worldwide banking study based on the ultimate owner methodology.

We also create a dummy variable to identify who the block shareholders are: DUSTRATEG is equal to 1 when the main shareholder is a "strategic entity", that is to say a corporation, a holding company or an individual. DUSTRATEG is equal to zero when the main shareholder is an institutional investor.

In addition, we construct two variables to account for the possible influence of stock-market liquidity on the predictive power of the DD. The first one is simply the year-end market capitalization of the exchanges where banks' shares are listed. The second one is the yearly turnover velocity of these exchanges, that is to say the ratio of the electronic order book turnover over the market capitalization. Both indicators were extracted from the web site of the World Federation of Exchanges (WFE). We create two dummy variables capturing these liquidity measures: DBIGCAPI equal to one when the exchange's capitalization is above the median of exchanges capitalizations in the sample, and DBIGTURNOVELOC equal to one when the exchange's turnover velocity is above the median. Finally, we also create a dummy DDHIGH equal to one when the bank's DD is above the median. It is

[14] The main reason is a legal one: in most countries, shareholders of listed companies have to disclose their block holding when it exceeds a 5% threshold of voting rights or cash flow rights. Therefore, this cutoff is the one at which information is systematically available. Berle and Means (1932) are the first to use the 5% threshold to define a firm as widely held ("management control" in their terminology).

[15] Adams and Ferreira (2008) recall that more than 40% of European firms have at least one control-enhancing mechanism such as multiple-voting shares or pyramids. It implies that a 5% cash-flow right very often gives more than 5% of voting rights.

used to verify that the key result is not driven by a nonlinear relationship between the rating change probabilities and DD.

Table 3 summarizes the definitions of variables used in the regressions and presents the main descriptive statistics. A situation of financial distress (a rating equal or below C) is observed in 25% of our bank/quarter observations while a rating at B/C or above applies to 75% of our bank/quarter observations. We have to bear in mind that, in the econometric estimates, downgraded banks are taken out of the sample immediately after the downgrade and are reintegrated only if they are upgraded before the end of the period under study[16]. Consequently, the number of cases in which the dependent variable is indeed equal to one in the regressions is low (15). That is why we choose a complementary log-log specification in the econometric estimates and test a similar model for upgrades which are more numerous events[17].

PLEASE INSERT TABLE 3

These descriptive statistics also reveal that high ownership dispersion is a rather frequent phenomenon in our sample since the first owner holds less than 5% of the outstanding shares in 22% of cases. Moreover, we can see that the main shareholder is a strategic entity in 56% of cases. In the TOBO database, any owner who is not an institutional investor specialized in investment management is defined as a “strategic entity”. This category is therefore composed of corporations, holding companies and individuals. Mean comparisons tests in Table 4 show that, when the first shareowner holds at least 5% of the outstanding shares of the bank, it is a strategic entity in 66% of cases. This percentage falls to only 21% when the ownership is dispersed (du5c1=0). In other words, for widely held banks, the biggest shareowner is an institutional investor in 79% of cases.

All the mean comparison tests displayed in Table 4 are significant at 1% or 5%. The two groups of banks (dispersed ownership versus concentrated ownership) have heterogeneous characteristics that must be accounted for in the regressions. We have conducted the same mean comparison tests for an ownership concentration threshold at 10% for the main shareowner and at 15% for the five main shareowners. We obtained the same results except for the degree of public support which becomes significantly higher for banks with dispersed ownership. We conclude that, in our sample, ownership

[16] Similarly, upgraded banks are taken out of the sample immediately after the upgrade and are reintegrated only if they are downgraded before the end of the period under study

[17] We have also tested probit and logit models and they give exactly the same results.

dispersion appears to be positively correlated with the size of the bank, the presence of an institutional investor as main block holder and the size of its stock market. It is negatively correlated with the distance to default and the stock market turnover velocity. No conclusion can be drawn as regards the degree of public support because the result of the mean comparison test changes with the ownership concentration threshold.

PLEASE INSERT TABLE 4

We will control for the impact of all these variables on the predictive power of the DD, in order to make sure that the ownership dispersion effect does not come from these correlations.

2.3. Methodology

To test prediction 1, we propose a two step methodology. In the first step, we build an early warning model of bank distress using five accounting variables (CAMEL ratios) and the distance to default (DD). This latter variable captures the informational content of stock prices, which reflects the efficiency of monitoring by shareholders. This benchmark model is useful to assess the quality of our data and econometric specification in comparison to similar studies. Because we could suspect that the monitoring by shareholders is weakened when the banks benefit from strong external support, we multiply the DD with the dummy DSUPP to assess whether there is a significant impact of the degree of public support on the predictive power of the DD.

In the second step, the DD is multiplied with the dummy DU5C1 capturing whether the banks have dispersed ownership or not. This allows us to assess whether the predictive power[18] of the DD is similar for all ownership structures or proves to be inferior in the case of dispersed ownership. We run exactly the same estimations and the same robustness tests for upgrades to B/C or above. And finally, we implement an event study of the rating downgrades to test the robustness and persistence of the ownership dispersion effect.

The main justification of this methodology is that we want to design tests concerning monitoring rather than influence (see, e.g., Flannery 2001; Bliss and Flannery 2002). The theoretical literature suggests that too much ownership dispersion may impair the information content of share prices

[18] Since an early warning model is not the reduced form of a particular theory of the determinants of failure or distress but rather a prediction tool exploiting the information content of independent variables, we do not talk about the "impact" of the independent variables on the dependent variable. We also willingly avoid the expression "explanatory power". We rather use terms like "predictive power" or "information content", even when we comment in sample estimation results.

because of weaker monitoring. From the supervisory point of view, it is important to detect financial difficulties in advance so as to implement prompt corrective action. It can also be useful to anticipate financial recovery in order to save the costs of unnecessary examinations. That is why we focus on the impact of ownership dispersion on the predictive power of the DD.

To estimate the early warning model, we chose a discrete time survival specification with a complementary log-log functional form for the hazard rate[19]. We tested more standard binary regression models (logit and probit models) and did not find different results. This approach is a convenient way to deal with our data, which are organized as bank/quarter observations (see, e.g., Jenkins 1995). The discrete time framework is justified by the fact that the exact dates of downgrades are not known but only the quarter in which they occur. Moreover, contrary to simple logit or probit models, the predicted variable is a hazard rate rather than a simple unconditional probability. In our model, this hazard rate is defined as the probability that a severe rating downgrade of bank i happens at a given quarter t conditional on not having been downgraded until this quarter t:

$$h_{it} = \Pr(T_i = t \mid T_i \geq t). \tag{1}$$

Our banks can be continuously downgraded at any point in time but we only observe quarters j beginning at date a_{j-1} and ending at date a_j. Survival time is interval-censored. Nevertheless, it is possible to derive an estimate of the underlying continuous time hazard if we use certain specifications of the hazard rate. Indeed, if we suppose that the underlying continuous-time hazard rate $\theta(t, X)$ satisfies the proportional hazard assumption, it can be written :

$$\theta(t, X_t) = \theta_0(t)\, e^{\beta' X}\,, \tag{2}$$

where X contains our time-varying covariates plus the intercept and $\theta_0\,(t)$ is the baseline hazard that only depends on the time elapsed. Since each discrete interval unit is of the same size (quarters), it can be normalized to unit length. It is then easy to show (see, e.g., Jenkins 1995) that the discrete time representation of the underlying hazard rate is:

$$h(j, X) = 1 - exp\,[-exp(\beta' X + \gamma_j)], \tag{3}$$

[19] See Männasoo and Mayes (2009) for another example of a discrete time survival specification in an early warning model.

where: $\gamma_j = \log\left[\int_{a_{j-1}}^{a_j} \theta_0(u)du\right]$ is the log difference between the integrated baseline hazard $\theta_0(t)$ evaluated at the end of the quarter a_j and the integrated baseline hazard evaluated at the beginning of the quarter a_{j-1}.

The advantage of using this complementary log-log specification is twofold. First, the estimated coefficients can be interpreted in terms of their effect on the hazard, which is a distress probability conditional on 'surviving' until the event. Second, the complementary log-log distribution is more adapted when the dependent variable has an asymmetric distribution, which is the case here since we drop the banks out of the sample after they are severely downgraded. The interpretation in terms of duration dependence is linked to the specification of the γ_j terms. Since severe rating downgrades do not occur every quarter and show neither a clear linear nor quadratic profile, we opt for a piece-wise constant specification. We thus create the time-interval dummies INT_k presented below. The structure of the data set can generate autocorrelation within each group (bank), and heteroskedasticity between the groups. As a consequence, the standard errors are adjusted for clustering at the bank level (using the Huber-White estimator of variance).

3. Results

We first estimate benchmark early warning models with independent variables shifted 2, 3, and 4 quarters ahead of the rating downgrade/upgrade. The time-interval dummies are not lagged because they capture the current baseline hazard rate. The general form of the regressions is:

$$\begin{aligned} Prob(Y_{ij}=1) = CLOGLOG\,[\, &\sum_{k=1}^{K} \alpha_k INT_k + \beta\, DD_{j-q} \times DSUPP_{j-q} + \beta'\, DD_{j-q} \times (1 - DSUPP_{j-q}) \\ &\lambda DU5C1_{j-q} + \chi\, DSUPP_{j-q} + \delta\, TOTASSET_{j-q} + \gamma_c\, C_{j-q} + \gamma_a A_{j-q} + \gamma_m M_{j-q} + \gamma_e E_{j-q} + \gamma_l L_{j-q} \,], \end{aligned} \tag{4}$$

where:

- Y_{ij} represents the dependent variable FRAGILE_C or STRONG_BC for bank *i* at time *j*. FRAGILE_C is equal to one for a rating downgrade at C or below; STRONG_BC is equal to one for an upgrade at B/C or above.

- INT_k stands for the K time-interval dummies. When the dependent variable is FRAGILE_C, there are four interval dummies INT_1_C, …, INT_4_C, but only the last three are introduced to avoid perfect collinearity[20].
- $DD_{j-q} \times DSUPP_{j-q}$ is the DD of the highly supported banks, q quarters ahead of the downgrade.
- $DD_{j-q} \times (1-DSUPP_{j-q})$ is the DD of the lowly supported banks, q quarters ahead of the downgrade.
- $DU5C1_{j-q}$ is a dummy equal to one when the bank's main shareowner holds at list 5% of the shares, q quarters in advance.
- $DSUPP_{j-q}$ is a dummy equal to one whenever the bank benefits from high public support, q quarters ahead of the downgrade.
- $TOTASSET_{j-q}$ is the bank's total asset at book value, q quarters ahead of the downgrade.
- C_{j-q}, A_{j-q}, M_{j-q}, E_{j-q} and L_{j-q} are are the accounting ratios measuring the bank's capital adequacy, asset quality, management soundness, earnings and liquidity, all q quarters ahead of the downgrade.

In these benchmark regressions[21], we find that the presence of a main blockholder at 5% of the outstanding shares (DU5C1=1) has a significant negative impact on the conditional downgrade probability three quarters ahead of the downgrade. However it also reduces the probability of an upgrade with a significant coefficient for all prediction horizons. The size of the bank (TOTASSET) significantly reduces the downgrade probability and increases the upgrade probability, three and four quarters in advance. The dummy capturing the degree of public support (DSUPP) has no direct impact on the downgrade probability nor on the upgrade probability. In the downgrade model, all the CAMEL variables have the correct sign and are significant at least for one lag, except the liquidity ratio which is never significant. The results are unchanged when we drop this ratio. A higher capital ratio (C) reduces the downgrade probability; higher ratios of loan loss provisions (A) and cost over income (M) increase the downgrade probability; a higher return on equity (E) lowers the downgrade probability. CAMEL variables are much less significant in the upgrade model: the asset quality ratio "A" is significant with

[20] Please note that, in some tables of results, we have not mentioned the coefficients of these dummies to save space.
[21] We can provide the detailed results upon request.

the correct negative sign three quarters in advance, and the management soundness one is significant with the correct sign four quarters in advance.

The distance to default DD is significant at every prediction horizon in the downgrade model and two and three quarters ahead in the upgrade model. Marginal effects of the DD are higher in absolute value for highly supported banks, but a Wald test reveals that this difference between strongly and weakly supported banks is never significant. Gropp et al (2006) display the same result in their study of European banks: though it affects the predictive power of the subordinated debt spreads, the degree of public support does not affect significantly the predictive power of the DD for European banks. As a consequence, in their final model, they only multiply the debt spread with the public support dummy, not the DD.

We can conclude that our DD indicator brings supplementary information that complements the accounting ratios, reflecting the information gathered by banks' shareowners. The effect of public support on the predictive power of this distance to default, captured by the interacted variable $DD_{j-q} \times DSUPP_{j-q}$, is not statistically significant.

To evaluate the impact of ownership dispersion on the predictive power of the distance to default, we now introduce the interacted dummy variable DU5C1 in place of the interacted dummy DSUPP. The model becomes:

$$\begin{aligned} Prob(Y_{ij}=1) = CLOGLOG\Big[& \sum_{k=1}^{K} \alpha_k INT_k + \beta\, DD_{j-q} \times DU5C1_{j-q} + \beta'\, DD_{j-q} \times (1 - DU5C1_{j-q}) \\ & + \lambda DU5C1_{j-q} + \chi\, DSUPP_{j-q} + \delta\, TOTASSET_{j-q} + \gamma_c C_{j-q} + \gamma_a A_{j-q} + \gamma_m M_{j-q} + \gamma_e E_{j-q} + \gamma_l L_{j-q} \Big], \end{aligned} \tag{5}$$

Banks with DU5C1 equal to one are those for which the main shareholder owns at least 5% of the shares. Results of the regressions are presented in Table 5 below. There is no noticeable change concerning the independent variables that are not interacted with the dummy DU5C1. In contrast, the impact of DU5C1 on the predictive power of the distance to default is a clear validation of Prediction 1, points i) and iii): the absolute values of the marginal effects of the DD are always much smaller when banks are widely held (DD×(1-DU5C1)). Moreover, the Wald tests show that the differences between the marginal effects of the DD in the two groups of banks are significant three and four quarters in advance, both in the downgrade and upgrade model[22]. This difference in marginal effects is sometimes important: up to 4 times, when the dependent variable is FRAGILE_C four quarters in advance, and up to 14.4 times when the dependent variable is STRONG_BC four quarters in advance.

PLEASE INSERT TABLE 5

We know from Tables 2 and 3 that, even though we are dealing with European firms, high ownership dispersion defined as DU5C1=0 is a rather frequent phenomenon affecting 22% of our sample. It is not surprising since Faccio and Lang (2002) show that European financial firms are more likely to be widely held than non-financial firms[23]. We have already explained the relevance of focusing on ownership dispersion at a 5% level in section 2.2. An important loss of predictive power affecting 22% of banks is not a negligible phenomenon[24].

Tables 6 and 7 show that these differences in predictive powers of the distance to default are economically meaningful because they do have an impact on the classification accuracy of early warning models. Firstly, in Table 6 we show that the model has good in-sample classification accuracy whatever the specification: in all downgrade models, the classification accuracy is slightly higher than the one obtained by Gropp et al (2006) in their best model that combines two market indicators, the DD plus a subordinated debt spread, and an accounting score[25].

PLEASE INSERT TABLE 6

Nevertheless, because of the results in Table 5, we suspect that the out-of-sample performance of this early warning model may be reduced when we use it on the sample of widely held banks. Table 7 presents the results of a particular out-of-sample exercise where we use the early warning model estimated over the period 1997-2005 to predict rating downgrades to C or below and upgrades to B/C or above. We use this model out-of-sample to predict downgrades and upgrades in the sub-sample of banks with concentrated ownership and, separately, in the sub-sample of banks with dispersed

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[22] With an ownership concentration threshold at 15% for the five main shareholders (du15c5), the Wald test is significant only in the upgrade model.

[23] In the Faccio and Lang'study, a firm is widely held when the first shareholder holds less than 20% of the voting rights.

[24] We have tested the effect of increasing the ownership dispersion threshold (with dummies DU6C1, DU7C1 and so on, instead of DU5C1): Wald tests are no longer significant, but the marginal effects remain bigger for banks with concentrated ownership up to a 9% cut-off value.

[25] This comparison with the results of Gropp et al (2006) is to be interpreted cautiously: they use monthly data, they do not have exactly the same sample of banks and they work on a different time period (January 1991-March 2001). Moreover, their early warning model is more complete than ours since they use both the DD and a subordinated debt spread. Nevertheless, they find that the marginal effect of the subordinated debt spread becomes very low beyond 6 months before the downgrade while the DD has its maximum marginal effect 18 months before the downgrade. We could not go further than 12 months ahead of the downgrade because of the loss of observations but, as we mainly focus on a predictive horizon of 9 and 12 months before the downgrade, the debt spread would probably not add much more useful signal.

ownership. The results in Table 7 show that the early warning model performs noticeably better when ownership is concentrated rather than dispersed, which is a validation of Prediction 1, point ii).

PLEASE INSERT TABLE 7

For the downgrade model, the global classification accuracy (percentage of correct predictions) is three percentage points lower in the case of dispersed ownership. Moreover, when the ownership is dispersed rather than concentrated, there is an important increase in type I errors (missed downgrades), from 9% to 25%, and a less important increase in type II errors (miss-classified non-downgrades), from 9% to 11%. In the case of upgrades (dependent variable=STRONG_BC), the early warning model is weakly efficient and we consequently obtain bad classification accuracy, but it remains true that it performs much better in the case of banks with concentrated ownership. The early warning model of bank distress and recovery is notably less powerful in the case of widely held banks.

4. Robustness test 1: Controlling for the determinants of ownership dispersion

Because some variables that could affect the predictive power of the DD are unevenly distributed between the two groups of banks (Table 4), we have to control for their influence. Indeed, the determinants of dispersed ownership may be the true determinants of the lower predictive power of the DD of banks with dispersed ownership. Helwege et al (2007) have clearly identified them. They show that the probability of becoming widely held is slightly influenced by the size of the firm and strongly influenced by the past performance of its stocks and the liquidity of its stock-market.

We multiply the variable DD with dummies accounting for the bank size (DBIG), the liquidity of the bank's stock-market (DBIGCAPI and DBIGTURNOVELOC), the nature of its main block holder (DUSTRATEG), and the level of its DD (DDHIGH), all described in Table 3 above. We could suspect indeed that DD is more predictive for small banks (DBIG=0) because they are less complex organizations allowing less costly monitoring. We could also suspect that the liquidity of the exchange on which a bank's stocks are listed affects the predictive power of the DD because more liquid markets facilitate information transmission. In addition, institutional investors (DUSTRATEG=0) may implement weaker monitoring than strategic entities because the latter have access to insider information. We could suspect as well that the non-linearity of the relationship between the DD and the downgrade probability drives the result because the DD is significantly higher for banks with concentrated ownership. We cannot introduce all these controls simultaneously because we need to do so in an interacted dummies framework: each supplementary dummy multiplied with the DD divides by two the number of cases in each category and we only have 16 cases of downgrade to C or below and 31 cases of upgrade to B/C. As a consequence, we perform these robustness tests sequentially. More precisely, for each interacted control dummy, we implement the following tests where DU_control stands either for DBIG, DBIGCAPI, DBIGTURNOVELOC, DUSTRATEG, or DDHIGH:

- step 1: we re-estimate the model presented in equation 5 above, replacing the interacted variables DD×DU5C1, DD×(1-DU5C1) with the interacted variables DD×DU_control, DD×(1-DU_control) and assess whether the predictive power of the DD is affected by these control variables using a Wald test. All these tests give the same result: these control variables considered alone do not affect significantly the predictive power of the DD.
- Step 2: we then estimate for each control dummy the following model:

$$\begin{aligned}
&\mathrm{Prob}\,(Y_{ij}=1) = CLOGLOG\,[\alpha_0 + \sum_{k=1}^{K} \alpha_k \mathrm{INT}_k + \beta\,\mathrm{DD}_{j\text{-}q} \times DU_control_{j\text{-}q} \times \mathrm{DU5C1}_{j-q} \\
&+ \beta'\,\mathrm{DD}_{j\text{-}q} \times (1 - DU_control) \times \mathrm{DU5C1}_{j-q} + \beta''\,\mathrm{DD}_{j\text{-}q} \times DU_control_{j\text{-}q} \times (1\text{-}\,\mathrm{DU5C1}_{j-q}) \\
&+ \beta'''\,\mathrm{DD}_{j\text{-}q} \times (1 - DU_control_{j\text{-}q}) \times (1\text{-}\,\mathrm{DU5C1}_{j-q}) + \lambda DU5C1_{j-q} + \chi\,\mathrm{DSUPP}_{j-q} \\
&+ \delta\,TOTASSET_{j-q} + \gamma_c\,\mathrm{C}_{j-q} + \gamma_a \mathrm{A}_{j-q} + \gamma_m \mathrm{M}_{j-q} + \gamma_e \mathrm{E}_{j-q} + \gamma_l \mathrm{L}_{j-q}],
\end{aligned} \tag{6}$$

  We implement the six possible Wald tests that can be realized with β, β', β'' and β'''. It allows us to assess whether the significant superiority of the predictive power of the DD for banks with concentrated ownership is restricted to small banks (DBIG=0), to banks listed on more liquid stock markets (DBIGCAPI=1 or DBIGTURNOVELOC=1), to banks whose main shareholder is a strategic entity holding insider information (DUSTRATEG=1), or to banks whose DD is higher than the median (DDHIGH=1). We obtain from this series of tests that the answer is no in every case[26].

We can conclude that, on this sample, the negative influence of ownership dispersion on the predictive power of the DD is not caused by higher banks' size, lower liquidity, weaker insider information or lower average DD combined with a non linear effect of the DD.

[26] All these results are available upon request. We could not perform satisfactorily step 2 with the control dummies DDHIGH and DUSTRATEG because, when we used them, there was no downgrade in some of the categories of interacted DD. Their coefficient cannot be estimated. Nevertheless, we performed step 1 for these control dummies and the Wald tests always led to the same conclusion: contrary to DU5C1, these variables alone do not significantly affect the predictive power of the DD.

5. Robustness tests 2: An event study of the rating downgrades

In the early warning models estimated on this sample of banks, the predictive power of the DD appears to be significantly lower when banks' ownership is dispersed. This suggests that ownership dispersion may reduce stock-market efficiency in the banking sector because small shareholders do not invest enough in monitoring activities. If this information gap persists up to the neighborhood of downgrade dates, then downgrades should surprise the shareowners of banks with dispersed ownership more than those of banks with concentrated ownership. We conduct an event study of our Fitch downgrades to assess whether the average cumulative abnormal returns (CAARs) of banks with dispersed ownership are significantly more negative than the CAARs of banks with concentrated ownership.

The events studied here are the 15 Fitch single-notch downgrades to C or below used above to define the dependent variable FRAGILE_C (Table 2). We obtain the precise day of the downgrade from FitchRatings' web site. We also carefully verify in the Dow-Jones Factiva database that no confusing event happens in the event windows. When we find that there is another rating change by Moody's and Standard & Poors, corresponding dummy variables are introduced. Nine of the 15 banks we study have concentrated ownership when they are downgraded, and six of them have highly dispersed ownership ($C1 \leq 5\%$). In the group of banks with dispersed ownership, National Bank of Greece and Alphabank announced their intention to merge just before they were downgraded to C by Fitch. This merger project was made public on 11/01/2001 and the two banks were downgraded on 11/21/2001. Finally the project was abandoned some months later. The merger announcement caused a stock price rally in Athens' bourse that clearly biases upward the CARs of these banks. We therefore have to drop these bank/events. That leaves us with only 4 downgraded banks with dispersed ownership, which is not sufficient to test the significance of their CAARs. That is why we decided to check whether the banks in our initial sample experienced a comparable Fitch downgrade to C from B/C after the end of our sampling period (December 2005). We discovered that, after 2001, Alphabank and National Bank of Greece have been upgraded and then downgraded again to C from B/C on 02/23/2010. We also found a one-notch Fitch downgrade to C for the Swiss bank UBS on 01/21/2009. We add these three banks (two event dates) to the 4 previous ones and perform the experiment with a total of 7 banks for the group of banks with dispersed ownership.

To test robustness, we use three types of market models and two different market indexes to compute the CAARs[27]. We first estimate a dummy variable model (DVM) similar to the one described in Degryse et al (2009)[28]. Adjusting for dividends and stock splits, we compute banks' daily stock returns, r_{jt}. We delete returns when the stock turnover is too low[29] and carefully check for exchanges closing days. We then estimate for each bank/event:

$$r_{jt} = \alpha_j + \beta_j r_{mt} + \sum_{k=D_0}^{k=D_1} \gamma_{jk} \delta_{jkt} + \varepsilon_{jt} \tag{7}$$

where r_{mt} is a measure of the market return (either the FTSE World Index or the FTSE Europe Index); δ_{jkt} are daily event dummies that take the value of 1 when day t is inside the event window and 0 otherwise. The event window starts at day $k=D_0$ and ends at day $k=D_1$. The estimation window starts 200 days before the event and ends 80 days after the event. The event window contains up to 20 trading days before and after the downgrade.

We also estimate a standard Market Model (MM) -which is the same equation without the event-window dummies- over an estimation period starting at day (−200) and ending at day (−40). The coefficients of the dummy and market model may be biased because stock prices are distorted in the periods before and after the event. Therefore, we also compute so-called market-adjusted abnormal returns (MAM). These are defined as the difference between banks' stock returns and FTSE market returns (Purda 2007).

We compute cumulative abnormal returns from these models and average them in each group of banks (dispersed versus concentrated ownership). We then use a two-tailed t-test to assess whether the CAARs of banks with dispersed ownership are significantly different from those with concentrated ownership. Table 8 displays these CAARs for the two groups of bank/events and the corresponding t-tests. The computed CAARs are rather unstable across models and event windows, but they do not contradict prediction 1 since there are two event windows over which the stock price behavior of widely held banks suggests that their shareholders are more surprised by the downgrade announcement. Firstly,

[27] Similar event studies of rating events can be found, for example, in Hand et al (1992) or Goh and Ederington (1993) and Ederington and Goh (1998) and, more recently, in Ongena et al (2003), and Purda (2007).
[28] See also Ongena et al (2003).
[29] We use here the same criteria as for the computation of the DD: less than one thousand stocks traded per day.

CAARs are significantly more negative for widely held banks over the event window [-20,-2], in four of the six models. We know that there are some information leakages in the weeks before rating downgrades. These new pieces of information seem to surprise more the shareowners of banks with dispersed ownership, but this information gap decreases when the downgrade event becomes closer. As a consequence, the differences in CAARs are no longer significant over the event windows [-10,-3], [+3,+10] and [-20,+20]. Nevertheless, the stock price behavior of widely held banks is also significantly different and surprising on the downgrade announcement day. Indeed, these banks experience positive abnormal returns of more than 3% while banks with concentrated ownership display a more usual behavior through negative cumulated abnormal returns of roughly 2%.

PLEASE INSERT TABLE 8

6. Conclusions

This paper uses early warning models and an event study of banks' rating downgrades to test whether dispersed ownership leads to weaker monitoring from shareowners. Even though market discipline involves both monitoring and influencing, we only focus on the former here because we want to assess the quality of the information gathered by bank shareholders and incorporated into share prices, not their ability to influence managerial decisions. Besides testing a prediction from corporate finance theories about the informational disadvantage of ownership dispersion, this analysis proves useful because of the widespread use by prudential supervisors of early warning models including leading indicators derived from share prices. It is thus important to assess whether the predictive power of such indicators is affected by banks' ownership dispersion. With the dispersion threshold we adopt (5% for the first shareowner), 22% of the banks we study are dispersed at least one quarter between 1997 and 2005.

In our sample of European banks observed quarterly between 1997 and 2005, ownership dispersion clearly reduces the efficacy of the distance to default as a predictor of bank distress and bank recovery. On the contrary, ownership concentration raises the predictive power of this indicator and, consequently, the classification accuracy of the model in the sample of banks held by large shareowners. This result is obtained using ownership data from Thomson's One Banker ownership database, which are updated frequently enough to implement reliable quarterly estimates. It passes various robustness tests and an event study of banks' rating downgrades shows that the informational disadvantage of dispersed ownership lasts up to 20 days before the official downgrade announcement.

Bank regulators may have to be cautious when they use share price signals of widely-held banks to predict distress probabilities in their early warning models. Of course, this result obtained on a sample of 76 European banks observed quarterly between 1997 and 2005 would need to be further investigated on other data samples. The subprime crisis has raised the opportunity to do so with more numerous severe downgrade events and even true banking failures.

APPENDIX : Tables

Table 1. Composition of the Sample.

This table reports the countries observed in our sample, the number of banks observed in each country, and the number of banks in each banking type. The figures in parentheses are the number of banks that have been downgraded to a Fitch individual rating of C or below at least one quarter during the period 1997-2005. The figures in brackets are the number of banks that have been upgraded to a Fitch individual rating of B/C or above at least one quarter during the period 1997-2005.

	Bank type[a]							
Country	Commercial Bank	Bank Holding & Holding Company	Savings Bank	Investment Bank & Securities House	Cooperative Bank	Real Estate & Mortgage Bank	Medium & Long Term Credit Bank	Total
Austria			1 (0) [1]					1 (0) [1]
Belgium		3 (0) [3]						3 (0) [3]
Czech Republic	1 (0) [0]							1 (0) [0]
Denmark	2 (0) [0]							2 (0) [0]
Finland	1 (0) [1]							1 (0) [1]
France	4 (0) [2]							4 (0) [2]
Germany	4 (3) [1]			1 (0) [0]		1 (0) [1]	1 (1) [1]	7 (4) [3]
Greece	5 (4) [3]							5 (4) [3]
Ireland	3 (0) [0]							3 (0) [0]
Italy	10 (2) [8]		1 (0) [0]		2 (2) [0]			13 (4) [8]
Netherlands	1 (0) [0]	1 (0) [0]						2 (0) [0]
Norway	1 (0) [0]		3 (0) [3]					4 (0) [3]
Poland	4 (2) [0]							4 (2) [0]
Portugal	1 (0) [1]	1 (0) [0]		2 (1) [0]				4 (1) [1]
Spain	8 (0) [5]							8 (0) [5]
Sweden	2 (0) [0]		1 (0) [0]					3 (0) [0]
Switzerland	1 (0) [0]	1 (0) [0]						2 (0) [0]
United Kingdom	4 (0) [0]	4 (0) [1]				1 (0) [0]		9 (0) [1]
Total	52 (11) [21]	10 (0) [4]	6 (0) [4]	3 (1) [0]	2 (2) [0]	2 (0) [1]	1 (1) [1]	76 (15) [31]

[a]The definitions of the types are from Bankscope.

Table 2. Downgraded and Upgraded Banks.

This table presents the downgraded and upgraded banks of our sample. The ratings are from Fitch/IBCA. Columns "c1" show summary statistics on the percentage of outstanding shares owned by the biggest shareholder. The downgrade day is specified for banks used in the event study (section 5).

Rating at C or below

Bank	Date of the downgrade	Duration of the rating (quarters)	c1		
			Mean	Min.	Max.
Banca Intesa	24/09/1998	21	15.10	14.88	17.13
Emporiki Bank Of Greece	23/12/1998	29	16.63	9.18	44.14
Banca Popolare Italiana	27/06/2000	23	3.82	2.35	7.00
Commerzbank	18/10/2001	17	8.86	1.35	23.55
Bank BPH	19/10/2001	9	69.65	37.00	71.24
Banca Popolare di Milano	19/11/2001	17	3.50	2.13	4.42
Bayerische Hypo-Vereinsbank	13/11/2001	17	26.53	13.66	92.11
Alpha Bank	Nov. 01	15	2.55	1.55	3.93
National Bank of Greece	Nov. 01	11	4.63	0.99	5.74
Bank Zachodni Wbk	05/02/2002	16	60.68	42.72	70.47
Capitalia	01/07/2002	13	17.02	7.16	28.77
IKB Deutsche Industriebank	08/11/2002	13	28.05	11.96	37.77
Deutsche Bank	31/10/2002	11	4.92	1.95	11.58
Banif	22/01/2003	12	49.37	33.37	72.13
Aspis Bank	28/01/2004	8	5.45	3.43	8.03
Number of downgraded banks = 15		Mean duration = 15			

Supplementary downgrades for the event study :

Bank	Date of the downgrade	Duration of the rating (quarters)	Mean	Min.	Max.
UBS	21/01/2009		2.30	0.48	8.17
Alpha Bank	23/02/2010		2.55	1.55	3.93
National Bank of Greece	23/02/2010		4.63	0.99	5.74

Rating at B/C or above

Bank	Date of the upgrade	Duration of the rating (quarters)	c1		
			Mean	Min.	Max.
Credito Emiliano	Dec. 97	33	75.29	72.39	84.40
Sparebanken Midt - Norge	Dec. 97	33	7.14	5.03	10.04
Sparebanken Rogaland	Nov. 97	33	5.58	4.89	9.80
Foreningssparbanken	Feb. 98	32	24.97	19.37	39.75
KBC	June 98	31	64.68	27.06	72.00
IKB Deutsche Industriebank	Oct. 98	16	28.05	11.96	37.77
Unicredito Italiano	Oct. 98	29	13.75	3.29	23.51
San Paolo Imi	Nov. 98	29	7.87	5.01	14.48
Banco Santander Ctl.Hisp.	April 99	27	6.13	1.22	28.76
Fortis	June 99	27	15.21	5.52	37.30
Oko Bank	July 99	26	23.24	5.72	32.08
Banca Lombarda	Oct. 99	25	3.90	3.29	4.41
BBV Argentaria	Jan. 00	24	1.93	0.71	7.46
Banco Espanol De Credito	May 00	23	89.85	46.97	97.96
National Bank of Greece	Sept. 00 & July 04	11	4.63	0.99	5.74
Sparebanken Vest	Aug. 00	22	5.72	2.80	9.98
Banco Espr.Santo	Dec. 00	21	43.69	35.23	47.56
Banco de Valencia	Dec. 00	21	37.83	36.43	44.25
Dexia	Nov. 01	17	15.54	9.85	23.96
Banca Popolare di Verona Novara	June 02	15	2.06	1.38	3.40
HBOS	July 02	14	3.77	2.80	4.29
Credit Lyonnais	April 03	11	21.05	9.77	93.35
Erste Bank	Sept. 03	9	41.08	32.27	49.24
Banca Intesa	Oct. 03	9	15.10	14.88	17.13
Banca Monte Dei Paschi	Dec. 03	8	60.65	49.00	80.06
Eurohypo	March 04	8	65.18	37.72	98.13
CIC 'A'	June 04	7	82.73	68.00	92.88
Bankinter 'R'	Oct. 04	5	8.69	5.79	13.33
Alpha Bank	July 05	20	2.55	1.55	3.93
Deutsche Bank	Aug. 05	24	4.92	1.95	11.58
Capitalia	Sept. 05	1	17.02	7.16	28.77
Number of upgraded banks = 31		Mean duration = 20			

Table 3. Summary statistics and definitions of main regression variables.
Sample consists of 76 Fitch-rated and listed banks from 18 European countries. Statistics are computed across banks and across the 36 quarters of observation. FRAGILE_C (respectively STRONG_BC) is a dummy variable equal to one whenever the bank's FITCH rating is C or below (respectively B/C or above). DD is the Merton-KMV distance to default. It is defined as the number of standard deviations of the (implied) asset volatility that separate the firm from its default point in which the (implied) asset value equals the debt value. C, A, M, E, L are accounting variables synthesizing the financial situation of the bank: capital funds over liabilities (C); loan loss provisions over net interest revenue (A); costs over income before provisions (M); return on average equity (E); liquid assets over total deposits and other short term borrowings (L). DSUPP takes a value of one if the bank's FITCH/IBCA Support Rating is 1 or 2 (highly supported bank) and a value of zero if this rating is 3, 4 or 5. TOTASSET is the bank's total asset at book value in thousand Euros. DBIG is equal to one if TOTASSET is greater than the median. DDHIGH is equal to one if DD is greater than the median. DBIGCAPI is equal to one if the bank is listed on a high market capitalization stock exchange (cutoff again at the median). DBIGTURNOVELOC is equal to one if the bank is listed on a stock exchange with high share-turnover velocity (cutoff at the median). DU5C1 is equal to one when the main shareholder of the bank holds at list 5% of the shares. DUSTRATEG takes a value of one if the main shareholder is a strategic entity and zero if the main shareholder is an investment manager.

Variables	N = 2736 – missing values	Mean	Std. Dev.	Min.	Max.
Dependent variables					
FRAGILE_C	2299	0.25	0.44	0	1
STRONG_BC	2299	0.75	0.44	0	1
Independent variables					
DD	2235	4.36	2.31	0.59	35.55
C	2241	7.84	2.21	2.68	17.89
A	2241	16.51	14.86	-59.12	141.87
M	2241	61.78	14.74	0.41	156.71
E	2241	13.71	9.15	-64.83	75.78
L	2235	20.15	13.77	0.02	71.43
TOTASSET	2241	140890734.62	197959615.37	615900	1125494016
DBIG	2241	0.50	0.50	0	1
DDHIGH	2736	0.50	0.50	0	1
DSUPP	2736	0.62	0.48	0	1
DBIGCAPI	2700	0.45	0.50	0	1
DBIGTURNOVELOC	2664	0.43	0.49	0	1
DU5C1	2736	0.78	0.41	0	1
DUSTRATEG	2736	0.56	0.50	0	1

Table 4. Variables that may affect the ownership effect: mean comparison tests (unequal variance).
This table reports two sub-sample *t*-tests for the difference in mean value of various variables in the sub-samples of banks with dispersed (DU5C1=0) and concentrated ownership (DUC51=1). Column "Difference≠0" reports absolute value of the *t*-Statistics for testing the two-sided hypothesis that the difference in mean value is non zero. ** and *** indicate significance at the 5%, and 1% levels.

Variables	Status (DU5C1)	Number of observations	Mean	Std. Error	Difference Mean(Status=0) – Mean(Status=1)	Difference≠0
DD	0	456	3.946	0.072	-0.522	5.641***
	1	1779	4.468	0.058		
DBIG	0	459	0.551	0.023	0.060	2.307**
	1	1782	0.491	0.012		
DSUPP	0	602	0.580	0.020	-0.057	2.519**
	1	2134	0.637	0.010		
DBIGCAPI	0	602	0.578	0.020	0.164	7.197***
	1	2098	0.414	0.011		
DBIGTURNOVELOC	0	602	0.379	0.020	-0.062	2.725***
	1	2062	0.440	0.011		
DUSTRATEG	0	602	0.206	0.016	-0.458	23.625***
	1	2134	0.664	0.010		

Table 5. Ownership concentration and the predictive power of the distance to default.

This table presents regression results of banks' rating change probability on early warning indicators and controls. Dependent variables are either FRAGILE_C in the columns "Downgrade to C or below" or STRONG_BC in the columns "Upgrade to B/C or above". All the variables are defined and described in Table 3 above. The estimation technique is a complementary log-log model in each case. Coefficients are marginal effects in elasticity. Standard errors (in parentheses) are adjusted for clustering at the bank level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
All regressions include time-interval dummies labeled INT2, INT3, and INT4. They are respectively equal to one between 1999q2-2001q2, between 2001q3-2003q3 and between 2003q4 and 2005q4. INT1 is not introduced to avoid perfect colinearity. All the variables except time-interval dummies are lagged by two, three, or four quarters.

	Downgrade to C or below			Upgrade to B/C or above		
	Two quarters in advance	Three quarters in advance	Four quarters in advance	Two quarters in advance	Three quarters in advance	Four quarters in advance
INT2_C	-0.33	-0.25	-0.24	-0.03	-0.03	0.01
	(0.36)	(0.41)	(0.35)	(0.12)	(0.13)	(0.14)
INT3_C	0.75***	1.13***	0.74**	-0.59***	-0.69***	-0.57**
	(0.29)	(0.38)	(0.30)	(0.23)	(0.23)	(0.25)
INT4_C	0.13	0.23	-0.17	-0.30	-0.36*	-0.20
	(0.34)	(0.47)	(0.49)	(0.21)	(0.22)	(0.26)
DD×(1 - DU5C1)	-0.78	-1.21***	-0.57	0.01	0.05	-0.07
	(0.50)	(0.46)	(0.42)	(0.15)	(0.16)	(0.18)
DD×DU5C1	-1.17*	-3.42***	-2.29***	0.58	0.93**	0.71*
	(0.64)	(1.08)	(0.74)	(0.39)	(0.39)	(0.41)
DU5C1	-1.82	-2.00	-0.81	-1.65	-1.91	-2.18*
	(1.34)	(1.49)	(1.50)	(1.32)	(1.26)	(1.23)
DSUPP	-0.44	-0.26	-0.04	0.38	0.52	0.30
	(0.40)	(0.42)	(0.60)	(0.40)	(0.39)	(0.41)
TOTASSET	-0.58*	-0.80**	-0.60*	0.16	0.21*	0.18
	(0.35)	(0.35)	(0.34)	(0.16)	(0.12)	(0.12)
C (capital ratio)	-4.47**	-4.36***	-3.03	-0.52	-0.51	-0.62
	(1.80)	(1.41)	(2.02)	(0.70)	(0.67)	(0.77)
A (loan loss	1.25***	1.67***	0.76***	-0.76	-0.73*	-0.10
provisions)	(0.35)	(0.31)	(0.22)	(0.53)	(0.44)	(0.43)
M (cost to income	1.58***	2.30***	1.21	-0.94	-1.23	-1.12
ratio)	(0.60)	(0.67)	(1.00)	(1.08)	(1.03)	(0.91)
E (return on	-1.74	-1.54	-2.22*	0.10	0.13	0.16
average equity)	(1.18)	(1.08)	(1.13)	(0.16)	(0.16)	(0.19)
L (liquid assets	0.52*	0.14	0.34	0.11	0.12	0.20
ratio)	(0.32)	(0.40)	(0.38)	(0.50)	(0.42)	(0.42)
Observations	1431	1455	1477	545	550	550
N. of banks	68	68	68	47	47	44
N. of cases Yi=1[a]	15(3)	15(5)	15(5)	29(5)	31(6)	29(6)
Chi2 statistic	185.23	177.36	270.90	203.98	229.46	216.72
Log-likelihood	-53.965	-48.362	-57.811	-98.055	-99.604	-100.281
Wald Chi2 test[b]	0.22	3.56*	4.01**	1.89	4.35**	3.06*

[a]The figures in parentheses are the number of widely held banks (DU5C1=0).
[b]χ^2 statistic for the hypothesis that the difference of the marginal effects of DD×(1 - DU5C1) and DD×DU5C1 is zero.

Table 6. In sample forecasting (Prediction of a downgrade to C or below).

This table presents the classification accuracy of three complementary log-log duration models estimated on the full sample between the first quarter of 1997 and the last quarter of 2005. The general specification is given in the text in equation 4 and 5. We use here three versions of this model: 1) without multiplying the DD with any dummy (first column); 2) DD interacted with DSUPP and (1-DSUP) (second column); 3) DD interacted with DU5C1 and (1-DU5C1) (third column). All independent variables except time-interval dummies are shifted 4 quarters ahead of the event.

	DD	DD interacted with DSUPP (equation (4))	DD interacted with DU5C1 (equation (5))
Classification accuracy	89%	87%	89%
Type I error	13%	13%	13%
Type II error	11%	13%	11%

Table 7. Out of sample forecasting (prediction of a downgrade to C or an upgrade to B/C).
This table presents the classification accuracy of the downgrade and the upgrade models. These models are estimated over 1997-2005 and used for prediction in two separated sub-samples. The first sub-sample is made of banks with concentrated ownership over the period 1997-2005, concentration being defined as DU5C1=1 (columns 1 & 3). The second sub-sample is made of banks with dispersed ownership over the period 1997-2005, dispersion being defined as DU5C1=0 (columns 2 & 4). All independent variables except time-interval dummies are lagged four quarters before the event (q=4 quarters).

	Downgrade model (Dependent: FRAGILE_C)		Upgrade model (Dependent: STRONG_BC)	
Sample	(1) Banks with concentrated ownership (DU5C1=1)	(2) Banks with dispersed ownership (DU5C1=0)	(3) Banks with concentrated ownership (DU5C1=1)	(4) Banks with dispersed ownership (DU5C1=1)
Classification accuracy	91%	88%	30%	23%
Type I error	9%	25%	71%	80%
Type II error	9%	11%	48%	50%

Table 8. Stock price reactions to rating downgrades. Average Cumulative Abnormal Returns.

This table presents average cumulative abnormal returns (CAARs) to banks that are downgraded by FITCH at C from B/C. Event windows are in parentheses. "diff" reports absolute values of the difference in CAARs between banks with dispersed and concentrated ownership. "ttest" reports absolute values of t statistics for the two-sided hypothesis that "diff" is zero. * and ** indicate significance at the 10% and 5% levels.

		DUMMY MODEL				MARKET MODEL				MARKET ADJUSTED MODEL			
		World		Europe		World		Europe		World		Europe	
		Dispersed	Concentrated	Dispersed	Concentrated	Dispersed	Concentrated	Dispersed	Concentrated	Dispersed	Concentrated	Dispersed	Concentrated
CAARs	(-20,-2)	-9,33	0,36	-7,84	-0,23	-9,38	0,04	-8,05	-0,52	-11,29	-0,48	-9,63	-0,99
diff		9,69		7,61		9,42		7,54		10,81		8,64	
ttest		2,04*		1,63		1,89*		1,64		2,41**		1,96*	
CAARs	(-10,-3)	-3,41	-1,32	-2,35	-1,21	-3,32	-1,21	-2,45	-0,98	-4,05	-1	-3,1	-0,95
diff		2,09		1,14		2,11		1,47		3,04		2,15	
ttest		0,79		0,34		0,74		0,41		1,01		0,63	
CAARs	(-1,+1)	3,46	-2,17	3,65	-2,52	3,29	-2,22	3,45	-2,66	3,2	-1,09	3,26	-1,53
diff		5,63		6,16		5,51		6,11		4,29		4,79	
ttest		2,27*		2,32**		2,22*		2,32*		1,95*		2,01*	
CAARs	(-20,+20)	-4,52	-2,27	-2,85	-2,45	-6,35	-3,33	-5,03	-3,36	-7,74	-1,17	-6,8	-1,45
diff		2,26		0,4		3,02		1,66		6,56		5,35	
ttest		0,33		0,06		0,43		0,26		0,96		0,76	
CAARs	(+3,+10)	1,12	-0,94	0,62	-0,48	1,34	-0,4	0,96	0,3	1,88	0,1	1,41	0,26
diff		2,06		1,09		1,75		0,65		1,79		1,15	
ttest		0,56		0,28		0,49		0,17		0,46		0,31	
CAARs	(+2,+20)	-0,22	-1,06	-0,47	-0,55	-0,26	-1,17	-0,43	-0,34	0,35	0,53	-0,43	0,89
diff		0,84		0,08		0,91		0,09		0,18		1,32	
ttest		0,19		0,02		0,2		0,02		0,04		0,3	

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