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An Early Warning Model for EU banks with Detection of the Adverse Selection Effect

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Détection de l'effet de sélection-adverse dans un modèle de prévision des faillites bancaires en Europe

Résumé

Nous estimons un indicateur avancé des faillites bancaires sur un panel de 82 banques européennes observées entre 1991 et 2005. Le papier propose deux contributions originales. Tout d'abord, nous construisons un indicateur de distance au défaut dérivé de la théorie des options (Merton) et nous évaluons son pouvoir prédictif. Les tests réalisés ici sont très similaires à ceux de Gropp, Vesala et Vulpes (2005), mais notre période d'étude est plus longue de quatre années et nous utilisons une définition plus restrictive de la faillite bancaire. Cette première partie du papier montre la robustesse de nos données et confirme la qualité de la distance au défaut comme indicateur avancé des faillites bancaires européennes. Notre seconde avancée réside dans l'introduction d'une variable de détection des problèmes de sélection adverse qui peuvent résulter de stratégies de croissance trop rapides. Nous montrons qu'une mesure de la croissance moyenne passée des actifs est un prédicteur significatif et puissant des difficultés bancaires à venir. Nous discutons l'origine et les conséquences de cet effet.

Mots-clés : faillites bancaires ; early warning systems ; ratios CAMELS; distance au défaut

An Early Warning Model for EU banks with Detection of the Adverse Selection Effect

Abstract

We estimate an early warning model of banks' failure using a panel of 82 EU banks observed between 1991 and 2005. We make two contributions to the literature. Firstly, we construct a distance-to-default indicator and test its predictive power. The tests implemented here are very similar to those realized by Gropp, Vesala and Vulpes (2005), but our time dimension is four years longer and we use a more restrictive definition of banks' "failure". This first part of the paper establishes the accuracy of our data and confirms the robustness of distance-to-default as an early indicator of EU banks' fragility. Our second advance consists in introducing a variable detecting the adverse selection problem that can be caused by rapid growth strategies. A measure of past average growth of assets is shown to be a very significant and powerful predictor of future banks' difficulties. We discuss the origins and implications of such an effect.

Key words: failures; early warning systems; CAMEL ratings; distance to default

JEL : G21; G33; G14; E58

1. Introduction

Early detection of bank difficulties is an important matter of concern for bank regulators. Indeed, it is probably the best way to avoid contagion by implementing prompt corrective actions before the propagation of liquidity or solvability problems. Thought in-site monitoring is probably the best way to gather valuable information -both quantitative and qualitative- about a bank's financial health, it is also a rather costly approach and it may be sometimes plagued by perception biases. That is why statistical Early Warning Models are widely considered as valuable complementary tools to provide efficient off-site detection means.

Until the early nineties, these statistical models mainly used balance-sheet and income-statement indicators, sometimes completed by macroeconomic variables. But the evolution of the banking industry has greatly increased the share of market-priced assets and liabilities in banks' balance-sheets. Nowadays, banks are not only under the scrutiny of public supervisors: they are also submitted to the market discipline of some of their creditors. These changes have promoted the use of market variables in Early Warning Models of banks' fragility. There is now a host of empirical papers focused on the US which show that market indicators provide very useful forward-looking information to predict banks' difficulties. Some similar studies also exist for EU banks, but they are more recent and less numerous. In particular, Gropp, Vesala and Vulpes (2005) have shown that a distance-to-default[1] computed on the basis of a Merton-inspired credit risk model appears to be a very efficient indicator since it is both *complete* and *unbiased*[2].

Nevertheless, as it has been recently suggested by King, Nuxoll and Yeager (2005), introducing market indicators is only a first step towards Early Warning Models that would be fully adapted to the new banking environment. In fact, this new environment also advocates for the introduction of more risk-focused and growth-focused indicators. Risk-focused approaches are warranted by the spread of asset-liability management strategies which increase the interest rate sensitivity of banks' earnings. They are also justified by the permanent importance of real-estate as a cause of bank failure. Growth-monitoring indicators are based on the idea that risky growth strategies generate adverse selection and moral hazard problems which can lead to failure if they are not detected early enough. As a consequence, indicators of a too fast growth of assets or loans, as well as variables capturing the attempt to switch towards non-core and non-market-priced funding, may have a significant impact on the probability on banks' failure.

In this paper, we make two contributions to the empirical literature, using a panel dataset on 82 EU banks observed between 1991 and 2005.

Firstly, we construct a distance-to-default indicator and test its predictive power for banks' failure. The tests implemented for this part of the paper are very similar to the one conducted by Gropp, Vesala and Vulpes (2005), but our time dimension is four years longer and we use a more restrictive definition of banks' "failure". This first part of the paper allows

[1] DD in the sequel.

[2] According to Gropp, Vesala and Vulpes (2005), an indicator of banks' fragility is said to be *complete* if it reflects the three major determinants of default risk (Market value of assets; leverage; volatility of assets). It is *unbiased* if it is decreasing in the value of assets and increasing in their volatility and with leverage.

us to show the accuracy of our data and especially of the distance-to-default indicator. It corroborates the results already obtained by Grop, Vesala and Vulpes.

Our second advance consists in introducing a variable detecting the adverse selection effect of rapid growth strategies. A measure of past average growth of assets is shown to be very significant and powerful as a predictor of future banks' difficulties. We discuss the origins and implications of such an effect.

The paper is organized as follows: in section II we recall the foundations of traditional Early Warning Systems and we discuss the introduction of new variables such as market indicators or growth-focused and risk-focused measures. Section III surveys the most important empirical results of previous estimates of banks' default probabilities. In section IV we describe our database and we explain the building of our dependent and independent variables. Our empirical results are discussed in section V and section VI concludes the paper.

2. Foundations of Early Warning Systems (EWS)

2.1. CAMELS indicators

An extensive literature has been devoted to the supervision of banking system in the US, and more recently in the EU. Most studies use bank-level data to explain why financial institutions either fail or survive.

Beaver (1966) and Altman (1968) first used Discriminant Analysis as well as different specifications of the so-called Z-score in order to distinguish between fragile and sound banks. The lower the Z-score, the more likely the company is to fail. More recent studies use Probit or Logit models to estimate the determinants of failure, but the fundamental technique has remained the same. Its objective is to identify a common set of variables, essentially financial ratios, that differ in a systematic way between failed and non-failed banks. To this extent, these first models of bank failure are based on a historical analysis ("backward-looking models").

The most significant improvement in that field was provided in the seventies by the American banking supervisors (the FDIC and the Federal Reserve) which formalized the CAMELS system. This global rating is attributed after an on-site visit and is based on 6 criteria: Capital, Assets quality, Management quality, Earnings, Liquidity and Sensitivity to market risks. Although the on-site visits are very useful to the whole notation system, the rating may become obsolete quite rapidly. Cole and Gunther (1998) show for example that a very simple model based on financial ratios (an "off-site examination model") performs better than a one year old CAMELS rating in predicting a failure.

The crucial point is to detect banks whose financial condition has substantially deteriorated since the last examination and to monitor institutions between two examinations. These Early Warning Systems (EWS) use as inputs the financial ratios from the banks' FDIC Call Reports and they forecast future ratings or alternatively, they aim at detecting deficiencies that are severe enough to cause an imminent failure or a critical shortfall in capital. The most popular are the SCOR (Statistical CAMELS Offsite Rating) implemented by the FDIC in 1998 and the SEER (System to Estimate Examination Ratings) adopted by the Fed in 1993.

2.2. Dynamic models with forward-looking variables

King, Nuxoll and Yeager (2005) argue that regulatory changes, financial and technological innovations have recently changed the banking environment and the causes of financial distress both in Europe and in the United States. Many banks have expanded into investment banking, insurance or other financial services, and an increasing fraction of their profits derives from fee income generated by these operations.

More generally, globalization, competitive environment and financial developments have impacted bank' management. Bankers are now closer to investors by the way they think in terms of portfolio optimisation to manage their activities.

The banking industry has changed, so has the path to distress. As King, Nuxoll and Yeager (2005) suggested, the prevailing EWS face two main criticisms: they are not well suited to the risk-focused approach of bank supervision and they are backward-looking. These current models primarily focus on credit risk and earnings. They do not include, for instance, interest rate risk, operational risk and they superficially analyse liquidity risk. New models are therefore developed by the regulators to account for the new, more risk-focused framework: a good example is given by the Real Estate Stress Test (REST)[3] which incorporates the experience of the New England real estate crisis of the early nineties. The Economic Value Model (EVE)[4] focuses on interest rate risk by calculating a duration model of the balance sheet. In both cases, such models need to be implemented with highly detailed accounting data. That is one reason why we won't be able to propose such an approach in the present study.

Nevertheless, as suggested by King, Nuxoll and Yeager (2005), another way to adjust previous models to the rapid change and growing complexity of the banking industry is to adopt a more forward-looking approach. Two directions are then worthwhile.

The first one, following Merton's theory, suggests that shareholders estimate an implicit default probability of the firm. In this view, EWS models can be completed with stock market data. In particular, a distance-to-default indicator derived from standard option-pricing theory can be calculated and integrated in econometric estimates of banks' probability of failure. This methodology has been successfully implemented by Gropp, Vesala and Vulpes (2005) who have demonstrated the high predictive power of such an indicator for EU banks. We will use a very similar methodology to introduce a distance-to-default indicator in our Early Warning Model.

A second direction consists in building some indicators to capture the adverse selection problems which might appear when banks are undertaking aggressive growth strategies. Indeed, these strategies might conduct them to adopt lower standards in the selection and monitoring of their new assets. This could then lead to a rise in their level of risk and generate solvability problems whenever these assets would appear to be of bad quality some months latter. As a consequence, King, Nuxoll and Yeager (2005) suggest that a rapid growth of assets, loans or non-core-market-priced funding can lead to higher estimated default

[3] See Collier, Forbush and Nuxoll (2003), « The vulnerability of banks and thrifts to a real estate crisis. », FDIC Banking review.
[4] See Embersit and Haupt (1991), « A method for evaluating interest rate risk in U.S. commercial banks », Federal Reserve Bulletin (august 1991).

probabilities. These kinds of effects are present for example in the FDIC's Growth Monitoring System (GMS), but we still lack evidence of the significance of such variables for EU banks. We will provide first-step estimates showing that an adverse selection detection variable might provide useful additional information in Early Warning Models for EU banks.

3. The usefulness of market-based indicators: recent evidence from the literature

As mentioned previously, market-based measures of banks' risks have several advantages. They may summarise information that cannot be extracted from other sources, they are intrinsically forward-looking and besides, they are available at a very high frequency. Recent empirical studies show that market prices (Stocks and Subordinated Bonds in particular) can be helpful in forecasting bank distress, both in the US and in Europe. To our knowledge, Gropp, Vesala and Vulpes (2005) and Distinguin, Rous, Tarazi (2005) are the first authors to clearly address the issue of an EWS for EU banks based on securities data.

In this paper, we focus on the use of stock market data to forecast financial difficulties of the banks. Nevertheless, other sources of information have proved to be useful and several authors have been studying the properties of Subordinated Debt Spreads as predictors of bank failure[5]. They argue that this indicator may be the most appropriate because it reflects the true banks' risks. To this extent, Subordinated Debt issuance has been often recommended as a discipline instrument. Indeed, the fact that subordinated debt-holders are uninsured gives them strong incentives to react to deteriorations in the bank's financial situation.

However, the Subordinated Debt indicator also has some major drawbacks. First, it is not straightforward to compute since one has to rely on a few conventions to decide what type of data to collect (the banks usually issue several bonds with different profile and time-to-maturity) and to choose the risk-free rate used as a reference for the calculation of the spreads. Second, the liquidity of these bonds can often be questioned.

Since we aimed at designing a flexible, operational EWS, we chose to use only stock prices and therefore, we closely followed the applications of Merton's model to derive a distance-to-default indicator. As described in Appendix B, this variable represents the number of standard deviations that separate the firm from its default point, measured in terms of the assets' volatility. This indicator seems to provide additional information relative to traditional financial ratios (see, among other studies applied to the US banking system, Gunther, Levonian and Moore (2001), Krainer and Lopez (2003), Curry, Elmer and Fissel (2004)).

Gropp, Vesala and Vulpes (2005) argue that a good market indicator should be decreasing in earnings, and increasing in earnings volatility and leverage ratio, that is *complete* (it is sensible to these three factors) and *unbiased* (it reacts in the expected way). Within this theoretical framework, the authors show that the distance-to-default indicator has predictive power for bank fragility since it helps to forecast a "failure" up to 18 months before the event, even when they control for the safety net effect. Moreover, the authors include in their models a synthetic measure of the financial situation of the bank (a score based on accounting data) and they show that the distance-to-default provides additional information

[5] Evanoff and Wall (2000) in the US, Gropp, Vesala and Vulpes (2005) in the EU, among others, have shown that the Subordinated Debt Spreads have leading properties over traditional indicators used by the regulator.

relative to accounting information. Finally, they report good statistics of Type I errors: a weak bank is classified as sound in less than 30% of the cases.

Distinguin, Rous, Tarazi (2005) use a slightly different approach than Gropp, Vesala and Vulpes (2005). They define different indicators based on equity prices in complement to more traditional financial information but they do not compute them in a monthly basis. Rather, they specify a model in which the information available at the 31st December of each year is used to forecast any rating downgrade (not only the severe downgrades) in the following quarters. Besides, they control for opacity effects and Too-Big-To-Fail effects and they conclude that the market-based indicators are useful in some way. However, they argue that the predictive power of these variables depends on the extent to which the bank's debt is market traded, which is a quite intuitive result.

4. The Dataset

Our panel dataset contains several subsets of variables relative to 82 European commercial banks, including financial ratios, stock market indicators and credit ratings. All these variables are defined in a monthly basis[6] and are potentially available over the period 1990-2005 but the global sample is unbalanced. We first describe the process of selection of the banks before we turn to the definition of all the variables we use in this study.

4.1. Sample selection

Our objective was to build a dataset similar to the one used in Gropp, Vesala and Vulpes (2005) for two primary reasons. First, we wanted to assess the quality of our database by running the same tests they did and by comparing our results. Second, we aimed at improving some aspects of their estimations. To do so, we used two different sources: Datastream for the stock prices and Bankscope for the financial ratios and the Fitch/ICBA credit ratings.

We defined a series of monthly variables and we constructed a first sub-sample of 85 banks on the basis of three criteria: (i) the commercial bank is a public company and the stock prices are available from the database Datastream, (ii) its total market capitalization exceeds 100 €m by the end of 2005, and (iii) it is -or used to be- rated by the rating agency Fitch. In practice, this last criterion of credit rating availability is the most restrictive since we could get only 376 credit ratings over more than 5000 European commercial banks identified by Bankscope.

Finally, we used a threshold for the turnover on equity to eliminate the companies whose stocks were not sufficiently traded over the period[7]. This lead to the suppression of 3 more banks and to the constitution of the database of 82 banks we used in this study. We give some descriptive statistics of this final sample in Appendix A.

[6] Not all these variables are available in a monthly frequency but we completed the dataset so that a specific "bank-month" observation reflects the information available at this date. For instance, if a financial ratio was published on January and July of a same year, we assigned to the months February to June the value of the ratio in January, and for the months August to December we used the value of July. The same is true for the individual ratings from the rating agency Fitch since they can be modified at any date.

[7] The banks whose stock was traded less than 1000 times a day in 25% of the trading days (or less) were deleted from the sample.

We are aware of the well-known sample selection problem that may affect our dataset since public companies may well not be representative of the entire universe of the European commercial banks. The firms rated by Fitch may also be bigger in average than the other banks in this universe. In fact, this intuition is confirmed by the data since the 82 banks from our dataset have an average market capitalization (15 €bn by the end of 2005) and an average Total of Assets (150 €bn by the end of 2005) significantly higher than the average of the 5000 banks available in Bankscope. Therefore, we shall underline the fact that our conclusions only apply to the biggest European commercial banks and the most actively traded on the stock market.

4.2. Definition of the variables and global description of the sample

Definition of the financial variables

To construct CAMEL ratios and a measure of the adverse selection effect, we use accounting data from Bankscope from 1990 to 2004. When available, these financial ratios are defined on a quarterly basis and otherwise, on a biannually or annually basis. Table 1 presents the financial ratio we use in our model and we describe the construction of these variables below.

Table 1: Definition of our financial variables

	Name of the variable	*Variable definitions*
C	Capfundtotassets	Capital funds / total assets
A	Impairedloansgrossloans	Impaired loans / gross loans
M	Costtoincomeratio	Cost-to-income ratio
E	Returnonaverageequityroae	Return on average equity
L	Liquidassetstotdepbor	Liquid assets / total deposits and borrowings
Adverse selection effect	assetgrowththMAV126	Asset growth

Capital funds / total assets: As capital funds (equity + hybrid capital + subordinated debt) are a cushion against asset malfunction, this ratio measures the amount of protection afforded to the bank by the capital/subordinated investors.

Impaired loans / gross loans: This ratio is a measure of the total loans that are doubtful. The denominator is the sum of loans and loan loss reserve.

Cost-to-income ratio: It represents the overheads or costs of running the bank, the major element of which is salaries, as a percentage of income generated before provisions.

Return on average equity is preferred to a classic return on equity to minimize the volatility of this performance indicator. The average equity is calculated on a period of two years.

Liquid assets / total deposits and borrowings measures the percentage of borrowers and depositors funds could be met if there were a suddenly withdraw. Subordinated debt or hybrid capital is excluded from the denominator.

Asset growth is a monthly year-on-year growth rate. In our model, we use a moving average calculated on twelve periods, between the asset growth in t–18 and t–6. We then specify this averaged asset growth variable with or without lag, depending on the horizon of the Model (see. Figure 2 in section 5.2).

Definition of the credit ratings and the credit events

We use the Individual Rating from the Fitch/ICBA database because it reflects the risks associated with the intrinsic activity of the bank, regardless of the financial profile of the holding it may be related to.

This notation takes values ranging from A (the best rating) to E (the worst) and can be potentially revised at any moment. Finally, we also consider a Support Rating from the same agency describing the intensity of the safety net the bank might benefit from in case of financial difficulties. As we will see, this rating will help us to control for *Too-Big-To-Fail* effects.

We created several dummy variables for five specific credit events, each one being equal to one at date *t* if the corresponding event realized during the month *t*.

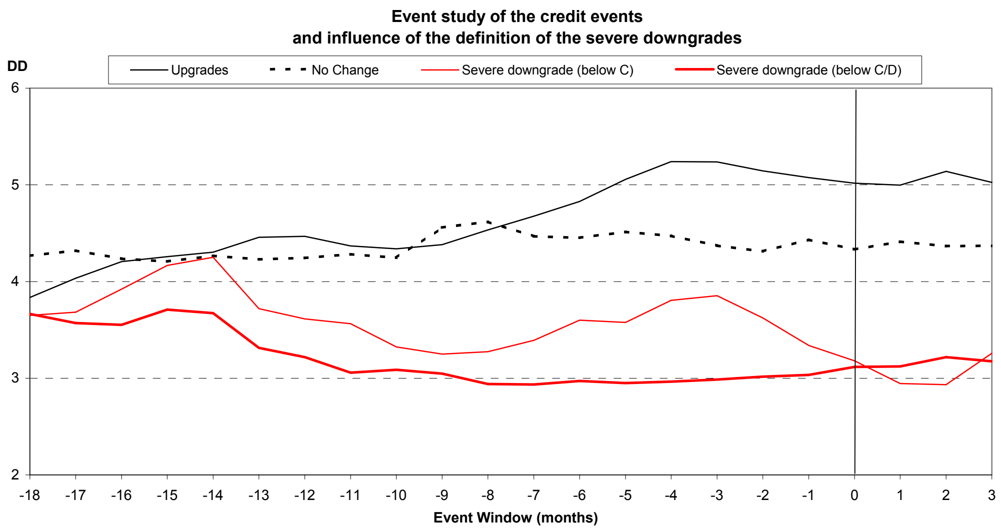
As usual, the variables *Upgrade*, *Downgrade* and *No Change* are equal to one if the Individual Rating is moved upward, downward or is confirmed by the rating agency. We also use two definitions for the so-called severe downgrades to identify the situations of financial fragility: the variable *FragileC*, equal to one whenever the rating falls to C or below and the variable *FragileCD*, equal to one if the rating falls to C/D or below[8]. Gropp, Vesala and Vulpes (2005) provide convincing arguments to assess the quality of such a rating-based indicator of bank fragility. We argue that the latter specification of financial distress is the most adapted to our sample for two reasons.

First, a detailed analysis of the series of ratings raises concerns about the homogeneity of the data. In particular, we argue that a couple of banks were given the rating C over some period of time, although they were not at all close to failure. One reason for this may be a change in the rating methodology used by Fitch[9]. More generally, the more restrictive the criterion of "financial fragility", the smaller the risk of "Type II errors" (when the indicator signals a failure and no failure follows).

Second, an event study conducted on the distance-to-default clearly shows that a threshold at rating C/D better discriminates between sound banks and fragile ones on the basis of this market indicator.

[8] As Gropp, Vesala and Vulpes (2005) do, we drop the downgraded banks from the sample after the event.
[9] The rating agency reported for example that the definition of Support Rating has been changed in July 2003.

Figure 1: Evolution of the DD indicator before a credit event



Construction of the "distance-to-default" indicator

To compute the distance-to-default indicator on a monthly basis, we need the following inputs: the total market capitalization, the level and maturity of the debt, the volatility of stock prices.

The market capitalization (€m) is extracted from Datastream. The definition of the debt we use is the KMV standard given by the sum of the short-term debt and the half of the long-term debt. Finally, the historical volatility of the stock at the date t is defined as the moving average of the daily returns on the stock. The only parameter of choice is the width of the moving average window, traditionally ranging from 1 to 12 months. We show in Appendix C how the width of this window influences the evolution of the volatility and the DD. We also tried alternative specifications of the debt (Total Debt, interpolated or not), but this had no significant effect on the values of the DD.

We finally chose to fix the window width to 6 months, as Gropp, Vesala and Vulpes (2005) did, to arbitrage between volatility smoothing and the quickness of reaction of the final indicator. We do not interpolate the value of the debt to avoid any inappropriate specification problem raised by Distinguin, Rous and Tarazi (2005), when the DD indicator uses future information (the future value of the debt) as an input to predict current rating changes.

5. The results

5.1. Testing the robustness of our distance-to-default as an indicator of bank fragility

In this first section we implement several tests designed to assess the predictive power of our distance-to-default indicator. These tests are conducted using a methodology which has already been used by Gropp, Vesala and Vulpes[10] (2005). The reason of this methodological

[10] GVV in the sequel.

choice is that we use a sample of EU banks which is very similar to their own sample, but on a more extensive period: 1991-2005 while they used 1991-2001. As a consequence, it is interesting to check whether their results are still valid when more recent observations are included in the panel.

Furthermore, these tests will provide a useful first-step assessment of our specific distance-to-default indicator. If it proves to be robust, we will be able in a second step to use it in our Early Warning Model of bank failures including a detection variable of the adverse selection effect. On the contrary, if we obtain a low and unstable predictive power of our distance-to-default indicator, this would raise some concerns about using it in any Early Warning Model of EU banks[11].

We estimate a standard (pooled) logit model of the form :

$$\Pr(\text{Fragile} = 1) = F(\beta_0 + \beta_1 \text{ddRx} + \beta_2 \text{dddsuppRx})$$

Where F(.) is the cumulative logistic distribution and *ddRx* is the x-months lagged distance-to-default indicator. $dddsuppRx = ddRx \times dsuppRx$ is an interacting term designed to test whether the predictive performance of the distance-to-default indicator is affected by the existence of a strong public support (safety net) to the bank.

As in GVV (2005), the model is estimated for different lags of the independent variables separately, because it allows us to identify at which horizon the predictive power of the distance-to-default indicator is the best. Since we use panel data and pooled estimations, observations are not independent within banks -which can generate autocorrelation- and they are independent across banks -which can produce heteroskedasticity. As a consequence, the standard errors are adjusted using the Hubber/White/Sandwich method.

Table 2 beneath reports the estimations of the model with the independent variables lagged 1, 3, 6, 9, 12 and 18 months behind.

As expected, the coefficient of the distance-to-default is negative, and it is significant from the 1-month lead up to the 12-month lead. These results therefore slightly differ from GVV(2005) since their coefficient for the 3-month lead was not significant while their 18-month lead coefficient was significant. We also see that, close to the downgrading event, the significance of the distance-to-default coefficient becomes weaker. This outcome was already underlined by GVV (2005), which interpreted it as a result of a decrease in banks' equity volatility close to the default point.

The coefficient of the interacting term *dddsuppRx* is never significant. This tends to prove that the safety net does not reduce the predictive power of our distance-to-default indicator.

[11] But this could also indicate a deterioration of the predictive power of this kind of indicator in Europe since 2001, and not necessary a failure of our specific distance-to-default indicator.

Table 2: Predictive performance of the distance-to-defaut indicator: Pooled logit estimations, all banks

Model 1 : one month in advance	**FragileCD**	**Model 2 : three months in advance**	**FragileCD**
ddR1	-0.53 (0.28)*	ddR3	-0.58 (0.29)**
dddsuppR1	-0.20 (0.17)	DddsuppR3	-0.18 (0.18)
Constant	-3.88 (0.84)***	Constant	-3.74 (0.87)***
Observations	6874	Observations	6792
LR test	10.46***	LR test	11.16***
Log likelihood	-82.97	Log likelihood	-82.47
Model 3 : six months in advance	**FragileCD**	**Model 4 : nine months in advance**	**FragileCD**
ddR6	-0.65 (0.24)***	ddR9	-0.56 (0.17)***
dddsuppR6	-0.17 (0.19)	DddsuppR9	-0.03 (0.19)
Constant	-3.54 (0.70)***	Constant	-4.18 (0.52)***
Observations	6567	Observations	6344
LR test	12.13***	LR test	7.35**
Log likelihood	-81.58	Log likelihood	-77.25
Model 5 : twelve months in advance	**FragileCD**	**Model 6 : eighteen months in advance**	**FragileCD**
ddR12	-0.58 (0.22)***	ddR18	-0.32 (0.38)
dddsuppR12	0.09 (0.22)	DddsuppR18	0.10 (0.24)
Constant	-4.47 (0.56)***	Constant	-5.47 (0.84)***
Observations	6124	Observations	5697
LR test	5.78*	LR test	1.94
Log likelihood	-71.28	Log likelihood	-66.08
Robust standard errors in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%			

These first series of result establish the accuracy of our distance-to-default indicator but the robustness of its predictive performance remains to be confirmed. In particular, it is necessary to check whether it provides some supplementary information in comparison to the Fitch individual rating considered at the same time-lead. We thus implement the same estimations controlling for the Fitch individual rating observed at the time the distance-to-default is also observed. Results of this test are given in Table 3 below.

The distance-to-default indicator is slightly less significant after the introduction of the lagged ratings, especially close to the 'failure' event. However it remains fairly powerful nine and twelve months before the event. As a consequence we can conclude that the market information conveyed in the distance-to-default is not redundant with the information content of the ratings. Furthermore, it is updated at a much higher frequency than any sort of ratings so that, even if it is less significant than the lagged ratings in these estimations, we can conclude that it is useful in an Early Warning Model of bank fragility.

Table 3: Predictive performance of the distance-to-defaut indicator:
Pooled logit estimations, controlling for the Fitch-IBCA individual rating before the event

Model 1 : one month in advance	**FragileCD**	**Model 2 : three months in advance**	**FragileCD**
ddR1	-0.32 (0.26)	ddR3	-0.37 (0.27)
dddsuppR1	-0.03 (0.16)	dddsuppR3	-0.03 (0.18)
ratingorderedR1	-2.17 (0.21)***	ratingorderedR3	-1.77 (0.20)***
Constant	6.96 (1.37)***	Constant	5.01 (1.38)***
Observations	6438	Observations	6364
LR test	25.51***	LR test	23.23***
Log likelihood	-48.76	Log likelihood	-49.81
Model 3 : six months in advance	**FragileCD**	**Model 4 : nine months in advance**	**FragileCD**
ddR6	-0.52 (0.29)*	ddR9	-0.53 (0.20)***
dddsuppR6	-0.03 (0.20)	dddsuppR9	0.07 (0.21)
ratingorderedR6	-1.55 (0.20)***	ratingorderedR9	-1.27 (0.18)***
Constant	4.30 (1.48)***	Constant	2.62 (1.30)**
Observations	6154	Observations	5944
LR test	22.86***	LR test	18.41***
Log likelihood	-49.73	Log likelihood	-51.67
Model 5 : twelve months in advance	**FragileCD**	**Model 6 : eighteen months in advance**	**FragileCD**
ddR12	-0.43 (0.18)**	ddR18	-0.16 (0.26)
dddsuppR12	0.09 (0.20)	dddsuppR18	0.12 (0.20)
ratingorderedR12	-1.04 (0.16)***	ratingorderedR18	-0.78 (0.18)***
Constant	0.98 (1.07)	Constant	-1.62 (0.99)*
Observations	5734	Observations	5325
LR test	13.81	LR test	6.72*
Log likelihood	-53.69	Log likelihood	-50.08
Robust standard errors in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%			

It remains to be checked now whether our distance-to-default indicator preserves its predictive power when usual CAMEL variables are introduced in the model[12]. This question is important because such a broad range of balance-sheet and income-statement ratios might eventually synthesize the most important part of the determinants of banks' probability of default. Besides, since these indicators are available to market investors when they price banks' stocks, there is a risk of redundancy of the information provided by the distance-to-default. We already argued that, even if it was the case, the distance-to-default indicator would still be useful in an Early Warning Model because it can be very frequently updated.

[12] Our database did not allow us to introduce any reliable indicator describing sensitivity to market risks. Consequently, we had to drop the "S" of CAMELS and focus only on Capital, Asset quality, Management, Earnings and Liquidity.

But it must be acknowledged that this high frequency availability has also its drawback: volatility of the distance-to-default might bring some excessive noise in the estimation of defaults' probability, conducting the EWS to overreact in some circumstances of high market volatility. Consequently, it would be reassuring if we could include both distance-to-default and CAMEL variables in our Early Warning Model.

Table 4 presents the results of our pooled Logit estimations augmented with five CAMEL variables, in the case of a twelve months advance before the failure event.

Table 4: Compared predictive performance of the distance-to-default indicator and CAMEL variables: Pooled logit estimations, all banks

	(1) FragileCD	(2) FragileCD	(3) FragileCD
	Twelve months in advance		
ddR12	-0.58 (0.22)***		-0.38 (0.23)*
DddsuppR12	0.09 (0.22)		-0.37 (0.27)
C:capfundstotassetsR12		0.08 (0.12)	-0.18 (0.12)
A:impairedloansgrossloansR12		0.17 (0.03)***	0.15 (0.08)*
M:costtoincomeratioR12		0.02 (0.02)	0.04 (0.02)*
E:returnonaverageequityroaeR12		-0.05 (0.02)**	-0.10 (0.03)***
L :liquidassetstotdepborR12		-0.02 (0.03)	-0.12 (0.08)
Constant	-4.47 (0.56)***	-8.47 (1.78)***	-3.54 (1.22)***
Observations	6124	5622	4223
Log likelihood	-71.28	-59.00	-30.76
LR test	5.78*	15.85***	15.87**
Pseudo R^2	0.04	0.12	0.21
Robust standard errors in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%			

Before commenting these results, it is necessary to recall that, in our database, balance-sheet and income-statement indicators are available either on an annual, biannual or quarterly basis[13] while the distance-to-default was computed at a monthly frequency. There are three different possible methods to deal with this problem. The first one would consist in interpolating the financial data to a monthly frequency and it would have two main advantages: firstly it would permit to keep a greater number of observations; secondly it

[13] At the beginning of the sample (1991), accounting data is at a yearly frequency but many banks adopted a quarterly frequency for the publication of their financial statements during the second part of the nineties.

would authorize to use the quarterly or biannual financial information when it is available. Nevertheless, as it is pointed out by Distinguin, Rous and Tarazi (2005), interpolations imply in some cases that future financial information is used to predict current rating changes. In the case of yearly accounting data for example, this problem will disappear only when the financial ratios are introduced with at list a twelve month lag.

A second way to tackle the problem is to switch all the data at a yearly frequency. It avoids the drawback of interpolations but it conducts to loose valuable information : the sample size is a lot reduced; biannual or quarterly accounting information is ignored; and, most importantly, arbitrary choices must be done concerning the identification of 'failures' when several rating changes occur within an accounting year[14]. Moreover, the downgrades occurring close to the end of the accounting year will tend to be artificially related to excessively good accounting statements produced at the beginning of the year, while end-of-the-year quarterly statements might have revealed the deterioration. As a consequence, this latter methodology could produce underestimation of the predictive power of financial accountings (and consequently overestimation of the significance of higher-frequency market data).

These caveats lead us to choose another methodology : we keep a monthly frequency for all the data, which means that accounting ratios are duplicated from one month to another until a new financial statement is published which happens every 12, 6 or 4 months in the Bankscope data. The main problem with this methodological choice is that it might generate some supplementary autocorrelation but it is corrected in our estimations where we use robust standard errors adjusted for clustering between banks.

The results in Table 4 show that the distance-to-default conveys some specific information which complements the information provided by CAMEL financial ratios. The distance-to-default remains significant when it is combined with the CAMEL ratios and the Pseudo-R^2 is neatly higher in the full model when compared with the model with only the accounting variables. Contrary to what is usually obtained in the studies of US banks, capital-related ratios do not seem to predict the failure of EU banks and the financial variables which have significant power are mainly related to earnings, asset quality and, interestingly, management efficiency. These results are not surprising concerning EU banks since they conform themselves to the Basel II regulatory framework and have in consequence rather homogenous capital ratios.

5.2. Introducing an adverse-selection indicator

Now that we have obtained an Early Warning Model of EU banks which behaves similarly to EU-focused models found in previous literature, we can implement a test designed to assess the existence of a possible adverse-selection effect for banks which have undertaken aggressive growth strategies. As suggested by King, Nuxoll and Yeager (2005), several competing indicators of such strategies have been tried: asset growth, variation of the capital ratio, loans growth, deposits growth, etc.

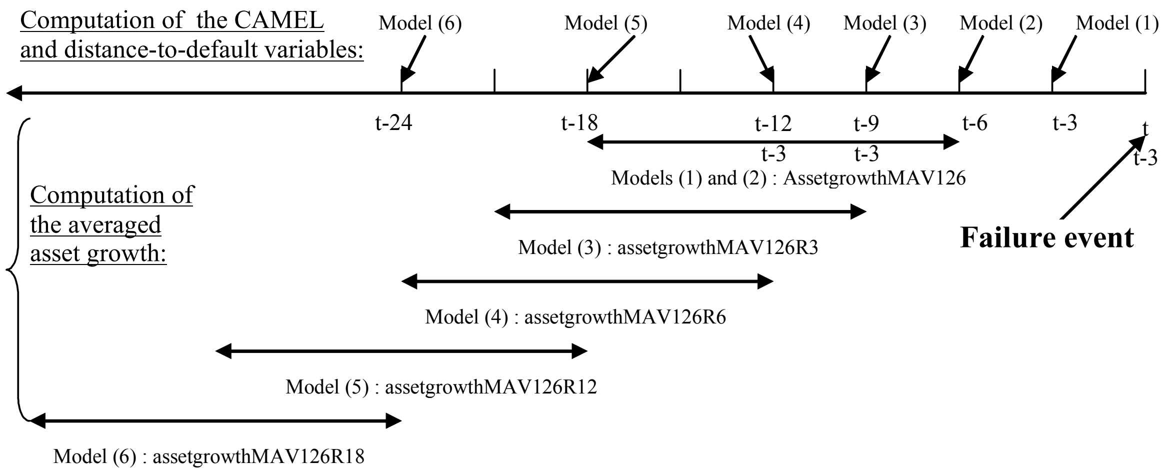
We found that the most significant and strong effect is produced by an averaged measure of past asset growth. Table 5 below presents the results of estimations conducted

[14] As an example, Distinguin, Rous and Tarazi (2005) ignore the downgrades when they follow an upgrade in the same year or when they are followed by an upgrade in the same year. This leaves them enough downgrade events to run robust estimations but this would not leave us enough *severe* downgrades (failure) events.

with a prediction horizon of 3, 6, 9, 12, 18 and 24 months. In each of these models, the failure probability is explained by CAMEL ratios and the distance-to-default which are lagged of respectively 3, 6, 9, 12, 18 and 24 months. We also introduce the averaged asset growth which is computed on a range of twelve months ending respectively 6, 9, 12, 18 and 24 months before the failure event in models (1) and (2), (3), (4), (5) and (6).

The construction of the independent variables in relation to the horizon of the different models is summarized in Figure 2 below.

Figure 2: horizon of the different Early Warning Models



The adverse selection variable is thus defined as follows :
AssetgrowthMAV126 = average of the rates of growth of asset from t – 18 to t – 6
AssetgrowthMAV126R3 = AssetgrowthMAV126 lagged of 3 months
AssetgrowthMAV126R6 = AssetgrowthMAV126 lagged of 6 months
AssetgrowthMAV126R12 = AssetgrowthMAV126 lagged of 12 months
AssetgrowthMAV126R18 = AssetgrowthMAV126 lagged of 18 months

The results in Table 5 show that the introduction of the adverse selection indicator produces interesting outcomes at every horizon. Past asset growth has a strong and very significant positive impact on banks' default probability, even at the 24 months horizon. Furthermore, since CAMEL and distance-to-default variables are still significant, we see that the introduction of this adverse-selection variable is not at all redundant with any of the other predictors already used.

If we compare, as an example, the previous twelve-months-behind horizon model (Table 4) with the results obtained at the same horizon in model (4) of Table 5, we can see that the econometric specification is clearly improved by the introduction of the adverse selection effect (assetgrowthMAV126R6): now all the CAMEL variables are significant except the capital-related one; the distance-to-default is still significant; and the Pseudo-R^2 rises from 0.21 to 0.28.

As a consequence we can draw a conclusion which is in accordance with theoretical predictions: when banks undertake aggressive (and risky) strategies leading to a faster-than-average growth of their assets, they tend to have a higher probability of failure in the sequel. As long as it is the asset growth variable which is found to have the highest predictive power, we can add that this phenomenon of adverse selection is not limited to the selection of loans:

Table 5 - Full Early Warning Model including the adverse selection effect,distance-to-default and CAMEL variables:pooled-logit estimations, all banks

	Model (1) 3 months in advance	Model (2) 6 months in advance	Model (3) 9 months in advance	Model (4) 12 months in advance	Model (5) 18 months in advance	Model (6) 24 months in advance
	FragileCD					
CAMEL variables						
C:Capfundstotassets[1]	-0.24 (0.23)	-0.09 (0.26)	-0.17 (0.23)	-0.04 (0.25)	0.04 (0.27)	-0.16 (0.38)
A:Impairedloansgrossloans[1]	0.24 (0.07)***	0.25 (0.07)***	0.17 (0.06)***	0.19 (0.04)***	0.16 (0.03)***	0.12 (0.03)***
M:Costtoincomeratio[1]	0.06 (0.03)**	0.07 (0.03)**	0.01 (0.05)	0.05 (0.02)**	0.03 (0.01)**	0.01 (0.03)
E:Returnonaverageequityroae[1]	-0.13 (0.03)***	-0.15 (0.04)***	-0.13 (0.03)***	-0.13 (0.03)***	-0.09 (0.03)***	-0.11 (0.05)**
L:Liquidassetstotdepbor[1]	-0.12 (0.09)	-0.13 (0.10)	-0.08 (0.04)**	-0.14 (0.07)*	-0.04 (0.06)	-0.05 (0.08)
Distance-to-default[1]	-0.31 (0.25)	-0.48 (0.25)*	-0.49 (0.25)*	-0.36 (0.19)*	-0.29 (0.23)	-0.98 (0.45)**
Adverse selection effect						
assetgrowthMAV126	2.75 (0.66)***	5.34 (1.62)***				
assetgrowthMAV126R3			4.21 (1.09)***			
assetgrowthMAV126R6				5.56 (1.56)***		
assetgrowthMAV126R12					4.27 (0.93)***	
assetgrowthMAV126R18						3.52 (1.39)**
Constant	-6.81 (2.44)***	-7.88 (2.31)***	-2.78 (4.37)	-6.98 (1.65)***	-7.77 (2.40)***	-2.19 (4.10)
Observations	4563	4627	4623	4623	4332	4011
Log likelihood	-34.20	-32.47	-34.13	-28.38	-31.95	-24.58
LR test	49.13***	39.97***	23.50***	21.53***	13.73*	14.12**
Pseudo R^2	0.42	0.38	0.26	0.28	0.18	0.22

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
1 Lagged 3 months in model (1), 6 months in model (2), …, 24 months in model (6)

it probably also affects other kinds of assets that banks acquire to satisfy their growth appetite.

6. Conclusion

First of all, our empirical results confirm the robustness of distance-to-default as an early indicator of banks' failure. Indeed, our results are similar to those already obtained by Gropp, Vesala and Vulpes even thought we used a longer dataset including more recent failure events. Moreover, we used a more restrictive definition of the "failure" event and it didn't decrease the predictive power of the distance-to-default. This indicator remains significant in the Early Warning Model even when it is joined with a full set of CAMEL accounting indicators; and its predictive power is still maintained after the introduction of a control variable accounting for the "Too-Big-To-Fail" effect.
More importantly, the second part of our empirical study shows that the introduction of a measure of the adverse selection effect clearly improves the early warning model. Averaged past asset growth has a strong and very significant positive impact on banks' future probability of default, even at the 24 months horizon. Furthermore, since CAMEL and distance-to-default variables are still significant after its introduction, we can argue that this new variable is a useful complement providing valuable supplementary information next to the traditional predictors.

This last conclusion is in accordance with the theories of banks behaviour in an asymmetric information environment: when banks undertake aggressive strategies characterized by a faster-than-average growth of their assets, they tend to adopt less selective standards in the selection of their assets. We have shown that this tends to rise their probability of failure, at list in the EU banks. We have argued that this phenomenon seems to affect not only the selection of loans but also other kinds of assets.

These results suggest that the introduction of new, risk-focused and growth-focused, variables may be a relevant track for future developments of Early Warning Models. There are still several research issues to be explored in this spirit. In particular, the lack of availability of detailed data has slowed down the building of good interest rate-risk measures. Another very interesting research topic in this field would be to build and introduce some indicators of a bank's sensitivity to contagion effects and systemic risks.

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Appendix A: Descriptive statistics of the sample

- Location and specialization:

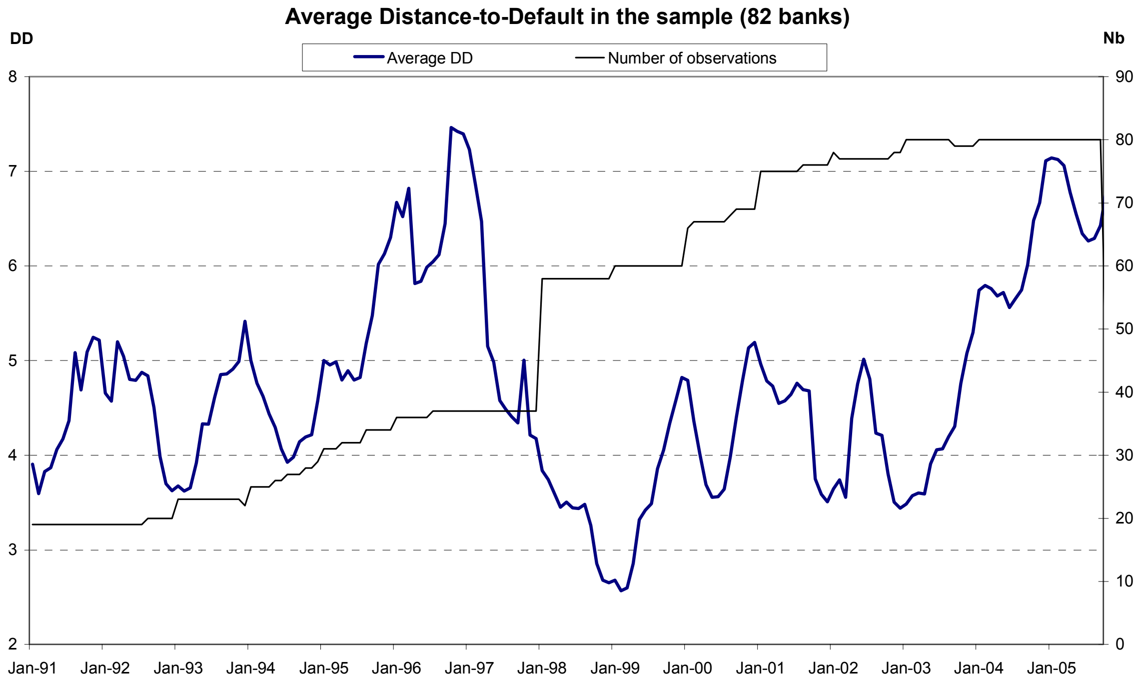
Country	Nb of banks
AUSTRIA	1
BELGIUM	3
CZECH REPUBLIC	1
DENMARK	2
FINLAND	1
FRANCE	4
GERMANY	7
GREECE	6
IRELAND	3
ITALY	15
NETHERLANDS	3
NORWAY	4
POLAND	5
PORTUGAL	4
SPAIN	8
SWEDEN	4
SWITZERLAND	2
UNITED KINGDOM	9
Total	**82**

Specialization	Nb of banks
Commercial Bank	55
Bank Holding & Holding Company	10
Savings Bank	6
Cooperative Bank	5
Investment Bank/Securities House	3
Real Estate / Mortgage Bank	2
Medium & Long Term Credit Bank	1
Total	**82**

- Credit events :

Events	Nb of occurrences
Severe Downgrades below C/D	20
Severe Downgrades below C	31
Downgrades	77
Upgrades	77
No Change	113
Total of events	*267*

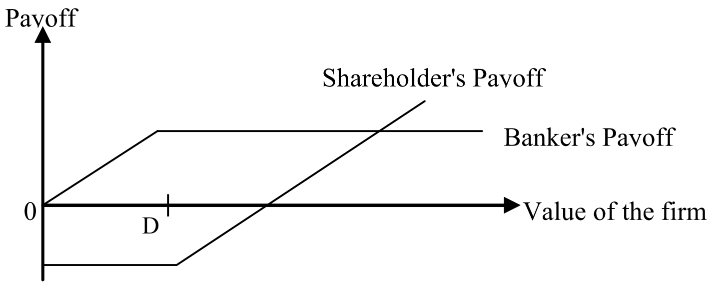
- Evolution of the average Distance-to-Default :



Appendix B : Merton's structural model of credit risk (1974)

We follow Merton's approach ("On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", 1974) by using an option-based structural model of credit risk. In this framework, the firm goes bankruptcy whenever the value of its assets falls below the face value of its debt at maturity. A measure of the creditworthiness of the firms is then given by the distance-to-default indicator, which represents the number of standard deviations (measured in terms of the assets' volatility) that separate the firm from its default point (defined by Total Assets = Total Debt). The smaller the distance-to-default, the higher the default risk.

However, the value of the firm's assets, as well as their volatility, are not observable. Since we have access to the price of equity, we can use the option-pricing formula derived by Black and Scholes (1973) to calculate these unknown values. Indeed, Merton (1974) shows that a firm's equity value is equivalent to an European call option on the asset value of the firm with strike price equal to the face value of debt under the assumptions of risk-neutrality[15].



As usual, we assume that the asset value of the firm, V_A, follows a Geometric Brownian Motion with drift equal to the risk-free rate, r, and volatility σ_A . The value of equity as an option on the firm's assets, as well as its volatility, are given by two formulae derived from the standard option pricing approach and depends on V_A, σ_A, r, D and T, the time to maturity.

$$V_E = V_A \cdot N(d_1) - D \cdot e^{-rT} N(d_2) \qquad \text{(Price of the option)}$$

$$\sigma_E = \frac{V_A}{V_E} \cdot N(d_1) \cdot \sigma_A \qquad \text{(Delta formula}^{16}\text{)}$$

Where N(d) is the cumulative distribution function for the standard normal distribution and $N(d_2)$ represents the probability that the debt D will be paid at maturity.

$$d_1 = \frac{\left[\ln(d) + (\mu + \sigma_A^2 \; / 2))T\right]}{\sigma_A \sqrt{T}} \qquad \text{and} \qquad d_2 = d_1 - \sigma_A \sqrt{T}$$

Reverse-engineering these two equations yields the asset value and the asset volatility. Finally, the distance-to-default is given by : $DD = \frac{V_A - D}{\sigma_A}$

[15] The risk neutral framework simplifies calculations since we do not need to estimate the drift of the asset value.

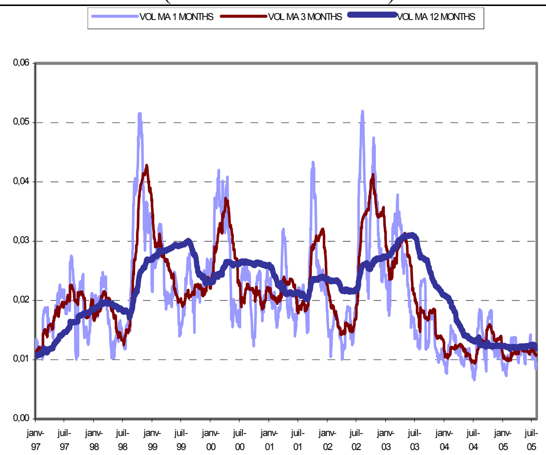
[16] Itô's Lemma implies $\sigma_E V_E = \frac{\partial V_E}{\partial V_A} \sigma_A V_A$. Besides, $\frac{\partial V_E}{\partial V_A} = N(d_1)$.

Appendix C: Definition of the historical volatility of stock prices

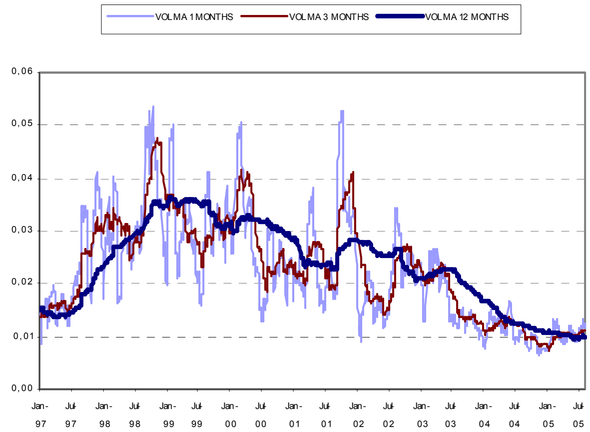
And impact on the distance-to-default indicator

The historical volatility of stocks used as an input in the calculation of the DD indicator is usually defined as the moving average of total daily returns (including dividends) with a window width of 1 to 12 months. The smaller the window, the more reactive is the volatility and thus the DD, as we can see it on two examples.

Historical volatility of the stock Barclays
(Source : Datastream)



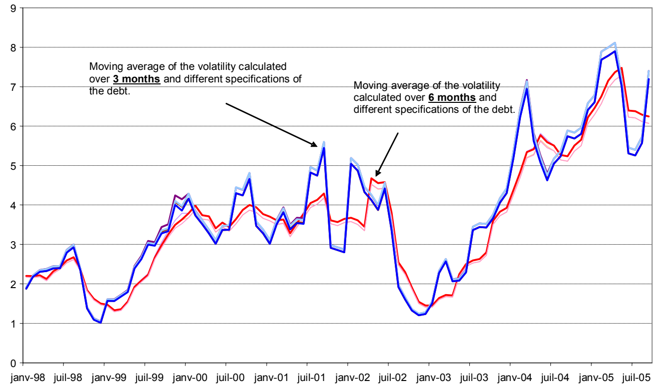
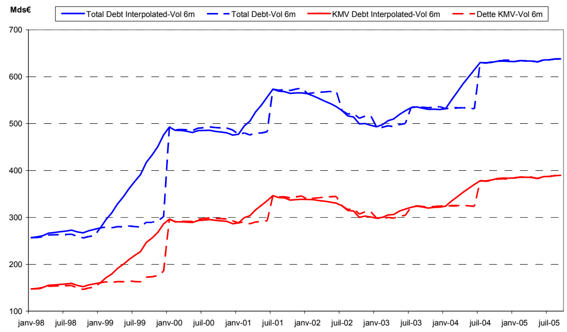
Historical volatility of the stock Standard Chartered
(Source : Datastream)



We also observed that the definition of the volatility had an influence on the value of the DD, in contrast to other inputs of this indicator. We calculated the values of the DD over the period 1995-2005 with 8 different specifications. While the maturity of the debt was fixed to one year, we allowed the definition of the volatility and the level of the debt to vary[17]. The crucial parameter is clearly the length of the window used in the calculation of the volatility, but the values of the assets in Merton's model are also influenced by the specification of the debt. In particular, the fact to interpolate or not the values of the debt within a specific year has no influence on the values of the DD.

[17] The moving average of the daily returns was calculated with a window of 3 and 6 months, whereas the debt was defined as the total liabilities and alternatively with the KMV definition. We then interpolate the values of the debt for each specification to obtain 4 definitions of the debt-to-equity ratio.

The same kind of pattern was observed for each one of the 82 banks in our sample.

Different specifications of the BNP Paribas DD	Values of the BNP Paribas Assets
	

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