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Market Impact of Rating Agencies' Decisions - January 2006

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ABSTRACT

Along with its report on credit rating agencies, published in compliance with the Financial Security Act of 1 August 2003[1], and a study of ratings in the securitisation industry, the AMF is also releasing two studies made in conjunction with the research staff at IXIS CIB, in connection with the Authority's Academic Advisory Board.

The results of the first study (1.) provide a more detailed picture of the impact that rating agencies' decisions had on the prices of French equities between 1990 and 2004.

Overall, the response of French equity prices is in line with that seen on credit markets and foreign equities markets.

- Equity prices react more strongly to rating downgrades or negative watches than to up upgrades or positive watches.
- Equity prices anticipate the agencies' decisions, probably because of the abundant information publicly available to the market about issuers.

Finally, the study shows that the impact of agencies' announcements on equity prices is even greater in the case of small, volatile and poorly rated securities or in a gloomy macroeconomic environment, especially when default rates are high.

The second IXIS CIB study looks specifically at the impact of rating changes on the performance of European ABS from January 1999 to May 2005. The sample of available ratings used for the study shows that rating changes are fairly rare in this market, but they are fairly substantial when they do occur.

The impact of credit rating changes on the performance of European ABS seems to be non-negligible in itself and it can be observed for downgrades, which is what we also find in the case of ordinary corporate bonds, as well as for upgrades.

These findings point to the important role that rating agencies play on the ABS market, in keeping with the intuitive notion that the complexity of ABS and the credit rating agencies' role their development mean that the agencies enjoy a real information advantage over the rest of the market.

[1] Article L 544-4 du code monétaire et financier.

1 IMPACT OF AGENCIES' DECISIONS: COMPARISON OF FRENCH EQUITIES AND INTERNATIONAL EXPERIENCES

Study by Evguenia Iankova, Florent Pochon, Jérôme Teïletche – IXIS CIB Research Department

Various economic agents, such as companies, investors and official bodies, are paying closer attention to credit rating agencies' decisions. The purpose of this study is to review the impact of the agencies' decisions, meaning rating changes or rating watches. We start with a literature review. This is followed by an evaluation of the impact of credit agencies' decisions in France, which is as exhaustive as possible for the period from 1990 to 2004, and by some proposals for methodological improvements. We compare our results with equivalent results for the USA and the rest of Europe found using the same methodological framework. Our study concludes with a preliminary analysis of the determinants of the magnitude of stock price reactions.

1.1 Introduction[2]

More attention has been paid to credit rating agencies' decisions in recent years. This new focus stems from the widespread downgrading of credit ratings from 2000 to 2003, especially with the downgrades of many companies in the new technology sector in the wake of their financial problems triggered by the huge debts contracted to finance major acquisitions during the late nineteen-nineties. During the same period, a number of well-known European companies were downgraded to the "speculative grade" or "high yield" status (with ratings under BBB-/Baa3) for the first time. This greatly diminished their ability to raise financing. On a more anecdotal level, some companies felt that the agencies were too "aggressive" in changing their credit ratings. On the other hand, some investors regretted that the agencies were too slow in responding to the deteriorating finances of some companies, which led to some spectacular business failures. The debate became particularly heated when, virtually simultaneously, the Basel Committee put forward the possibility of relying on agency ratings to calculate banks' capital adequacy requirements under the future Basel II framework.

Without going into detail[3], the purpose of this article is to analyse the impact of credit rating agencies' decisions on the prices of financial assets, and more specifically, on equity prices. This means our approach to the agencies' role in financial markets is more positive than normative. The issue is a fundamental one for both pricing a portfolio of assets and for risk management. From the theoretical viewpoint, the impact of agencies' decisions is indeterminate. On the one hand, the credit rating is one of the main criteria – along with maturity and liquidity – for discriminating between debt securities. Furthermore, when a credit rating change signals a change in the solvency and the profitability of the company, or it is merely likely to change the terms under which the company can obtain financing, then it may lead to a significant change in the stock price. On the other hand, the theory of market efficiency[4] suggests that the market should anticipate the agencies' decisions, if they are based on public information. Agencies' practices, and more specifically, the fact that they rely partially on inside information and that their decision-making still relies in part on qualitative considerations, mean that things may

[2] This article presents the preliminary finding of work by the Research Department at IXIS CIB for the consultations conducted by the Academic Advisory Board of the Autorité des Marchés Financiers (AMF) on the role of international credit rating agencies. We would like to thank the Council members for their remarks and suggestions. We would also like to thank Anne Breton for her help in compiling the data and Jean-David Fermanian for his suggestions.
[3] See, for example Gonzales et al. (2004) for a more detailed discussion.
[4] The theory of market efficiency, which is the reference in finance, has been attributed to Bachelier, Samuelson and Fama. This theory states that, in an efficient market, all of the available information has already been incorporated into prices. If we accept the assumption that agents make perfect predictions, then only perfectly unpredictable news will have an impact on the prices of financial assets. See Fama (1991) for an overview of the literature.

be different in reality and that the only answer that we can give to the question of the impact of their decisions is an empirical one.

There is a vast literature on this question, but initially it focused entirely on the USA because of the age and the size of American markets. The purpose of this article is to present an analysis of the impact that credit rating agencies' decisions have on the stock prices of French companies. To our knowledge, only one study of this type has been available in the recent period (François-Heude and Paget-Blanc, 2004). Our study covers a longer time period and, most importantly, we have made substantial improvements to the methodology used in the previous studies and in the rest of the literature. Our study also goes further than the previous literature by offering an analysis of the determinants of the reaction.

The organisation of this article is as follows. Section 2 presents a rapid literature review about the impact of credit rating changes on financial asset prices. Section 3 provides details about the methodology and Section 4 presents the findings of the empirical study. Section 5 is the conclusion.

1.2 A rapid review of the literature

An ample literature focuses on verifying the impact of credit rating changes on financial asset prices. Authors have mainly conducted event studies, which look at changes in a company's share or bond prices around the time of the credit rating agencies' announcements. The following section contains a more detailed explanation of the methodology.

Even though older studies are available[5], it is more reasonable to restrict ourselves to those produced within the last two decades because of the credit rating agencies' recent improvements in their operations. The agencies have added more qualitative assessments to their ratings, with information about possible rating trends in the short run (watches) and in the long run (outlook)[6]. Between 1971 and 1982, the main credit rating agencies also phased in finer rating "notches", which led to a threefold expansion of the rating scale. Several authors (Liu, Seyyed and Smith (1999), Kliger and Sarig (2000)) have also shown that, in the case of a specific agency, the finer notches have had a significant impact. This finding in itself is a preliminary indication of the role played by credit rating agencies' decisions, even though the exceptional and normally non-recurring nature of such a move means that we must be wary about interpreting its impact.

The findings in the literature vary greatly; nevertheless a few do stand out with regularity [7].

(1) Credit rating downgrades have a bigger impact than upgrades, and this asymmetric impact is more pronounced for equity prices.

(2) Markets tend to anticipate credit rating changes, with significant abnormal returns being observed primarily in the period before the agency's announcement (up to six months in advance).

(3) The economic impact on issuers with low credit ratings (especially speculative grade ratings) is very substantial, bringing some 10% to 15% in cumulative stock price changes.

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[5] See Norden and Weber (2004) for a fairly complete list.

[6] Watches first appeared in the nineteen eighties. A watch indicates that the agency is likely to change the rating in the short-term, usually within three months. Watches can be positive, negative or, in rarer cases, neutral. Originally, watches were supposed to be a way for agencies to respond to exceptional circumstances, such as a merger or acquisition, recapitalisation or regulatory action. But in practice, watches increasingly seem to be precursors of rating changes, even in the absence of any exogenous events. Outlooks are given for all long-term ratings to show their probable long-term trend. However, the outlooks for most ratings are "neutral".

[7] The main studies are by Hand, Holthausen and Leftwich (1992), Goh and Ederington (1993), Dichev and Piotroski (2001), Hite and Warga (1997), and Norden and Weber (2004).

There are various explanations for the asymmetric impact. In the specific case of equities, shareholders do not always see the announcement of an upgrade as good news. An upgrade could mean that the company's behaviour is too virtuous and that it is not using leverage to increase shareholder value. If we take this reasoning to the extreme, a shareholder could see a credit rating downgrade as good news, but the empirical findings do not seem to show that this is the prevailing mechanism. In more general terms, Goh and Ederington (1993) show empirically that the reaction is not linked to transfers of wealth between shareholders and bondholders. Ederington and Goh (1998) provide an alternative explanation, stating that companies prefer to announce only good news, which means that bad news is announced by other players, such as credit rating agencies. One last explanation is that credit rating agencies focus on cases where creditworthiness declines, rather than the opposite, because their reputations suffer much more when they fail to anticipate a default than when they fail to predict an unexpected improvement in a company's earnings.

More recent studies have analysed the impact of credit rating agencies' decisions on credit default swaps (CDS). CDS are credit derivatives that have undergone exponential growth. Under a CDS contract, the buyer of protection periodically pays the seller a premium over the reference money market rate. In exchange, the seller undertakes to repay the uncollected portion of the debt in the event that the underlying entity (the entity on which the CDS is written) defaults. The advantage for our purposes is that CDS are "pure" measurements of the underlying credit risk and they are more liquid than the equivalent bonds[8]. The studies have shown that watches have more impact than actual rating announcements (and outlook announcements) and that the market tends to anticipate the credit rating agencies' decisions. Because of the relative youth of the CDS market, these studies are based on the most recent period alone and they focus almost exclusively on rating downgrades.

The purpose of the rest of this article is to document the price impact of credit rating agencies' decisions on French equities between 1990 and 2004. We look at both rating changes and watches. Rating changes shall be defined on the basis of the finest rating notches (AAA/AA+/AA/AA-, etc.) and not the aggregated ratings (AAA/AA/A/BBB, etc.) For the sake of comparison, we shall conduct the same exercise for Europe and the USA over the same period.

1.3 Methodology

As a rule, empirical work relies on event studies to analyse the impact of credit rating agencies' decisions on financial asset prices (shares and bonds). This methodology is often used in finance. It focuses on price variations during the event window, making a statistical measurement (e.g. cumulative return), collecting data about other similar events, and then using statistical tests to assess the impact[9]. In order to isolate the exact effect of the event, all other influences on price variations must be stripped out, especially general market price movements. As a rule, this can be done simply by working on the deviation between the return on the security affected by the event and the mean return for the market as a whole. In the specific case of equities, the authors also adjust for the share's beta, which expresses its exposure to market risk, and its alpha, which is its level of return when the market is stable.

In more formal terms, let R_t denote the return on the security in the period *t*. The abnormal return, or return in excess of the market return, is written $AR_t = R_t - \alpha - \beta R_{mt}$. α and β denote the alpha and beta of the security, which are obtained by estimating the market model over a control period that generally does not include the event date. Another definition of excess return is written $AR_t = R_t - R_{mt}$, in the specific case where $\alpha = 0$

[8] See Hull, Predescu and White (2004) for a presentation of the CDS market and a comparison with the "cash" market, meaning the bond market.
[9] See MacKinlay (2001) for an overview of the literature on event studies.

and $\beta = 1$. AR_t corresponds to a return over a single period, such as a day or a week. We can also work on cumulative returns to study the persistence of the impact of an event. These returns are written $CAR = \sum_{t=t_1}^{t_2} AR_t$ or $CAR = \left(\prod_{t=t_1}^{t_2}\left(1 + AR_t\right)\right) - 1$ [10]. The dates t_1 and t_2 denote the start and end of the event impact observation period. Three different cases can be defined.

- Both t_1 and t_2 come before the event date. Usually, in this case, the work focuses on determining whether the market anticipated the event.
- The event comes after t_1 and before t_2. In this case, the effect of the event is measured around the time it occurs.
- Both t_1 and t_2 come after the event, which means the work is an attempt to measure the reaction after the event, stripping out the instantaneous and contemporaneous effects.

The process is repeated for a set of similar events, indexed with *i*, where $i = 1, \ldots, N$. The impact is ultimately assessed by conducting significance tests on the cumulative abnormal returns. The conventional test is the t-test, which is used to test the null hypothesis for the mean cumulative abnormal returns. If $\overline{CAR}$ denotes the mean of the *N* cumulative returns and σ_{CAR} denotes the associated standard deviation, the t-statistic is given by $\overline{CAR} / \left(\sigma_{CAR} / \sqrt{N}\right)$ and follows a t-distribution with $N - 1$ degrees of freedom. This process is virtually the unanimous choice in the literature. However, it does have various drawbacks. It is based on the mean, which makes it sensitive to extreme observations that may lead to biased results. It is also a parametric test that assumes a normal distribution of cumulative returns. Figure 1 shows an example of the density function for cumulative abnormal returns. In this case the returns are associated with downgrades in France within a 30-day event window, but similar problems arise in other cases. We can see that the distribution is skewed[11] and that it features fat tails. As a joint result, the Jarque-Bera test broadly rejects the null hypothesis of normal distribution.

Ultimately, this example shows that the inference based on the t-test and its standard assumption may be erroneous and biased. We adopted two types of solution to overcome this problem. First, we have used non-parametric tests, which are less sensitive to extreme values, because they concentrate on the median and are, by definition, not subject to a specific distribution. More specifically, we have used the sign test and the Wilcoxon signed-rank test. The centred statistics associated with each of the tests are given by:

$$\text{Sign} = \left(N^+ - N/2\right) / \sqrt{N/4}, \quad N^+ = \sum_{i=1}^{N}\left(CAR_i > 0\right)$$

$$\text{Wilcoxon} = \frac{\sum_{i=1}^{N} CAR_i^+ - N\left(N+1\right)/4}{N\left(N+1\right)\left(2N+1\right)/24}$$

where CAR_i^+ denotes the rank of CAR_i in the overall series of absolute returns, if it is a positive value, or else zero. The other solution is to use the bootstrap technique. This consists of simulating the distribution of a statistic

[10] The difference between the two definitions lies in the compounding of returns, which is ignored in the first case. Ultimately, the first definition is merely a first order approximation of the actual cumulative return, but it has the advantage of being simple. In the literature, returns are calculated using the first difference of the logarithm of the prices in order to overcome this problem and this is the solution we have adopted here.
[11] Negative skewness means that the distribution shows a larger mass of probabilities in the left tail (negative returns).

by recalculating it, using a set of randomly drawn samples, which are replaced in the original sample for each drawing. The bootstrap method is establishing itself in economics and finance because it is extremely flexible and powerful[12]. In the findings below, the significance of each statistic (t-test, sign test and Wilcoxon test) is assessed on the basis of the bootstrap distribution.

We have used different pairs of values for t_1 and t_2 ranging from 90 business days before the event to 90 business days after the event. The beta has been estimated by applying the market model over 50 to 250 days, with no data from within 90 business days of the event. In other words, the beta is estimated using all of the data available between 340 and 91 days before the event.

For the purposes of comparison, the model is applied to three geographical areas. We have analysed the cases of French, European[13] and US companies separately. The market indices used to estimate the alpha and beta parameters for the market model are taken from the SBF 120, the Stoxx Large and the Wilshire 5000. The samples for each of these areas are obtained using several filters. We start by checking Bloomberg to identify all of the companies that have had their credit rating changed by one of the three main agencies (S&P, Moody's, Fitch) between 1990 and 2004[14]. For example, 2,962 rating events (changes and watches) have been identified in France, which break down into 1,410 decisions by S&P, 1,207 by Moody's and 345 by Fitch. These decisions concerned 332 companies. We then apply different filters to these initial samples in order to conduct the impact study:

- We selected by the "LT Local Issuer Credit" ratings by S&P and "Senior Unsecured Debt" ratings by Moody's and Fitch.
- We have ignored new ratings, withdrawals of ratings and ratings based on public information (PI).
- We have selected only companies for which prices are available.
- We have applied the liquidity and price availability rules over a period that is long enough to estimate the beta and to assess the impact of the decision.

The resulting French sample is made up of 401 rating changes covering 68 companies. The list of these companies can be found in Appendix 1.

It should be noted that each agency's decisions are analysed with no regard for what the other agencies have decided. More specifically, one agency's decision may follow a similar decision by another agency concerning the same company. This solution enables us to avoid arbitrarily defining an event window that sets a minimum time limit for considering two decisions as distinct from each other[15]. For the sake of clarity, we have reported the results for each agency separately. This also enables us to avoid the pitfall stemming from the fact that the market attributes different meanings to the agencies' decisions, depending on the agency for a specific type of decision.

1.4 Results

We start by presenting the results of the impact study for France, then for Europe and the USA. We conclude with a preliminary analysis of the determinants of the impact of credit rating changes on French equities.

[12] See Mac Kinnon (2002) or Flachaire (2000) for an overview of the literature.
[13] Europe here is defined as the European Union, except France, plus Switzerland and Norway.
[14] Bloomberg's RATC function provides a complete history of rating changes by all of the credit agencies throughout the world. The rating histories can be downloaded as Excel files with the following data: company name, date, credit rating agency, old rating, and new rating. We then do a search of the Bloomberg and Datastream lists of stocks in the current broad stock indices and the lists of firms that were delisted for various reasons, such as bankruptcies or takeovers, in order to identify the listed shares linked to the companies. For French equities, which are the focus of this study, we also did a case-by-case search.
[15] See Norden and Weber (2004) for a discussion.

1.4.1 Impact study

After applying the various filters, we obtained the following structure of events for France:

	S&P	Moody's	Fitch	Total
Downgrades	92	59	27	178
Upgrades	32	30	12	74
Positive watches	14	16	5	35
Negative watches	64	30	20	114
Total	**202**	**135**	**64**	**401**

Figure 2 shows the distribution of the associated decisions over time. It shows clearly that watches emerged quite late and that credit rating changes are concentrated in the recent period. Tables 1A, 1B and 1C show the results of the impact tests separately for each agency and for each type of decision. Figure 3 shows the mean change in cumulative abnormal returns around the event dates. In each case, the tables show that the abnormal returns are skewed, either in the deviation between the median and the mean or, more precisely, by the skewness test and the fact that the Jarque-Bera test frequently shows a non-normal distribution. This justifies the use of non-parametric tests and the bootstrap technique, because the normal distribution assumption underlying the standard t-test that is usually applied under these circumstances is a very far stretch in this case, especially when we consider the relatively small sizes of the various samples.

If we look at the detailed results, we see that, on average, downgrades result in a fall in prices prior to the decision and that prices tend to bounce back slightly after the decision. However, the two effects are not significant for all three agencies simultaneously, since the fall in prices is only significant for Moody’s (in the 90 days before the event) and the bounce is only significant for S&P (1 to 30 days after the event) and for Fitch (between 31 and 60 days after the event). Ultimately, over the whole 181 business days (or some 8 to 9 months) before and after the agency’s decision, the cumulative price impact ranges between –1.2% for S&P, -3.6% for Fitch and –8.5% for Moody’s. However, the impacts are not significant for all three agencies.

The results for negative watches follow the same pattern, with a fall in prices preceding the decision and a rise afterwards. The fall in prices before the watch announcement is especially significant for S&P’s decisions and it continues to be significant around the event itself. For the other agencies, the fall in prices is concentrated in the period between 60 and 31 days preceding the event. Stock prices seem to bounce back relatively late, since the bounce for all three agencies is significant during the period from 61 to 90 days after the event.

The results for upgrades vary much more between the three agencies. Upgrades by Moody’s seem to lead to a rise in stock prices, with a significant rise prior to the decision that persists for 30 days after the decision. The opposite pattern is observed for the other agencies. S&P’s decisions lead to significantly negative returns just before the decision is announced and long afterwards. Fitch’s upgrades are preceded by a fall in prices.

The results for positive watches are more uniform. All three agencies’ decisions are preceded by significant price increases. However, the magnitude of the increases varies greatly, with the mean cumulative abnormal returns over the 30 business days preceding the announcement standing at +5.5% for S&P, +6.2% for Moody’s and +24.0% for Fitch. However, the last number must be interpreted with extreme caution because of the very small number of observations. In S&P’s case there are more observations and we see that the overall impact during the event window is very large (cumulatively 33%) and very significant.

All in all, the results obtained confirm those obtained by François-Heude and Paget-Blanc (2004). However, the significance of watches in a narrow event window is seriously called into question when we give more consideration to the specific nature of the abnormal returns. The results are also in line with those obtained in American literature. We see that downgrades have a more pronounced impact that upgrades and that watches have a substantial impact.

Figures 4 and 5 take these comparisons further, showing the results of the impact study on agencies' decisions in Europe and America, using the same methodology as that used for French equities[16]. One notable difference concerns the number of observations, particularly in the USA. The number of downgrades by all agencies combined stood at 384 in Europe and 3,993 in the USA. The corresponding figures for upgrades are 165 and 1,925. The figures for positive watches are 46 and 695, and those for negative watches are 219 and 1,994.

The results for Europe are more or less in line with the results obtained for France, but with very different reactions around upgrades and a fall in prices preceding downgrades, followed by a slight bounce afterwards. One notable difference is that the period around watch announcements seems to show a greater response. This phenomenon is significant for all three agencies in the case of negative watches.

The American results are clearly more uniform between agencies and more significant. This shows that problems of testing accuracy and power may arise when we work on samples that are too small, as is sometimes the case with France and Europe. Downgrades lead to significant falls in prices both before and immediately after the event. This difference compared to France and, more generally, to Europe may be explained by the greater predictability of decisions in Europe or by the fact that the decisions are more predictable over time, since the European sample is more biased towards the end of the period than the American sample is. Downgrades have a massive impact. The cumulative impact in the 181 days around the event varies between –18% for Moody's, -26% for S&P and –33% for Fitch. Upgrades by all three agencies lead to significant falls in prices in the 90 days following the announcement. On the other hand, the period preceding the announcement is also uncertain and the final result depends on the agency. We shall conclude by noting that watches also seem to have a significant impact, both in the period preceding the announcement (especially in the case of negative watches), but primarily around the announcement date. Watch announcements by all three agencies lead to significant price variations, with prices rising in response to positive watches and falling in response to negative watches, in various time intervals around the announcement dates.

1.4.2 Determinant analysis

The academic literature includes many impact studies that quantify the effects of the agencies' announcements on equity and bond prices. On the other hand, there is much less literature on the determinants of the magnitude of the impact.

However, some results can sometimes be found in the literature. Many studies have shown the break created by a downgrade from investment grade to the high yield category. This effect may be explained by market segmentation, since many investors are not allowed to hold high-yield securities, or by the non-linear relationship between ratings and the probability of default[17] ((Holthausen and Leftwich [1986], Jorion and Zhang [2005]). These implications of the initial rating can also be seen within categories, Hand, Holthausen and Leftwich (1992) showed that the implications of downgrades are greater within the speculative-grade category than they are within the investment grade category. At first glance, it seems that the magnitude of the reaction would naturally depend

[16] The complete detailed results are available on request.
[17] The non-linear relationship stems from the fact that a one-notch rating change does not give the same change in the implied default rate, when the change is from AAA to AA+, or from BB- to B+, for example.

on the size of the rating change. Some empirical confirmation of this phenomenon can be found (Hand et al. [1992]), but it has been refuted by Goh and Ederington (1999). Dichev and Piotroski (2001) show that, as far as abnormal returns are concerned, we have to adjust the returns for the conventional effects of size and the book value/market value ratio of companies. Vassalou and Xing (2003) show that much of the reaction depends on the anticipated probability of default and the probability following the rating change. Several authors (Goh and Ederington [1999], Dichev and Piotroski [2001]) have shown a strong correlation between abnormal returns preceding the announcements and abnormal returns after the announcement. This means that a downgrade would drive down prices even more if the price fell sharply before the announcement, which may indicate that the company has undergone a steady deterioration of its financial situation, for example.

Based on these results, we have attempted to identify the determinants of the abnormal return profile more precisely in France. Our analysis is restricted to downgrades and negative watches, which are the only events that clearly trigger significant reactions in France. For this purpose, we have established a joint sample of the three agencies and we have broadened the field of the determinants analysed in the literature. More specifically, we have used four types of factors (see Appendix 2 for the complete list).

- Characteristics of the decision in terms of ratings: initial rating, breaching of significant rating levels (high yield grade), time elapsed since the previous decision, decision by another agency in the preceding 90 days, etc.
- Microeconomic characteristics of the company: beta, volatility of shares, market capitalisation (relative to total market capitalisation), financial or non-financial sector, financial ratios (Debt/EBITDA, P/BV, EBITDA/Interest Expense), ratio of upgrades to downgrades for the sector (in the euro area), etc.
- Macroeconomic conditions: GDP for France and the OECD, short-term and long-term interest rates, volatility of the CAC index, aggregate ratio of upgrades to downgrades (in the euro area), overall default rate.
- Other news: earnings announcements in the month around the announcement date.

We start by analysing downgrades. Our endogenous variable is the cumulative abnormal return between 30 and 1 days preceding the announcement. Our explanatory variables include a dummy variable to capture the outlier related to the behaviour of Alcatel shares in November 2002, when their abnormal return stood at approximately +50% during a very strong technical rebound on the market. The best specification we obtained is as follows.

$$\begin{aligned} CAR = {} & \underset{(2.72)}{0.11} - \underset{(-1.68)}{0.13} \times VolShare + \underset{(1.79)}{3.83} \times CapiShare - \underset{(-2.59)}{0.08} \times I\{Rating \leq BBB\} \\ & - \underset{(-2.01)}{0.05} \times I\{\Delta Rating > 1\,\text{notch}\} - \underset{(-2.70)}{0.03} \times DefaultRate - \underset{(-1.83)}{0.05} \times I\{Financial\} \\ & R^2 \text{ adjusted} = 0.25, N = 156. \end{aligned}$$

The variables denoted VolShare, CapiShare, DefaultRate refer to the current year. $I\{x\}$ denotes the index function, which is 1 if condition x is true and 0 if it is not. Downgrades have more impact, meaning bigger negative returns, if the share is volatile, represents a small capitalisation and carries a low rating (under BBB). Rating changes of more than one notch have more impact. Finally, downgrades seem to have more impact on financial companies and when the overall quality of credit risk is bad (meaning the default rate is high).

The endogenous variable for negative watches is the cumulative abnormal returns for the 60 days preceding the announcement and the announcement date. The best specification for this is as follows.

$$
\begin{aligned}
CAR = \underset{(4.12)}{0.63} - \underset{(-2.52)}{0.06} \times \beta\_Share - \underset{(-1.72)}{0.08} \times I\{Rating < BBB\} \\
- \underset{(-1.72)}{0.08} \times DefaultRate - \underset{(-3.21)}{0.09} \times RateFrance \\
R^2 \text{ adjusted} = 0.28, N = 106.
\end{aligned}
$$

Once again, we include a dummy variable to isolate Scor shares in June 2003, when abnormal returns before the decision reached approximately +66% and then fell. The variables β_Share, RateFrance, DefaultRate refer to the current year. This specification is simpler. The negative impact of a negative watch is greater if the share has a high beta and a low rating, and if the default rate and the interest rate are high. As was the case for downgrades, this preliminary analysis shows that it is probably necessary to combine microeconomic characteristics with macroeconomic factors.

1.5 Conclusion

The purpose of this study was to review the impact of credit rating agencies' decisions on the prices of financial assets and, more specifically, share prices, with a special focus on French shares. We have shown that share prices seem to react more sharply to negative announcements – that is, downgrades and negative watches – than they do to positive announcements, meaning upgrades and positive watches. This finding is in line with the existing literature. It is significant for regulators, issuers and investors, who may consider strategies based on this asymmetry, or for risk managers, who must take this effect into account when managing their overall portfolio of equities and bonds. We have also shown that issues of accuracy and power make it tricky to focus on overly narrow segments. For example, this means that similar studies on the CDS market in a country like France cannot yet be reproduced. In addition, we have put forward some methodological improvements that are critical for coping with the specific nature of abnormal returns around the agencies' announcements and, even more specifically, their non-compliance with standard hypotheses.

We think that very productive further work could be done on a more systematic analysis of the determinants of the magnitude of stock price reactions to agencies' decisions. We feel that the literature on this aspect is too sparse, especially with regard to analysis of the price impact per se. Our preliminary findings suggest that a combination of microeconomic aspects and macroeconomic fundamentals could shed new light in this area. As an example to illustrate this need, we present the performance of France Telecom shares compared to the market as a whole over the period from 1999 to 2005. It shows very clearly that the share price response to the same type of news is very different, depending on market circumstances. The figure suggests that we probably should continue working on methodological improvements as well, since there is clearly an endogeneity problem that arises[18]: do prices anticipate the agencies' decisions or do prices trigger the decisions? Thus, the question of price impact still has to be investigated.

[18] During our seminar presentation at the Academic Advisory Board of AMF, this has been suggested as a further research route by Michel Aglietta.

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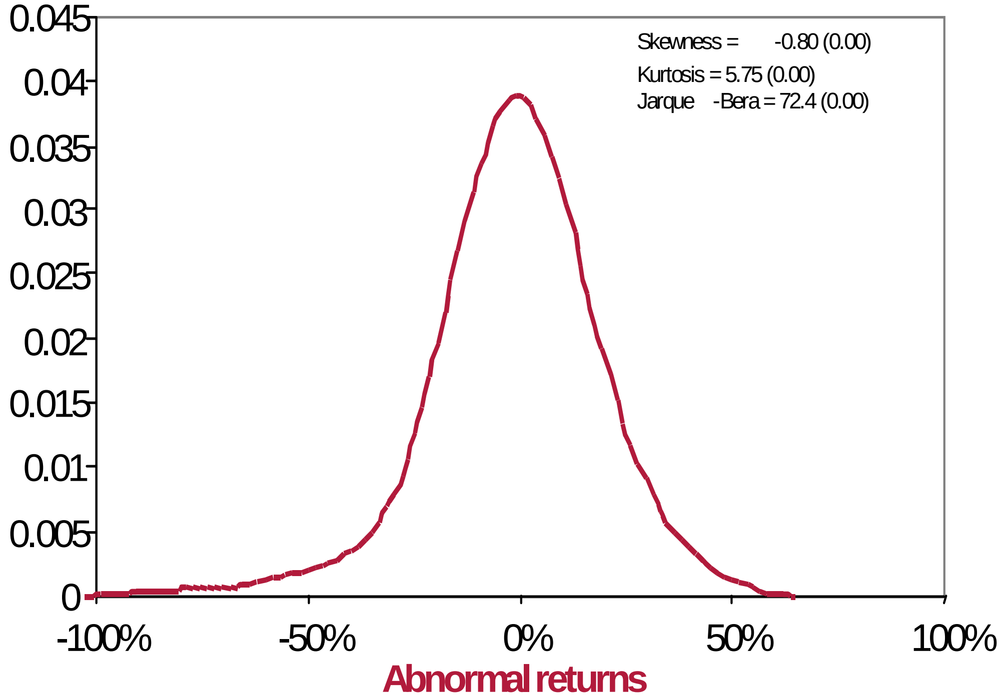
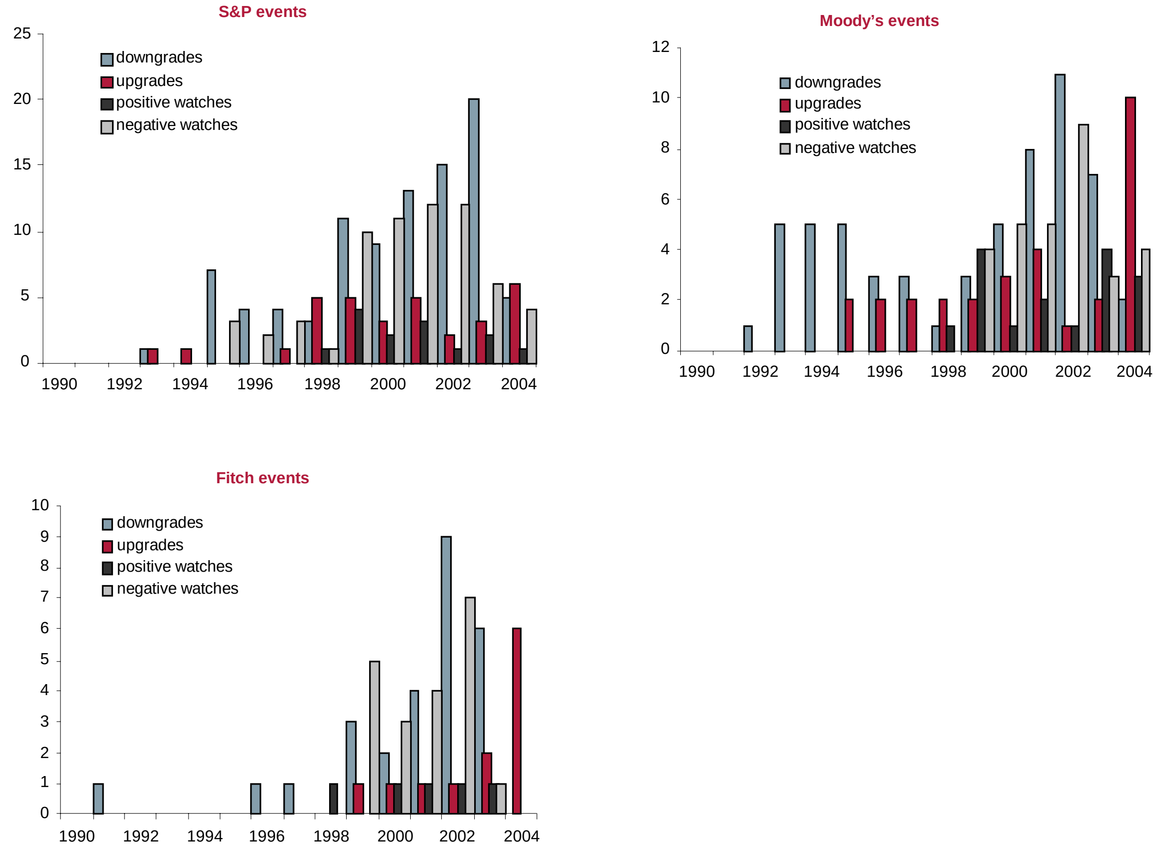
Figure 1. Example of the density function for cumulative abnormal returns



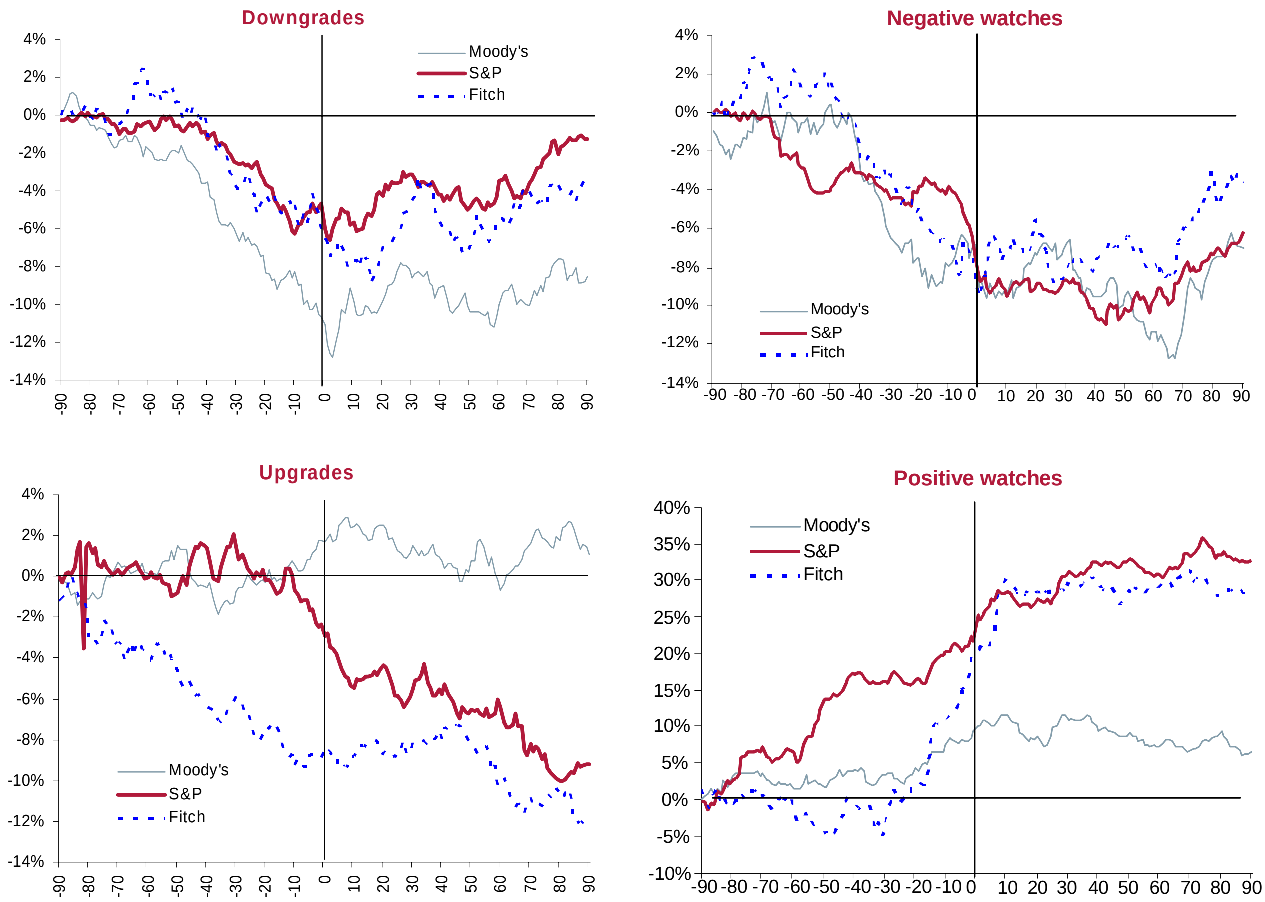
Source: authors' calculations. The figure shows the empirical density function (estimated using an Epanechnikov kernel) of cumulative abnormal returns related to downgrades of French companies' credit ratings during a period of 30 days around the event. The numbers in parenthesis after the skewness, kurtosis and Jarque-Bera test for normality statistics are the probabilities that the null hypotheses will be rejected wrongly. The fact that these probabilities are less than 1% in every case means that the distribution is skewed with fat tails and non-normal.

Figure 2. Distribution over time of the final sample of agencies' decisions regarding French companies



Source: Bloomberg, authors' calculations.

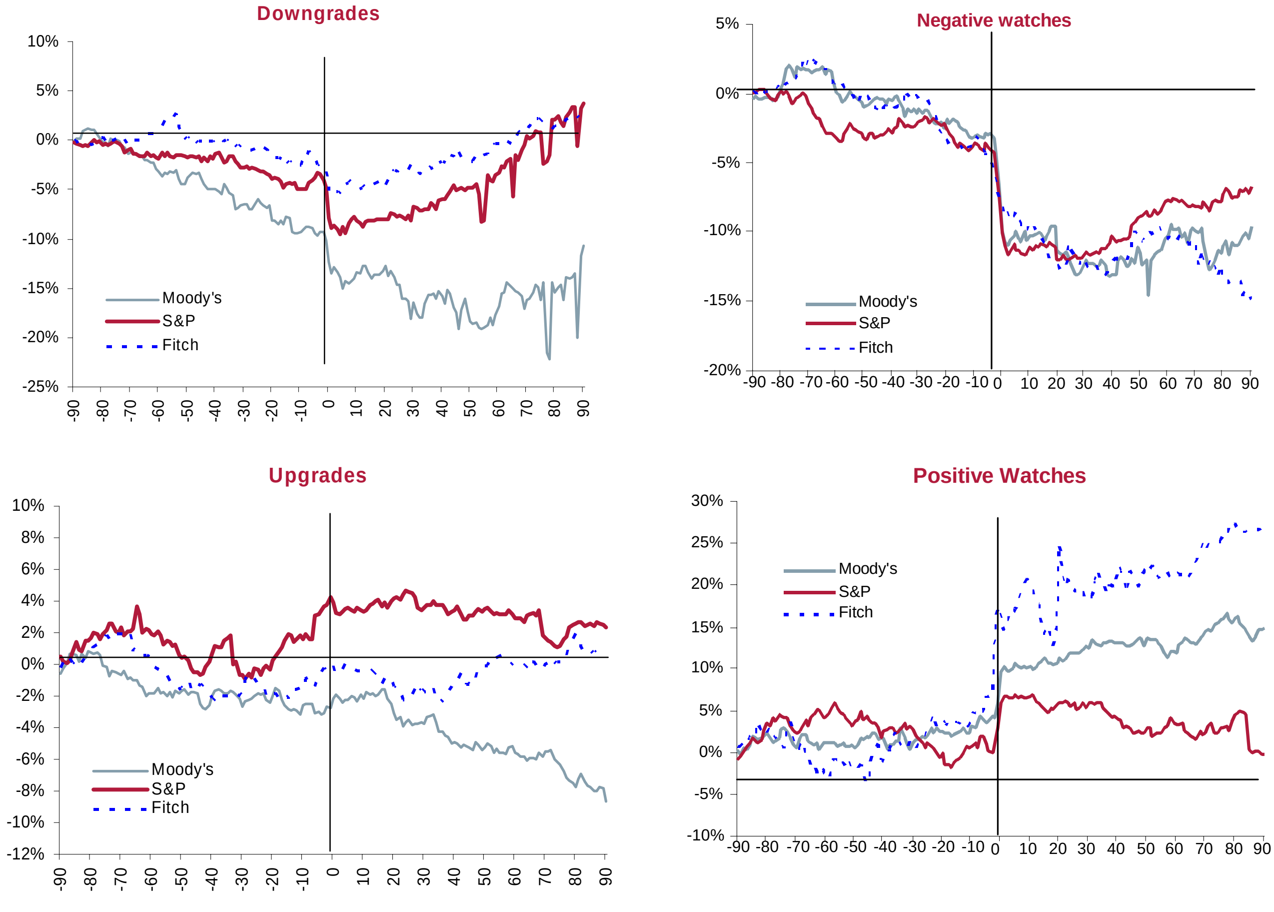
Figure 3. France: Mean impact of different agency decisions on cumulative abnormal returns (1990-2004)



Source: Bloomberg, authors' calculations.

Notes. The x-axis represents the number of days around the event, with 0 denoting the event date.

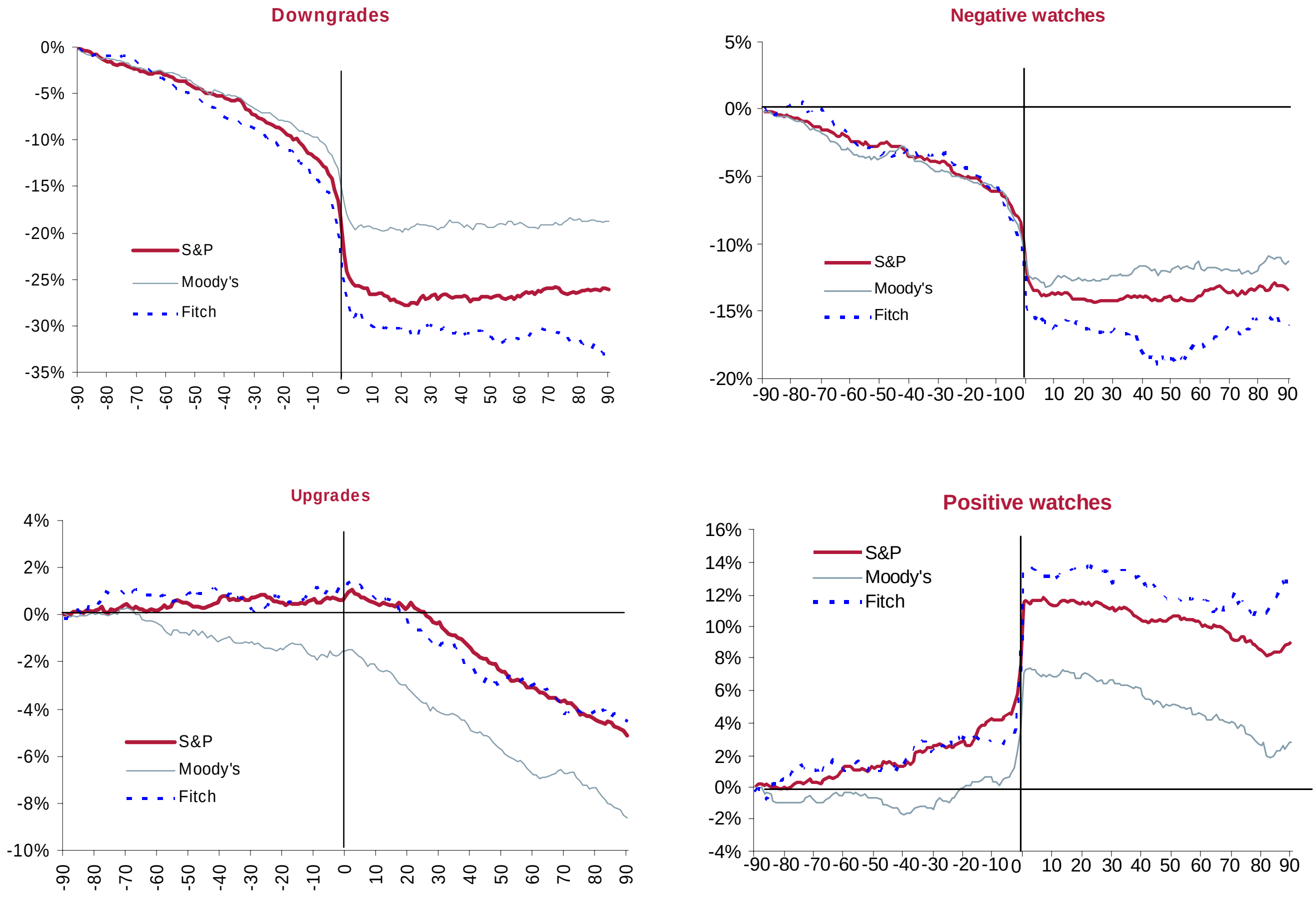
Figure 4. Europe: Mean impact of different agency decisions on cumulative abnormal returns (1990-2004)



Source: Bloomberg, authors' calculations.

Notes. The x-axis represents the number of days around the event, with 0 denoting the event date.

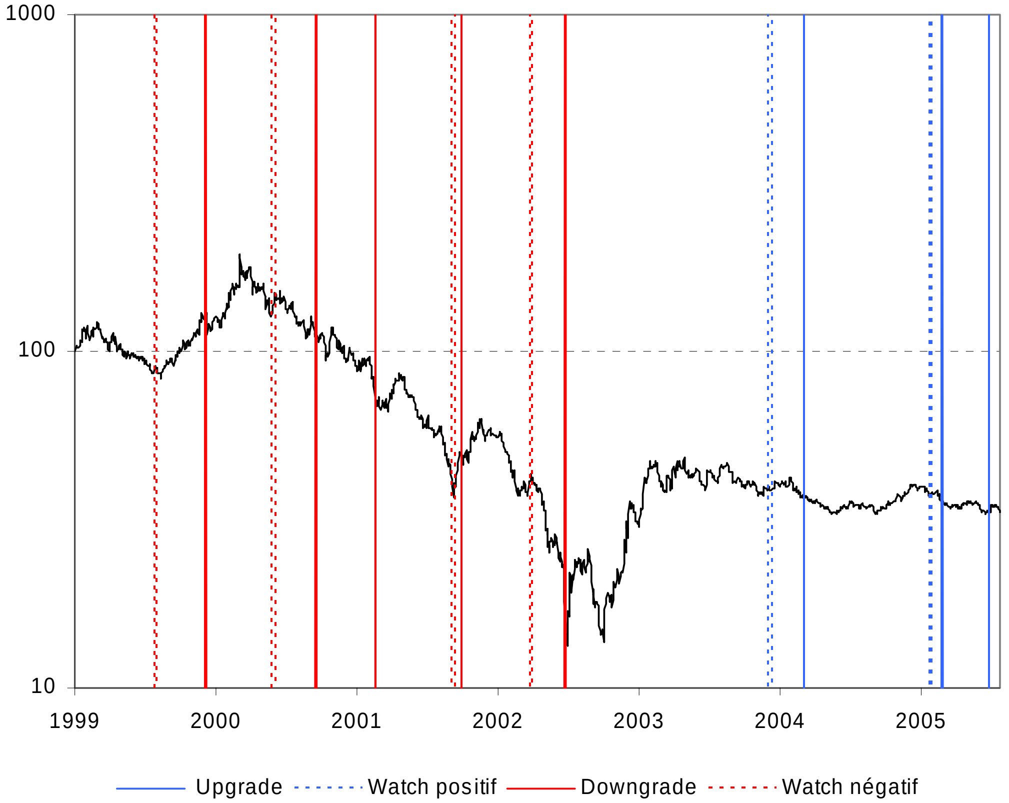
Figure 5. USA: Mean impact of different agency decisions on cumulative abnormal returns (1990-2004)



Source: Bloomberg, authors’ calculations.

Notes. The x-axis represents the number of days around the event, with 0 denoting the event date.

Figure 6. Ratings and stock prices: the case of France Télécom (logarithmic scale)



Source: Bloomberg. The figure shows the France Télécom share price over the period the period from January 1999 to July 2005 and compares it to overall market prices (captured by the SBF 250 index). The solid vertical lines represent credit rating upgrades or downgrades and the dotted vertical lines represent watches. This figure uses decisions made by Moody's as an example.

Table 1A. France: stock price impact of decisions by S&P (1990-2004)

Downgrade	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	92	92	92	92	92	92	92	92	92	92	92	92
Mean	-0.415	-2.029	-2.223	-1.591	2.902	-0.371	2.234	-4.667	4.765	0.484	-0.936	-0.678
Median	0.107	-0.239	-0.422	-0.088	2.061	-0.311	0.750	-4.073	4.442	0.050	0.247	-1.968
Standard dev	11.988	14.409	13.744	9.713	13.257	12.435	14.409	27.513	21.070	14.939	15.306	16.566
Skewness	-0.30	0.08	-1.01	-1.72	0.92	-0.26	1.12	-0.49	1.42	0.97	-0.40	-0.14
p-value	0.26	0.75	**0.00**	**0.00**	**0.00**	0.33	**0.00**	**0.06**	**0.00**	**0.00**	0.13	0.60
Kurtosis	4.07	5.52	5.74	9.87	6.10	5.51	6.36	4.05	8.29	9.47	4.57	3.59
p-value	**0.08**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.09**	**0.00**	**0.00**	**0.01**	0.40
Jarque-Béra	5.70	24.52	44.22	226.34	49.91	25.11	62.60	7.94	138.39	174.90	11.88	1.60
p-value	**0.06**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	**0.00**	**0.00**	**0.00**	0.45
T-stat	-0.3321	-1.3507	-1.5515	-1.5706	2.1000	-0.2862	1.4867	-1.6271	2.1692	0.3108	-0.5864	-0.3928
p-value	0.75	0.18	0.12	0.12	**0.04**	0.77	0.15	0.10	0.04	0.77	0.55	0.70
Sign	0.2085	-0.4170	-0.6255	-0.2085	2.7107	-0.2085	0.2085	-1.2511	1.2511	0.2085	0.4170	-0.6255
p-value	0.75	0.61	0.47	0.75	**0.00**	0.75	0.75	0.18	0.16	0.75	0.60	0.47
Wilcoxon	-0.1869	-0.9890	-1.0552	-0.6970	2.1144	-0.3115	0.9462	-1.4797	1.8691	0.4050	-0.4322	-0.4166
p-value	0.85	0.45	0.42	0.53	**0.04**	0.76	0.37	0.14	0.12	0.70	0.72	0.75

Upgrade	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	32	32	32	32	32	32	32	32	32	32	32	32
Mean	-0.121	2.176	-4.395	-0.336	-2.663	-0.844	-2.776	-2.340	-6.283	-5.541	-4.680	-7.612
Median	0.362	4.964	-2.583	-0.360	-2.715	-2.614	-1.586	-2.080	-5.607	-3.526	-2.964	-8.525
Standard dev	13.046	9.488	10.817	5.070	7.839	10.182	11.062	15.540	18.246	8.314	14.055	14.570
Skewness	0.52	-0.75	-1.00	0.86	-0.25	0.59	0.32	0.34	-0.20	-1.05	-1.03	-0.59
p-value	0.27	0.11	**0.04**	**0.07**	0.60	0.21	0.51	0.47	0.68	**0.03**	**0.03**	0.22
Kurtosis	3.58	3.26	5.49	4.27	2.10	4.33	4.57	2.83	2.73	5.54	5.81	2.76
p-value	0.86	0.88	**0.03**	0.38	0.18	0.35	0.24	0.56	0.49	**0.03**	**0.01**	0.51
Jarque-Béra	1.89	3.10	13.59	6.08	1.41	4.25	3.81	0.67	0.31	14.50	16.24	1.92
p-value	0.39	0.21	**0.00**	**0.05**	0.49	0.12	0.15	0.71	0.86	**0.00**	**0.00**	0.38
T-stat	-0.0525	1.2972	-2.2982	-0.3747	-1.9216	-0.4687	-1.4198	-0.8518	-1.9479	-3.7699	-1.8837	-2.9555
p-value	0.96	0.20	**0.03**	0.72	**0.06**	0.65	0.18	0.39	**0.06**	**0.00**	**0.07**	**0.01**
Sign	0.0000	1.7678	-2.1213	-0.3536	-1.0607	-0.7071	-1.7678	-0.3536	-2.1213	-3.8891	-2.1213	-1.0607
p-value	0.85	**0.05**	**0.02**	0.61	0.21	0.38	**0.05**	0.59	**0.02**	**0.00**	**0.02**	0.22
Wilcoxon	-0.2057	1.7390	-2.1504	-0.6732	-1.7203	-0.7854	-1.8886	-0.9536	-1.6829	-3.5902	-1.9073	-2.4870
p-value	0.84	0.22	**0.08**	0.52	**0.09**	0.58	0.12	0.36	**0.09**	**0.00**	**0.07**	**0.02**

Positive watch	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	14	14	14	14	14	14	14	14	14	14	14	14
Mean	6.875	9.360	5.478	2.372	6.130	-0.507	2.002	21.713	7.625	8.630	11.412	15.026
Median	3.162	6.627	0.261	2.336	6.067	-1.852	1.733	18.952	9.950	9.040	13.573	13.050
Standard dev	16.199	16.059	14.581	6.482	8.648	5.675	11.562	26.601	14.697	11.847	19.262	21.192
Skewness	1.07	1.37	0.97	1.06	1.25	0.58	-0.80	0.95	-0.53	0.26	0.62	0.21
p-value	0.19	**0.09**	0.24	0.20	0.13	0.47	0.33	0.25	0.51	0.75	0.45	0.80
Kurtosis	4.13	5.99	3.52	5.66	5.22	2.23	3.57	4.31	3.22	3.96	3.85	2.40
p-value	0.96	0.27	0.77	0.35	0.50	0.31	0.79	0.88	0.64	0.97	0.92	0.35
Jarque-Béra	3.41	9.57	2.34	6.74	6.50	1.14	1.69	3.10	0.69	0.69	1.32	0.32
p-value	0.18	**0.01**	0.31	**0.03**	**0.04**	0.56	0.43	0.21	0.71	0.71	0.52	0.85
T-stat	1.5882	2.1809	1.4056	1.3694	2.6525	-0.3343	0.6479	3.0542	1.9412	2.7258	2.2168	2.6530
p-value	0.15	**0.07**	0.19	0.22	**0.03**	0.74	0.53	**0.01**	**0.07**	**0.01**	**0.05**	**0.02**
Sign	1.0690	2.1381	0.5345	0.5345	1.6036	-1.0690	0.0000	1.6036	1.6036	2.1381	1.6036	1.6036
p-value	0.18	**0.01**	0.42	0.43	**0.06**	0.17	0.79	**0.06**	**0.06**	**0.01**	**0.06**	**0.06**
Wilcoxon	1.1614	2.2286	1.0986	1.2241	2.4797	-0.3453	0.9730	2.6680	1.9147	2.3541	1.9147	2.2913
p-value	0.30	**0.03**	0.45	0.23	**0.01**	0.77	0.38	**0.00**	**0.06**	**0.02**	**0.08**	**0.02**

Negativewatch	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	64	64	64	64	64	64	64	64	64	64	64	64
Mean	-2.693	-1.270	-3.518	-2.341	-0.241	-0.806	3.276	-7.481	2.229	-5.271	-4.649	-4.677
Median	-1.607	-0.448	-3.059	-2.122	-1.264	1.681	3.002	-5.280	-1.028	-2.279	-2.159	-3.608
Standard dev	11.640	11.530	12.877	8.203	15.975	11.858	13.796	25.259	24.931	14.633	18.289	21.168
Skewness	-0.30	0.48	0.20	-0.81	0.57	-0.49	0.86	0.29	1.13	-0.86	-1.22	-0.77
p-value	0.35	0.13	0.54	**0.01**	**0.08**	0.12	**0.01**	0.37	**0.00**	**0.01**	**0.00**	**0.02**
Kurtosis	3.85	4.21	3.47	6.41	8.93	2.74	6.77	4.66	8.88	4.81	7.00	5.69
p-value	0.32	0.12	0.67	**0.00**	**0.00**	0.48	**0.00**	**0.02**	**0.00**	**0.01**	**0.00**	**0.00**
Jarque-Béra	2.88	6.35	1.01	38.10	97.19	2.77	45.64	8.27	105.91	16.67	58.38	25.58
p-value	0.24	**0.04**	0.60	**0.00**	**0.00**	0.25	**0.00**	**0.02**	**0.00**	**0.00**	**0.00**	**0.00**
T-stat	-1.8510	-0.8808	-2.1858	-2.2830	-0.1209	-0.5436	1.8999	-2.3693	0.7153	-2.8820	-2.0335	-1.7674
p-value	**0.06**	0.38	**0.03**	**0.03**	0.90	0.59	**0.07**	**0.02**	0.50	**0.01**	**0.05**	**0.09**
Sign	-1.5000	-0.5000	-2.5000	-2.2500	-0.7500	0.2500	1.5000	-2.2500	-0.2500	-1.5000	-1.0000	-1.5000
p-value	0.11	0.54	**0.01**	**0.02**	0.38	0.72	0.11	**0.02**	0.71	0.10	0.26	0.11
Wilcoxon	-1.8123	-1.0499	-2.3273	-2.4409	-0.5885	-0.0334	1.8524	-2.5145	0.5350	-2.4677	-1.6384	-1.7321
p-value	**0.10**	0.41	**0.02**	**0.01**	0.58	0.99	**0.08**	**0.03**	0.73	**0.05**	0.13	**0.09**

Sources: Bloomberg, authors' calculations.
Notes. The mean, median and standard deviation of cumulative abnormal returns are expressed as percentages. The numbers printed in boldface represent tests where the null hypothesis is rejected at the 90% confidence level. In the case of the impact tests (T-stat, Sign, Wilcoxon), the probability of rejecting the null hypothesis wrongly (*p*-value) is calculated using the bootstrapped distribution.

Table 1B. France: stock price impact of decisions by Moody's (1990-2004)

Downgrade	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	59	59	59	59	59	59	59	59	59	59	59	59
Mean	-1.664	-4.369	-4.600	-1.644	2.432	-1.352	1.463	-10.633	2.543	-1.236	-2.348	-2.599
Median	-0.447	-2.819	-3.254	-0.416	1.984	-1.583	0.907	-1.099	2.749	-0.550	-1.756	-2.089
Standard d	12.517	13.388	17.721	7.584	13.309	16.694	16.265	28.632	25.501	10.799	15.179	18.183
Skewness	-0.24	-1.15	-0.09	-2.54	0.15	1.11	0.23	-0.96	-0.18	-0.90	-0.21	-0.54
p-value	0.48	**0.00**	0.79	**0.00**	0.66	**0.00**	0.50	**0.00**	0.59	**0.01**	0.52	0.11
Kurtosis	3.47	4.88	3.92	14.84	7.38	8.68	7.81	3.92	3.95	5.89	4.10	4.81
p-value	0.70	**0.01**	0.30	**0.00**	**0.00**	**0.00**	**0.00**	0.30	0.28	**0.00**	0.19	**0.02**
Jarque-Béra	1.11	21.67	2.16	408.20	47.35	91.25	57.48	11.05	2.54	28.54	3.43	10.91
p-value	0.57	**0.00**	0.34	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.28	**0.00**	0.18	**0.00**
T-stat	-1.0211	-2.5067	-1.9939	-1.6652	1.4039	-0.6220	0.6909	-2.8526	0.7661	-0.8788	-1.1881	-1.0979
p-value	0.31	**0.02**	**0.05**	0.12	0.16	0.54	0.50	**0.01**	0.45	0.40	0.24	0.29
Sign	-0.3906	-1.1717	-0.9113	-1.1717	1.6925	-0.6509	0.3906	-0.9113	1.1717	-0.3906	-0.6509	-0.1302
p-value	0.61	0.20	0.30	0.19	**0.07**	0.43	0.61	0.31	0.20	0.60	0.44	0.80
Wilcoxon	-0.6491	-2.0153	-1.7738	-1.3586	1.5926	-1.0718	0.5586	-2.0757	1.0567	-0.4302	-1.0265	-0.8378
p-value	0.54	**0.04**	**0.09**	0.24	0.10	0.29	0.59	0.38	0.30	0.67	0.31	0.40
Upgrade	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	30	30	30	30	30	30	30	30	30	30	30	30
Mean	0.207	-1.521	3.064	0.164	-0.219	-2.144	1.721	1.750	-0.642	1.728	2.654	2.794
Median	1.613	-2.232	2.742	0.067	0.944	-1.424	0.728	1.060	-1.593	2.393	3.526	3.853
Standard d	8.732	8.964	9.758	2.634	6.364	11.051	9.174	17.922	12.994	6.778	10.020	13.242
Skewness	-0.99	-0.09	-0.21	0.70	-0.15	-2.53	0.26	-0.20	-0.09	0.27	-0.48	0.10
p-value	**0.05**	0.86	0.68	0.16	0.76	**0.00**	0.61	0.68	0.86	0.59	0.33	0.83
Kurtosis	4.87	3.48	3.65	3.18	2.34	11.91	3.73	3.80	3.46	3.06	3.30	3.42
p-value	0.16	0.97	0.83	0.81	0.29	**0.00**	0.77	0.72	0.98	0.72	0.89	0.99
Jarque-Béra	9.21	0.32	0.75	2.47	0.65	131.12	0.99	1.01	0.31	0.36	1.28	0.28
p-value	**0.01**	0.85	0.69	0.29	0.72	**0.00**	0.61	0.60	0.86	0.84	0.53	0.87
T-stat	0.1297	-0.9295	1.7201	0.3409	-0.1888	-1.0626	1.0277	0.5348	-0.2707	1.3959	1.4507	1.1555
p-value	0.90	0.37	**0.10**	0.74	0.84	0.32	0.31	0.60	0.78	0.18	0.16	0.26
Sign	0.7303	-1.0954	2.1909	0.3651	0.7303	-0.7303	0.3651	1.4606	-0.7303	0.7303	1.4606	2.1909
p-value	0.35	0.21	**0.02**	0.59	0.37	0.36	0.60	**0.10**	0.37	0.37	**0.10**	**0.02**
Wilcoxon	0.8330	-1.1210	2.0260	-0.0720	-0.1543	-0.6685	0.8947	0.7713	-0.3805	1.3884	1.5529	1.2032
p-value	0.43	0.32	**0.05**	0.94	0.91	0.53	0.43	0.46	0.72	0.23	0.13	0.25
Positive watch	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	16	16	16	16	16	16	16	16	16	16	16	16
Mean	2.240	1.092	6.175	1.724	0.861	-3.587	-0.782	9.506	-3.508	5.067	5.132	7.517
Median	-1.067	4.112	6.203	0.209	1.650	-3.610	-1.824	11.836	-1.620	5.416	5.751	8.881
Standard d	12.488	9.161	13.867	6.231	6.575	7.873	10.197	25.230	16.103	8.280	13.581	18.927
Skewness	0.50	-0.74	0.44	1.98	0.45	0.13	0.25	-0.41	-0.43	0.07	0.58	0.11
p-value	0.50	0.32	0.56	0.01	0.54	0.86	0.74	0.58	0.56	0.93	0.44	0.89
Kurtosis	2.92	2.32	3.98	6.68	3.08	3.37	3.33	3.45	3.18	2.90	3.25	2.69
p-value	0.54	0.32	0.95	**0.08**	0.61	0.74	0.73	0.78	0.66	0.53	0.69	0.45
Jarque-Béra	0.68	1.76	1.15	19.53	0.55	0.13	0.24	0.59	0.52	0.02	0.94	0.09
p-value	0.71	0.42	0.56	0.00	0.76	0.94	0.89	0.75	0.77	0.99	0.63	0.95
T-stat	0.7175	0.4766	1.7810	1.1067	0.5237	-1.8222	-0.3068	1.5071	-0.8714	2.4479	1.5114	1.5887
p-value	0.48	0.64	**0.10**	0.31	0.62	**0.09**	0.76	0.15	0.40	**0.03**	0.15	0.15
Sign	-0.5000	1.5000	1.0000	0.5000	1.0000	-1.5000	-0.5000	2.0000	-0.5000	1.0000	1.0000	1.0000
p-value	0.46	0.07	0.21	0.46	0.21	0.08	0.46	0.02	0.44	0.21	0.21	0.22
Wilcoxon	0.2068	0.3620	1.7064	0.6205	0.2585	-1.8615	-0.5171	1.6030	-0.6205	2.1201	1.3961	1.3961
p-value	0.87	0.77	0.09	0.55	0.80	0.06	0.62	0.12	0.54	0.04	0.18	0.19
Negative watch	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	30	30	30	30	30	30	30	30	30	30	30	30
Mean	-0.990	-4.912	-0.935	-1.600	2.400	-4.627	4.287	-6.837	2.060	-1.639	0.196	-0.835
Median	2.573	-5.775	0.590	0.318	0.842	-1.853	2.887	-3.872	0.480	1.122	1.283	5.191
Standard d	14.718	11.718	11.845	9.985	17.473	16.212	13.967	28.426	28.830	15.574	13.667	16.888
Skewness	-0.24	-0.35	-0.53	-2.51	1.28	0.02	1.49	-0.68	1.59	-0.84	-0.96	-0.54
p-value	0.63	0.48	0.28	**0.00**	**0.01**	0.97	**0.00**	0.17	**0.00**	**0.09**	**0.05**	0.27
Kurtosis	2.57	4.14	3.88	9.51	6.01	3.56	7.24	3.07	7.37	4.44	3.94	3.60
p-value	0.40	0.49	0.67	**0.00**	**0.01**	0.91	**0.00**	0.72	**0.00**	0.33	0.62	0.87
Jarque-Béra	0.52	2.23	2.39	84.51	19.53	0.39	33.66	2.29	36.45	6.09	5.75	1.92
p-value	0.77	0.33	0.30	**0.00**	**0.00**	0.82	**0.00**	0.32	**0.00**	**0.05**	**0.06**	0.38
T-stat	-0.3684	-2.2960	-0.4324	-0.8777	0.7525	-1.5632	1.6810	-1.3174	0.3915	-0.5765	0.0785	-0.2710
p-value	0.72	**0.03**	0.68	0.40	0.47	0.14	0.12	0.20	0.71	0.58	0.94	0.78
Sign	0.3651	-2.1909	0.3651	0.3651	0.7303	-0.3651	1.8257	-0.3651	0.0000	1.4606	0.7303	0.3651
p-value	0.62	**0.01**	0.58	0.58	0.36	0.58	**0.04**	0.59	0.85	0.13	0.37	0.58
Wilcoxon	-0.2365	-2.2317	-0.1543	0.0514	0.4628	-1.0181	1.4706	-1.0181	-0.0720	0.2982	0.6890	-0.2160
p-value	0.90	**0.04**	0.89	0.95	0.65	0.37	0.14	0.31	0.94	0.79	0.50	0.95

Sources: Bloomberg, authors' calculations.
Notes. See notes to Table 1A.

Table 1C. France: stock price impact of decisions by Fitch (1990-2004)

Downgrade	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	27	27	27	27	27	27	27	27	27	27	27	27
Mean	2.066	-5.614	-2.640	-1.431	2.034	-1.034	1.940	-6.188	2.939	-2.814	-2.479	-0.984
Median	0.343	-3.280	0.350	0.013	1.971	1.092	0.063	0.246	9.386	0.175	1.211	-0.151
Standard d	9.509	15.601	13.111	9.815	16.232	13.275	12.119	29.632	23.606	15.798	23.498	22.209
Skewness	0.35	-1.69	-0.70	-3.16	-1.97	-0.24	1.17	-1.42	-1.06	-0.59	-2.27	-2.11
p-value	0.51	**0.00**	0.19	**0.00**	**0.00**	0.65	**0.03**	**0.01**	**0.04**	0.26	**0.00**	**0.00**
Kurtosis	2.47	5.80	3.80	17.23	11.02	3.42	4.73	5.70	4.38	5.27	9.42	9.17
p-value	0.35	**0.04**	0.77	**0.00**	**0.00**	0.95	0.26	**0.04**	0.42	0.10	**0.00**	**0.00**
Jarque-Béra	0.86	21.59	2.92	272.79	89.71	0.45	9.51	17.33	7.20	7.37	69.62	62.89
p-value	0.65	**0.00**	0.23	**0.00**	**0.00**	0.80	**0.01**	**0.00**	**0.03**	**0.03**	**0.00**	**0.00**
T-stat	1.1291	-1.8698	-1.0464	-0.7574	0.6510	-0.4048	0.8316	-1.0851	0.6469	-0.9256	-0.5482	-0.2302
p-value	0.27	**0.10**	0.31	0.53	0.56	0.70	0.42	0.29	0.52	0.37	0.61	0.82
Sign	0.1925	-0.5774	0.1925	0.1925	0.5774	1.7321	0.1925	0.1925	0.9623	0.1925	0.5774	-0.1925
p-value	0.70	0.45	0.71	0.70	0.46	**0.06**	0.71	0.71	0.25	0.71	0.45	0.70
Wilcoxon	0.7688	-1.3214	-0.6487	-0.5526	1.2733	0.1682	0.4324	-0.5526	1.0811	-0.6727	0.2162	0.6246
p-value	0.52	0.21	0.64	0.64	0.21	0.87	0.69	0.65	0.45	0.61	0.82	0.61
Upgrade	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	12	12	12	12	12	12	12	12	12	12	12	12
Mean	-3.734	-2.410	-2.822	0.338	0.195	-2.181	-1.953	-8.966	-3.939	-0.137	-0.924	-1.975
Median	-0.976	-1.677	-0.245	0.423	0.357	-2.303	-1.521	-9.864	-3.147	-0.492	0.319	2.446
Standard d	7.106	5.379	7.138	2.053	10.236	8.272	8.393	12.944	19.813	6.233	9.438	11.552
Skewness	-0.62	-0.69	-0.66	0.05	-0.20	-0.03	-1.16	0.00	0.01	0.08	-0.81	-1.48
p-value	0.50	0.45	0.47	0.96	0.83	0.97	0.21	1.00	0.99	0.93	0.38	0.11
Kurtosis	2.27	3.13	2.39	2.33	2.96	2.48	5.41	2.35	2.79	3.20	3.11	4.27
p-value	0.32	0.58	0.35	0.34	0.52	0.38	0.56	0.34	0.47	0.60	0.57	0.99
Jarque-Béra	1.04	0.95	1.05	0.23	0.08	0.14	5.61	0.21	0.02	0.03	1.33	5.21
p-value	0.59	0.62	0.59	0.89	0.96	0.93	**0.06**	0.90	0.99	0.98	0.51	**0.07**
T-stat	-1.8203	-1.5522	-1.3696	0.5699	0.0658	-0.9133	-0.8062	-2.3997	-0.6888	-0.0763	-0.3391	-0.5923
p-value	0.10	0.15	0.20	0.57	0.95	0.37	0.45	**0.04**	0.50	0.93	0.74	0.57
Sign	0.0000	-0.5774	0.0000	0.5774	0.0000	-1.1547	-1.1547	-1.7321	-0.5774	-0.5774	0.0000	1.1547
p-value	0.77	0.37	0.78	0.39	0.77	0.15	0.14	**0.04**	0.40	0.38	0.77	0.15
Wilcoxon	-1.1767	-1.4120	-0.8629	0.6276	0.0000	-1.0198	-0.7060	-1.9612	-0.7060	-0.3138	0.0000	0.3138
p-value	0.43	0.16	0.51	0.51	0.97	0.30	0.47	0.04	0.47	0.74	0.97	0.78
Positive watch	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	5	5	5	5	5	5	5	5	5	5	5	5
Mean	0.891	-5.946	24.029	1.279	9.571	-0.784	-0.756	18.974	8.031	19.716	26.170	34.801
Median	-0.360	2.266	20.759	0.222	4.591	-0.674	-3.451	17.641	1.861	19.044	18.182	33.369
Standard d	7.815	12.639	8.780	2.593	11.540	5.172	7.151	9.056	15.305	9.511	19.829	13.628
Skewness	0.26	-0.71	1.86	1.81	1.44	0.42	1.94	0.94	0.76	0.98	0.72	0.37
p-value	0.90	0.74	0.38	0.40	0.50	0.84	0.36	0.66	0.72	0.65	0.74	0.86
Kurtosis	2.26	2.18	4.72	4.64	4.07	3.24	4.83	3.94	2.97	3.54	2.98	2.40
p-value	0.34	0.34	0.63	0.62	0.54	0.44	0.64	0.53	0.42	0.48	0.42	0.36
Jarque-Béra	0.17	0.56	3.50	3.30	1.96	0.16	3.84	0.92	0.49	0.86	0.43	0.19
p-value	0.92	0.76	0.17	0.19	0.38	0.92	0.15	0.63	0.78	0.65	0.81	0.91
T-stat	0.2548	-1.0519	6.1198	1.1032	1.8545	-0.3389	-0.2363	4.6849	1.1733	4.6355	2.9511	5.7100
p-value	0.80	0.29	**0.08**	0.42	0.24	0.74	0.66	**0.01**	0.32	**0.01**	**0.09**	**0.02**
Sign	-0.4472	0.4472	2.2361	0.4472	1.3416	-0.4472	-1.3416	2.2361	0.4472	2.2361	2.2361	2.2361
p-value	0.43	0.42	**0.00**	0.43	**0.09**	0.43	**0.09**	**0.00**	0.43	**0.00**	**0.00**	**0.00**
Wilcoxon	0.1348	-0.4045	2.0226	0.9439	1.7529	-0.4045	-0.6742	2.0226	0.9439	2.0226	2.0226	2.0226
p-value	0.92	0.62	**0.00**	0.26	**0.01**	0.58	0.33	**0.00**	0.31	**0.00**	**0.00**	**0.00**
Negativewatch	[-90:-61]	[-60:-31]	[-30:-1]	[-1:1]	[1:30]	[31:60]	[61:90]	[-90:-1]	[1:90]	[-10:+10]	[-20:+20]	[-30:+30]
n	20	20	20	20	20	20	20	20	20	20	20	20
Mean	1.664	-5.126	-5.067	-2.092	1.240	0.575	4.130	-8.528	5.944	-0.531	-0.656	-4.893
Median	4.191	-8.689	-1.507	0.606	2.770	3.185	4.299	-7.927	4.692	1.929	1.664	-4.348
Standard d	12.137	13.584	15.050	8.786	16.599	14.133	9.589	27.572	19.707	17.901	14.469	19.677
Skewness	-0.08	0.68	-1.60	-2.93	0.16	0.58	0.03	0.09	0.41	-0.71	-0.57	-0.43
p-value	0.90	0.28	**0.01**	**0.00**	0.81	0.37	0.96	0.88	0.52	0.27	0.37	0.50
Kurtosis	2.98	2.85	6.41	12.03	3.46	4.55	4.31	2.52	3.01	4.90	2.80	2.40
p-value	0.60	0.54	**0.04**	**0.00**	0.87	0.52	0.64	0.39	0.61	0.36	0.51	0.34
Jarque-Béra	0.02	1.58	18.19	96.57	0.26	3.10	1.42	0.22	0.57	4.70	1.12	0.92
p-value	0.99	0.45	**0.00**	**0.00**	0.88	0.21	0.49	0.90	0.75	**0.10**	0.57	0.63
T-stat	0.6133	-1.6876	-1.5056	-1.0651	0.3340	0.1819	1.9259	-1.3833	1.3489	-0.1328	-0.2027	-1.1120
p-value	0.55	0.11	0.18	0.36	0.74	0.86	**0.07**	0.19	0.20	0.90	0.84	0.27
Sign	0.8944	-1.7889	-0.4472	0.4472	0.4472	0.4472	2.2361	-0.8944	0.8944	0.8944	0.4472	-0.4472
p-value	0.26	**0.04**	0.51	0.50	0.51	0.49	**0.01**	0.28	0.26	0.26	0.50	0.50
Wilcoxon	0.5973	-1.5680	-1.1946	-0.4480	0.4107	0.2613	1.9413	-1.3066	1.1573	0.3733	0.0373	-0.8960
p-value	0.63	0.20	0.32	0.73	0.71	0.84	**0.05**	0.20	0.25	0.74	0.96	0.36

Sources: Bloomberg, authors' calculations.
Notes. See notes to Table 1A.

Appendix 1. List of French companies in the sample

Finabail
Credit Agricole SA
Societe Assurances Generales de France
Air Liquide
Elf Aquitaine
Autoroutes du Sud de la France
Aventis SA
Eridania Beghin-Say
Groupe Danone
BNP Paribas
Carrefour SA
CA Ile de France
Cap Gemini SA
Credit Industriel et Commercial
CA Normandie Seine
Entenial
Coflexip SA
Alcatel SA
Credit Lyonnais SA
CA Nord de France-CCI
Casino Guichard Perrachon SA
CA Atlantique Vendee-CCI
CA Centre Loire
CA Touraine Poitou
AXA
Dexia Credit Local
Endesa SA
Vivendi Universal SA
Credit Foncier De France
Societe Fonciere Lyonnaise
Total Fina Elf SA
Valeo SA
Banque AGF
HSBC CCF
France Telecom
Compagnie Generale de Geophysique SA
Gecina SA
Societe Generale
Usinor SA
Natexis Banques Populaires
Lafarge SA
Klepierre
Legrand
Compagnie de Navigation Mixte SA
Compagnie Generale des Etablissements Michelin
Nexans SA
CPR SA
Paribas
Pinault-Printemps-Redoute
Remy Cointreau
Rhodia SA
Renault SA
Tereos
SCOR
Cie de Saint-Gobain
Selectibail
Sophia SA
Schneider Electric SA
Sodexho Alliance SA
Suez SA
Technip-Coflexip SA
Banque Tarneaud SA
Union du Credit-Bail Immobilier
Union Pour le Financement d'Immeubles de Societes
Via Banque
Vivendi Environnement
Provimi SA
Financiere Pour la Location d'Immeubles Industriels et Commerciaux

Appendix 2. List of variables

Variable	*Source:*
Beta	Ixis CIB
Historical volatility	Ixis CIB
Latest rating	Bloomberg
Rating change	Bloomberg
Fallen angels dummy	Bloomberg
Rising stars dummy	Bloomberg
Number of days since the latest decision	Bloomberg
Year of the event	Bloomberg
Financial/Non-financial sector	Bloomberg
GDP growth – France	INSEE
GDP growth – OECD	OECD
Long-term interest rate at t and t-1	Datastream
Market capitalisation of the CAC40 index	Bloomberg
Market capitalisation of the SBF250 index	Bloomberg
Historical volatility of CAC40	IXIS CIB
Ratio of upgrades to downgrades in the sector	Bloomberg
Aggregate ratio of upgrades to downgrades	Bloomberg
Debt/Ebitda ratio	Bloomberg
Ebitda/Interest expense ratio	Bloomberg
Capitalisation (compared to market)	Bloomberg
Price-to-book ratio	Bloomberg
Tier I capital	Bloomberg
Nonperforming Loans (Banks)	Bloomberg
Reserves/Capital (Insurance)	Bloomberg
High Yield Dummy	Bloomberg
Investment Grade Dummy	Bloomberg
Number of days since the watch was announced (for downgrades and upgrades preceded by a watch)	Bloomberg
Default rate	S&P
Earnings announcements in the month around the announcement date.	Bloomberg

2 IMPACT OF CREDIT RATING AGENCIES' DECISIONS ON NEW BOND PRODUCTS IN EUROPE: THE CASE OF ASSET-BACKED SECURITIES (ABS)

Study by Mathieu Mancini, Université Montesquieu-Bordeaux IV and Jérôme Teiletche, IXIS CIB

Asset-Backed Securities (ABS) account for an increasing share of investors' portfolios. Credit ratings are a key element for pricing these structured bond products. Our study is a preliminary analysis of the impact that the main credit rating agencies' decisions had on the pricing of a set of European ABS between 1999 and 2005. We find that bond prices and spreads react strongly to credit rating downgrades and, more surprisingly, to upgrades as well. This tends to validate the hypothesis that credit rating agencies play an even greater role on ABS markets as sources of information and benchmarks.

2.1 Introduction

Asset-backed securities (ABS) account for an increasing share of investors' portfolios. ABS are at the very heart of the move to transfer claims and risks that were previously the exclusive domain of banks to the rest of the financial community, as part of the overall process generally referred to as securitization[19]. ABS have seen outstanding growth because of the substantial advantages that they offer to investors and issuers alike. For issuers, securitisation is a way of improving market financing terms and facilitating asset and liability management. For investors, ABS broaden the range of opportunities available on bond markets and usually offer an excellent return for risk[20].

One of the keys to these advantages is the credit rating attributed to the structure. An ABS is usually more complex and less transparent than another bond investment. Unlike a conventional bond, issued by a single company that is usually well known and closely monitored by the financial community, the underlying assets for ABS are more dispersed, less familiar and they require an understanding or the development of complex models or models with uncertain parameters[21]. The role of credit rating agencies in analysing these structures and disseminating information has therefore become even more critical.

Despite the exponential growth of ABS and the special role played by ratings, the literature contains hardly any studies on ABS and, more specifically, on the impact of credit rating agencies' decisions on ABS. One exception is the paper by Ammer and Clinton (2004), who analyse the impact of rating changes on the American market

[19] In general terms, securitization involves a credit institution's sale of a set of claims (which are thus removed from its balance sheet) to a Special Purpose Vehicle (SPV) created specially for this purpose. This vehicle then finances its acquisition of the claims by issuing securities that are collateralised by the revenue stream from the claims, which now constitute its assets. Definitions may vary, but Asset Backed Securities (ABS) fall into three main categories. Most of them are securitised mortgage claims, either Commercial Mortgage-Backed Securities (CMBS), or Residential Mortgage-Backed Securities (RMBS). The second category is the historical category when securitization first started in the USA in the mid-nineteen eighties, that is securities that are backed by claims on households, such as student loans, credit card payments, car loans, financial leases and various consumer loans. The third category is made up of Collateralised Debt Obligations (CDOs), which are backed by loans to businesses (Collateralised Loan Obligations –CLOs) or corporate bond issues (Collateralised Bond Obligations – CBOs). This more recent category of ABS has seen very rapid growth. It is also a rapidly changing category where many new hybrid products have emerged, such as synthetic CDOs where the underlying assets are credit derivatives, such as Credit Default Swaps (CDS), CDOs of CDOs or CDOs of ABS.

[20] One of the notable characteristics of ABS is that they usually have a high rating and, consequently carry a low default risk. As we show below, European ABS often have AAA ratings. However, the spreads on ABS (the excess return compared to the risk-free rate) are often greater than the spreads offered by issuers with equivalent ratings, such as central governments, quasi-governmental entities and international institutions.

[21] There are many examples. Such parameters may include the macroeconomic probability of early repayment or default by households in the case of mortgages, or the correlation of defaults by a group of companies in the case of CDOs.

between 1996 and 2003 in a study covering 1,300 upgrades and downgrades. Their study reveals that reactions to downgrades are stronger than those observed in the case of conventional bonds. Our article proposes to conduct the same type of event study for the European ABS market. We start with an overview of the ABS market in Europe, including recent rating trends.

2.2 An overview of growth and recent rating trends in the ABS market in Europe

ABS, which were unheard of in the mid-nineteen eighties, have enjoyed strong growth in the bond market. In the USA, ABS now account for more than USD 1,800bn in debt securities, which represents approximately 9% of total outstanding debt securities (excluding Treasuries). In Europe, their growth got off to a later start, but it has been just as spectacular. ABS now account for nearly 10% of outstanding non-government euro-denominated debt securities, or EUR 470bn. Figure 1 shows details of euro issues ABS for each year, along with two of their main rivals, which are corporate debt securities issued by non-financial companies and Pfandbriefe and other covered debt securities. The latter category also includes bonds created by securitising real estate loans. However, we have not included such bonds in ABS, since they are very different by virtue of the fact that the underlying loans are still shown as assets on the issuers' balance sheets and there is no intermediate entity. In some cases, such bonds even come with some form of government guarantees (e.g. German state Länders). It is noteworthy that ABS market is now as big as the one for such bonds, which has traditionally been a very large market in Europe. On the whole, S&P (2005a) notes that worldwide bond issues in 2005 have been driven by ABS and, more specifically, by CDOs.

In response to these developments, credit rating agencies devote major resources to rating and analysing European ABS. At the end of 2004, S&P had given ratings to nearly 3,400 European securitisation vehicles (S&P (2005b)) and Fitch had rated nearly 2,500 (Fitch (2005)). Fitch also highlighted the increase of 57% in 2004 alone, with nearly half the growth coming from CDOs[22]. The agencies' recent publications report a substantial improvement in the quality of credit in 2004, with a ratio of 2.4 upgrades for every downgrade according to Fitch and a ratio of 1.2 upgrades per downgrade according to S&P. This trend, which was in contrast to the early years of the market's growth between 2000 and 2003, continued into the early months of 2005. Some of the improvement can be attributed to better business conditions since 2003[23]. In addition, Fitch reports a record number of defaults, but it attributes this primarily to market growth, rather than an increase in the probability of default. If we make a broader comparison of rating dynamics (using rating transition matrices) between ABS and conventional bonds, we can make the following observations (see Table 1).

- ABS ratings are more stable, as can be seen in the higher probabilities along the diagonal of the transition matrix. In any case, stability is greater for the very good ratings, which are attributed to the bulk of bonds.
- The default rate is lower for ABS, at all rating levels.

All else being equal, this means that ABS, in addition to having very high mean ratings, involve a very low intrinsic risk. The fact that ratings rarely change is a major characteristic of this market. It is partially offset by the fact that when changes do occur, they are usually bigger changes than those announced for conventional bonds. Mean rating changes for ABS involve shifts of 2.5 to 3 notches, while mean changes for conventional bonds involve shifts of 1.5 notches. The usual explanation, put forward by Ammer and Clinton (2004), is that credit rating

[22] Fitch also highlighted an important difference compared to the much larger and more diversified US market, where CDOs play a smaller role.
[23] This argument is especially valid in the United Kingdom, more so than in the euro area. As a rule, the change in the quality of credit within ABS is likely to be affected by major cyclical and macroeconomic factors. For example, RMBS are very dependent on the level of interest rates and the unemployment rate.

agencies do not track ABS as regularly as they do non-financial and financial sector issuers, which often provide a stream of news by publishing quarterly earnings. Ultimately, we have to keep these circumstances in mind when conducting our empirical study.

2.3 Empirical study of the impact of rating changes on European ABS

2.3.1 Description of the sample

We have applied the methodology of Ammer and Clinton (2004) to European data in order to analyse the impact of rating changes on ABS pricing. More specifically, we based our work on the composition of the Merrill Lynch indices downloaded from Bloomberg and covering two areas: the United Kingdom and the euro area[24]. We used these two areas because they enable us to come up with more reasonable samples[25]. Unlike the American market, the European ABS market is still young and it is difficult to obtain reliable price information. This means the benchmarks are simplified[26]. This study is only a preliminary attempt at analysis and that further work is bound to be required to supplement it.

We classified the securities according to their ISIN code. Then, for each one, we obtained the maturity, composite credit rating, par value, benchmark tranche, yield to maturity, price, duration, Option Adjusted Spread (OAS, which is the spread over treasury yield curve), Asset Swap Margin (ASM, which is a spread over the swap yield curve) and the total return (including capital gains and coupon payments)[27]. The ratings and amounts given in the Merrill Lynch index are updated at the end of each month only. Furthermore, the ratings in the index are composites of two ratings from Moody's and S&P. They are an average rating obtained by combining the two agencies' respective rating scales (Fitch ratings are not included). Each security has three descriptive fields: the ticker code, the serial code and a class identifier. As a rule, the ticker code gives the name of the sponsor and the serial code specifies the special purpose vehicle (SPV), which is the entity that owns the underlying assets and issues the ABS. The class corresponds to the specific tranche that the securities are from (senior debt, mezzanine debt or equity), but this information is often missing. Only senior tranches are covered, which does not imply that the other assets are not part of the same tranche.

Table 2 provides a description of the data on different dates. We can see that the sample has grown from just over 30 securities to 170. The United Kingdom accounted for nearly two thirds of the bonds over the whole period. The vast majority of securities are rated AAA, especially in the euro area, where, in 2005, they still accounted for 80% of the index. This stems from a market feature that has already been mentioned. The medians shown in Table 2 show a standard ABS with much longer duration and maturity than the ones presented by Ammer and Clinton (2004). This effect can be attributed to the Sterling market where average maturity is much longer than on the euro market. By way of comparison, the duration of British securities is nearly double the duration of euro securities, and the maturity is four times longer, whereas Euro and US ABS have comparable medians. Asset Swap Spreads and Option Adjusted Spreads both posted wide fluctuations over the period, increasing between 1999 and 2001, as the quality of credit declined in Europe on both markets, and decreasing rapidly after that. The pattern of events matches that seen on more conventional credit markets.

Like that of Ammer and Clinton (2004), our analysis is conducted monthly, since that is the frequency with which composite ratings are updated. In any event, the lack of liquidity, and the ensuing difficulty in coming up with

[24] More specifically, the reference currency for the bonds is used to make the distinction. In practice, this criterion creates a very similar structure to the structure by geographical origin. However, some of the underlying assets are not European; they are issued by companies located in the Cayman Islands and the USA.
[25] The detailed results for each individual zone are available on request.
[26] It should be remembered that Pfandbriefe are not included in our study.
[27] The type of underlying asset is also reported, but this information is not very helpful since most of the securities fall into the Miscellaneous category.

relevant prices, mean that it would be pointless to try to conduct a study based on a higher frequency of observations. A downgrade or an upgrade is recorded when the rating of a security is different from the previous month's rating. This means that single-notch rating changes by one agency or another may not lead to a change in the composite credit rating, if the average rating remains the same. However, the probability of this is slight. Table 3 shows credit rating changes on the markets under consideration. We came up with a count of 28 downgrades (including 20 in the Sterling market) and 19 upgrades (including 16 in the Sterling market). However, the numbers of credit rating changes is reduced to 25 downgrades and 17 upgrades if we only count issuer-level rating changes affecting several tranches of securities. This leaves us with only 47 observed rating changes, which are reduced further to 42, after we eliminate duplicate changes on the Sterling market. Most of the rating changes occurred after 2002, when there was an overall improvement in credit quality (see above). Most of the changes involved a move of just one notch. One-notch changes in the composite rating may stem from a change of two notches or more by a single agency, if the other agency's rating remains the same. We should also note that the lack of precise information about their performance around the event meant that we had to exclude three securities whose ratings changed from investment to speculative grade (known as "fallen angels") and one security whose rating changed from speculative to investment grade (known as a "rising star").

2.3.2 Estimates and results

Table 4 shows the test results. Unlike Ammer and Clinton (2004), we do not use the t-test alone to test the significance of credit rating changes. We also use non-parametric tests, such as the Sign test and the Wilcoxon signed-rank test, to take account of several problems relating to the sample, including its small size and the non-normal distribution of returns[28]. These tests are conducted for three different measurements of securities performance in order to refine the results. The measurements are abnormal returns, Option Adjusted Spread and Asset Swap Margin. All three are calculated as excess to the whole market, meaning the difference from the equivalent measurement for the market as a whole over the same period. This is done to strip out the impact of general market trends and to focus on the effects caused by changes in the credit ratings of securities. We test the impact over the whole month during which the rating changed.

The first column shows the test results for downgrades observed in the overall sample. In the event of a downgrade, we expect to see a negative return and positive variations in the OAS and ASM. In the broader sample, the mean impact on returns is -4.6% (in excess of the whole market return). This is a substantial impact compared to the -2.9% impact found by Ammer and Clinton (2004) in the USA and compared to the equities market, even though the variance of equities is much greater than the variance of ABS bonds[29]. The t-test shows a significant impact at the 5% level. The non-parametric tests give even more significant results. Both tests show that credit rating changes have a very significant impact. This result is perfectly logical if we consider the fact that downgrades lead to an excess negative return on the security in more than 80% of the cases. Once again, the effects observed are much stronger than on other markets. Ammer and Clinton (2004) report a proportion of only 60% of negative returns. The results of the tests on OAS and ASMs are slightly less straightforward. The only significant test for ASMs is the t-test and the only significant test for ASMs and OAS is the Sign test, but the percentages of positive values are fairly high at 64% and 71% respectively. One noteworthy result concerns the similar magnitude of the variation in OAS (159 basis points), compared with the variation that Ammer and Clinton (2004) identified for the American market. The impact on ASMs is smaller, but it is still greater than the impact

[28] See the companion article by Iankova, Pochon and Teïletche (2005) for more details.
[29] See Norden and Weber (2004) or Iankova, Pochon and Teïletche (2005) for a quantification covering several geographical areas.

identified on the spread markets for more conventional issuers[30]. On the whole, the large differences between the mean and median values clearly show the skewness of the distributions of variations in the variables.

The third column also deals with downgrades, showing the test results after stripping out duplicate results in cases where issuer rating changes affect the ratings of several different tranches. Because the tranches in question are not specified in our sample, the elimination of duplicate results is arbitrary, but random. These tests are ultimately just as significant overall as the tests on the whole sample. In fact, the observed effect is even stronger in terms of variations in the variables (-5.1%, vs. -4.6% for returns, 177.8 versus 158.9 for OAS, and 67.8 versus 60.7 for asset swap spreads), but the loss of power stemming from the smaller number of observations does affect the significance of the impacts somewhat.

The second and fourth columns show the results for upgrades. In this case, we would expect a significant positive return and significant decreases in the spreads. The mean effects are smaller than for downgrades. With the notable exception of returns, the significance of the effects is nonetheless remarkably high if we look at the p-values, especially in comparison to downgrades, where there are more observations. The latter results are very different from those found by Ammer and Clinton (2004), who did not identify any significant impact. However, these authors used only a simple t-test and we have already seen that such a test also failed to show any convincing effects in the case of Europe. On the whole, we could expect the differences between test results to be large, in view of the skewness of the distributions of variables that we observe. We should also note that the literature on conventional bonds shows that upgrades generally do not have a significant impact on either equities or bonds (see references cited above). This makes our results all the more remarkable. As in the case of downgrades, stripping out duplicate rating changes does not lead to any significant change in the results.

We then look at the sensitivity of reactions to the various known characteristics of the ABS. Tables 5a and 5c show the detailed results of regressions for each type of performance measurement and for each month in which a credit rating event occurred. In each case the table shows the expected sign of each of the variables. With an adjusted R-squared of 97%, as opposed to 66%, the model seems to provide better explanation of the impact of downgrades than it does of the impact of upgrades. This is consistent with the idea of wide dispersion of reactions to upgrades, which explains the lack of a significant impact of upgrades on returns. In any event, the goodness-of-fit criteria are very clearly better than the ones that Ammer and Clinton (2004) obtained (38% and 13% respectively). The other measurements show equivalent results in the case of downgrades, with adjusted R-squared values of 99% and 95% for the OAS and the ASMs respectively. These measurements also show lesser significance for upgrades (64% and 52%, respectively).

Of all of the explanatory variables that we have considered, duration seems to have the most impact. It affects all of the measurements significantly at the 1% level by increasing the natural impact of a rating change. The fact that duration has an impact on the spread measurements, as well as on returns, shows that this impact is not merely the mechanical effect linking price variation and duration[31]. The number-of-notches variable affects the magnitude of the reaction of returns, as shown in the findings of Ammer and Clinton (2004). The greater the change in the rating, the greater the reaction of returns. On the other hand, this variable has no effect on the OAS or the ASM reactions. The initial rating[32], which has frequently been highlighted in studies of conventional bonds (Jorion and Zhang (2005)), of equities (Iankova, Pochon and Teïletche (2005)), of CDS margins (Norden and Weber (2004)), and of US ABS (Ammer and Clinton (2004)) does not seem to have any significant impact here. One possible explanation is that there are no “speculative grade” securities available to study. The par value of a bond has an impact on the OAS only in the case of downgrades. Ammer and Clinton did not find any specific

[30] See Norden and Weber (2004) for CDS in the recent period.
[31] Duration is the first derivative of the price of bond with respect to yield to maturity.
[32] Ratings have been coded to give the best ratings the lowest values (AAA = 1, A1 = 2, etc.).

impact in this case. The dummy United Kingdom variable for returns and OAS indicates the more pronounced reactions for ABS denominated in Sterling. Nevertheless, this result is difficult to interpret. Maturity does not seem to have any significant impact, but it should be noted that this variable is somewhat redundant with the duration variable.

2.4 Conclusion and discussion

In this article, we have analysed the European ABS market and, more specifically, the impact of credit rating changes on various measurements of the performance of such bonds. For this purpose, we started with the methodology proposed by Ammer and Clinton (2004) for the US market. We transposed this methodology to a set of European bonds and expanded it by introducing non-parametric tests.

This led us to identify some important significant effects. This holds true for downgrades, which is fully in line with the results in the literature, but it also holds true for upgrades. The latter result is a new finding and should be tested again. Overall, the strong reactions that we have identified tend to support the hypothesis that credit rating agencies play an even greater role for ABS, which are bonds based on more complex and/or less transparent underlying assets[33]. It must be kept in mind that it is difficult to come up with quality data on ABS. The situation is improving rapidly and we should soon be able to reproduce our results with a much larger sample of issuers.

[33] More specifically, the results are even more notable since we have focused on medium-term changes (monthly variations) and not just the very short-term effects.

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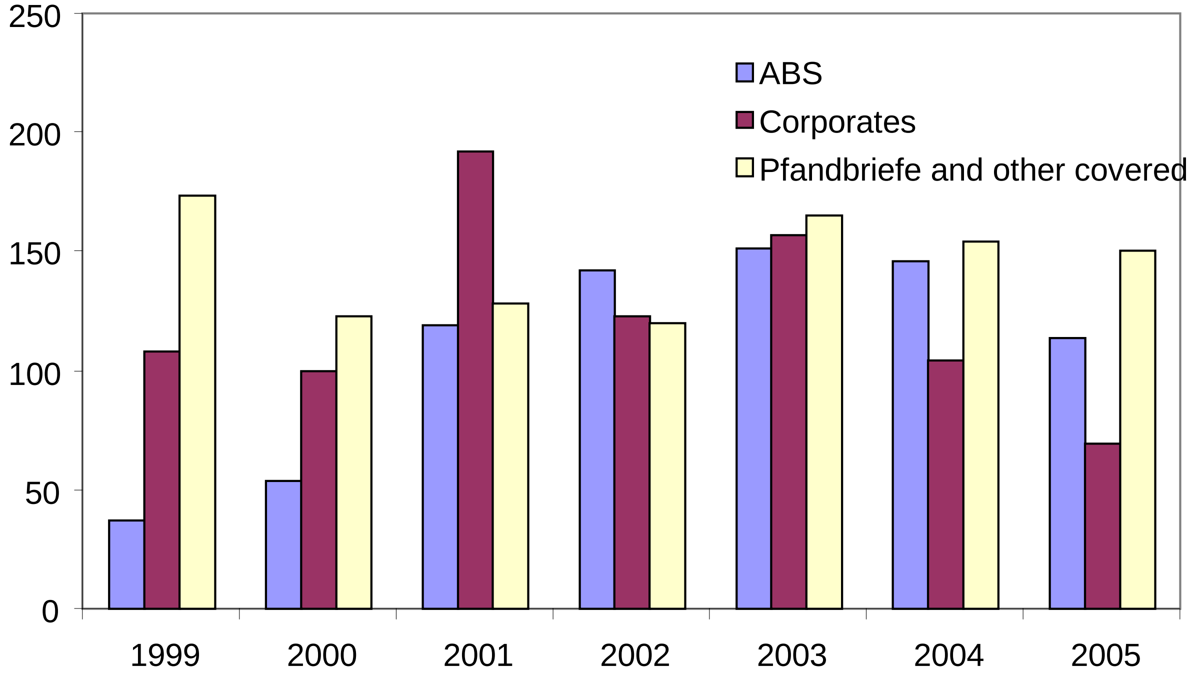
Figure 1 – Gross Issuance on the euro market



Sources: Capital Data Bondware, IXIS CIB

(*) includes Obligations foncières and Cedulas Hipotecarias

Table 1: One-year credit rating transition matrix (%)

All issuers (1981-2004)								
	New rating							
Original rating↓	AAA	AA	A	BBB	BB	B	CCC/C	D
AAA	90.0	9.3	0.5	0.2	0.0	0.0	0.0	0.0
AA	0.2	89.9	9.5	0.4	0.0	0.0	0.0	0.0
A	0.0	2.2	92.1	5.4	0.2	0.0	0.0	0.0
BBB	0.0	0.2	4.3	91.5	3.0	0.6	0.2	0.3
BB	0.0	0.0	0.2	3.9	86.0	8.0	0.6	1.2
B	0.0	0.0	0.4	0.7	6.8	78.4	6.5	7.2
CCC/C	0.0	0.0	0.0	0.0	0.0	12.5	31.3	56.3
ABS issuers (1987-2004)								
	New rating							
Original rating↓	AAA	AA	A	BBB	BB	B	CCC/C	D
AAA	97.3	2.0	0.3	0.4	0.0	0.0	0.0	0.0
AA	3.2	92.0	4.0	0.5	0.3	0.1	0.1	0.0
A	1.5	3.3	91.3	2.9	0.5	0.2	0.2	0.0
BBB	0.5	0.7	2.3	92.0	3.0	0.6	0.8	0.1
BB	0.2	0.0	0.2	4.4	84.8	4.2	5.4	0.9
B	0.0	0.0	0.0	0.0	4.8	71.0	22.5	1.6
CCC/C	0.0	0.0	0.0	0.0	0.0	1.7	64.0	34.3

Sources: S&P (2005b), S&P (2005c).

Table 2: Description of the sample of ABS on the aggregate European market

	31/12/1998	31/12/1999	31/12/2000	31/12/2001	31/12/2002	31/12/2003	31/12/2004	31/05/2005
Number	32	56	75	95	115	152	163	170
Median								
maturity (years)	9.5	8.5	14.7	18.2	19.3	19.7	18.6	18.6
duration (years)	7.4	6.7	7.5	8.1	8.8	8.9	9.1	9.1
par value (euro millions)								
median	252.9	243.8	237.5	250.0	246.0	252.5	250.0	250.0
mean	301.0	303.8	293.2	333.6	323.3	342.1	330.3	328.5
ASM (basis points)								
rated AAA	40.6	23.4	39.0	38.7	37.1	31.1	21.6	24.1
rated <AAA	137.9	94.4	138.3	149.9	136.3	100.0	82.3	80.9
OAS (basis points)								
rated AAA	81.8	67.2	102.9	65.3	62.3	46.3	45.1	47.2
rated <AAA	223.4	190.9	224.0	187.0	181.1	117.7	106.3	104.3
Composite rating								
AAA	78.1%	69.6%	64.0%	61.1%	56.5%	58.6%	55.2%	55.3%
AA1	0.0%	1.8%	1.3%	1.1%	0.0%	0.0%	0.6%	0.0%
AA2	3.1%	1.8%	4.0%	4.2%	4.3%	3.3%	6.7%	7.1%
AA3	3.1%	3.6%	4.0%	5.3%	4.3%	4.6%	3.7%	3.5%
A1	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%	1.2%	1.2%
A2	9.4%	14.3%	13.3%	14.7%	14.8%	11.8%	10.4%	10.0%
A3	6.3%	5.4%	2.7%	2.1%	5.2%	8.6%	8.0%	7.1%
BBB1	0.0%	0.0%	5.3%	3.2%	3.5%	3.3%	2.5%	3.5%
BBB2	0.0%	1.8%	5.3%	7.4%	9.6%	5.3%	9.2%	10.6%
BBB3	0.0%	0.0%	0.0%	1.1%	1.7%	3.9%	2.5%	1.8%

Sources: Merrill Lynch, Bloomberg, authors' calculations.

Table 3: Sample of credit rating changes on the aggregate European market

	Downgrades	Upgrades	Total
ABS rating changes	28	19	47
Issuer rating changes	25	17	42
Number of notches			
1	22	18	40
2	4	1	5
3	2	0	2
Rating prior to event			
AAA	3	0	3
AA1	1	0	1
AA2	0	1	1
AA3	0	3	3
A1	1	0	1
A2	6	2	8
A3	7	3	10
BBB1	6	3	9
BBB2	4	3	7
BBB3	0	4	4
Reclassification as Investment Grade	3	0	3
Year of the event			
1998	0	0	0
1999	1	0	1
2000	3	1	4
2001	2	1	3
2002	3	2	5
2003	7	2	9
2004	7	11	18
2005	5	2	7
Country of issue			
Switzerland or Netherlands	1	1	2
United Kingdom	8	13	21
Ireland	5	0	5
Italy	3	1	4
Cayman Islands	5	1	6
Luxembourg	1	2	3
Netherlands	4	0	4
USA	1	1	2

Table 4: Reactions of the measurements under consideration to credit rating changes on the aggregate European market

	Security Downgrade	Security Upgrade	Issuer Downgrade	Issuer Upgrade
Returns				
Mean	-4.617	-0.239	-5.088	-0.255
t-test: p-value	0.044	0.855	0.045	0.849
Median	-0.733	-0.462	-0.770	-0.462
Proportion of correct signs (negative for downgrades and positive for upgrades)	82.1%	15.8%	80.0%	11.8%
Sign test: p-value	0.000	0.998	0.000	0.999
Wilcoxon signed-rank test: p-value	0.008	0.998	0.022	0.999
OAS				
Mean	158.9	-3.7	177.8	-3.5
t-test: p-value	0.125	0.027	0.126	0.056
Median	4	-2	6	
Proportion of correct signs (positive for downgrades and negative for upgrades)	64.3%	84.2%	64.0%	88.2%
Sign test: p-value	0.044	0.000	0.054	0.001
Wilcoxon signed-rank test: p-value	0.410	0.029	0.420	0.001
ASM				
Mean	60.7	-3.7	67.8	-3.5
t-test: p-value	0.094	0.032	0.095	0.050
Median	5	-3	5	-2
Proportion of correct signs (positive for downgrades and negative for upgrades)	71.4%	73.7%	72.0%	82.4%
Sign test: p-value	0.006	0.010	0.007	0.001
Wilcoxon signed-rank test: p-value	0.105	0.188	0.096	0.005
Observations	28	19	25	17

Sources: Bloomberg, Merrill Lynch, authors' calculations.
Notes.
The "Security Downgrade" and "Security Upgrade" samples include all securities, whereas the "Issuer" samples are limited to a single decision per period concerning the same issuer.
All of the variables (returns, OAS, ASM) are expressed as a difference from the equivalent measure for the market as a whole over the same period. The p-value for each test corresponds to the probability of wrongly rejecting the null hypothesis of no significance. All of the tests are unilateral, which means that they are conducted on only one of the distribution tails. In prosaic terms, a p-value smaller than 10% denotes a significant variation around the rating change. The t-test is used to test the null hypothesis for the mean variation of the variables, while the Sign test and the Wilcoxon signed-rank test are used to test the null hypothesis for the median.

Table 5a. Determinants of the reaction of returns to a credit rating change

	Downgrades		Upgrades	
Constant	(-)	-4.627	(+)	0.092
		(0.000)		(0.704)
Duration	(-)	-1.289	(+)	1.037
		(0.000)		(0.000)
Number of notches	(-)	-3.244	(+)	1.335
		(0.004)		(0.092)
Log par value	(?)	-1.8215	(?)	0.367
		(0.178)		(0.422)
Initial rating	(-)	-0.050	(+)	-0.087
		(0.851)		(0.330)
Sterling market	(?)	-2.087	(?)	-0.883
		(0.079)		(0.072)
Maturity > 10 years	(-)	1.130	(+)	0.518
		(0.305)		(0.252)
R squared		0.974		0.776
Adjusted R squared		0.966		0.663
Observations		28		19

Sources: Bloomberg, Merrill Lynch, authors' calculations.
Notes.
All of the variables, except for the dummies (Sterling and Maturity > 10 years) are expressed as the difference from their mean value for all observations.
The p-values corresponding to the individual significance tests are shown in parentheses under the coefficients.

Table 5b. Determinants of the reaction of the OAS to a credit rating change

	Downgrades		Upgrades	
Constant	(+)	174.03	(-)	-6.586
		(0.000)		(0.008)
Duration	(+)	73.08	(-)	-8.522
		(0.000)		(0.000)
Number of notches	(+)	-41.36	(-)	-8.127
		(0.226)		(0.229)
Log par value	(?)	114.70	(?)	-0.059
		(0.016)		(0.988)
Initial rating	(+)	-23.96	(-)	-0.739
		(0.013)		(0.345)
Sterling market	(?)	84.59	(?)	7.238
		(0.036)		(0.090)
Maturity > 10 years	(+)	-73.30	(-)	-3.900
		(0.054)		(0.324)
R SQUARED		0.989		0.761
Adjusted R squared		0.986		0.641
Observations		28		19

Sources: Bloomberg, Merrill Lynch, authors' calculations.
Notes.
All of the variables, except for the dummies (Sterling and Maturity > 10 years) are expressed as the difference from their mean value for all observations.
The p-values corresponding to the individual significance tests are shown in parentheses under the coefficients.

Table 5c. Determinants of the reaction of the ASM to a credit rating change

	Downgrades		Upgrades	
Constant	(+)	63.13 (0.001)	(-)	-6.38 (0.017)
Duration	(+)	23.29 (0.000)	(-)	-7.19 (0.003)
Number of notches	(+)	7.31 (0.740)	(-)	-6.72 (0.363)
Log par value	(?)	22.75 (0.434)	(?)	2.30 (0.603)
Initial rating	(+)	-5.45 (0.355)	(-)	0.423 (0.621)
Sterling market	(?)	34.57 (0.177)	(?)	6.522 (0.160)
Maturity > 10 years	(+)	-22.94 (0.340)	(-)	-3.347 (0.441)
R SQUARED		0.957		0.677
Adjusted R squared		0.945		0.515
Observations		28		19

Sources: Bloomberg, Merrill Lynch, authors' calculations.
Notes.
All of the variables, except for the dummies (Sterling and Maturity > 10 years) are expressed as the difference from their mean value for all observations.
The p-values corresponding to the individual significance tests are shown in parentheses under the coefficients.