Instituto Universitário de Lisboa

Department of Finance

Essays on Credit Rating Announcements

Paulo Viegas de Carvalho

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Supervisor:

Professor João Pedro Pereira

Assistant Professor of Finance, ISCTE - IUL

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Thesis Committee

President

Professor João Pedro Nunes, Professor, ISCTE-IUL

Committee Members

Professor João Pedro Pereira, Assistant Professor, ISCTE-IUL
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Professor Miguel Almeida Ferreira, Professor, FE-UNL
Professor Paul Anthony Laux, Professor, University of Delaware
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Abstract

This thesis is composed of three separate research papers on credit rating announcements. The first paper, in Chapter 1, addresses the effects of rating announcements issued by Fitch, Moody's and S&P on the idiosyncratic volatility of a firm's stock return. Such measure of volatility is quantified both in absolute terms and relative to total firm's volatility, and the results obtained are in general consistent. The paper documents significant increases in volatility after downgrades, especially multi-agency downgrades, whereas no effect of upgrades is evident. Effects are largest for small and low rated firms. Volatility effects of S&P ratings downgrades are larger than those of other ratings agencies, implying that investors' reactions depend not only on the type of announcements, but also on the agency making the announcement.

The second paper, in Chapter 2, reports systematic evidence on some unintended effects of rating downgrades on future credit defaults. Based on complementary causality methodologies and using an extensive database of long-term corporate obligation ratings issued by Moody's, S&P and Fitch, from 1990 to 2012, the paper shows that downgrades crossing the threshold between investment grade and speculative grade may cause an increase of at least 3% in the 1-year probability of default. The increase in the probability of default seems to be stronger for deeper rating downgrades. The effect is also likely to be stronger for firms that already have a low initial rating.

The third paper, in Chapter 3, focuses on the quasi-regulatory role of credit ratings, which depends on the extent to which ratings are stable and reflect a through-the-cycle credit risk assessment. Introducing a new measure of rating dynamics summarizing all observed rating transitions, the paper examines if corporate ratings from the three major agencies fulfill such requirement. Changes in ratings are found to be greater around recessions, with S&P seeming more sensitive than Moody's and Fitch to the conditions of the business cycle. Despite this sensitiveness to the business cycle, ratings remain a less volatile, though potentially less accurate, measure of credit risk than accounting-based models of default prediction.

JEL classification: D83; G24

Keywords: Forecasting; Information transmission; Credit ratings; Default risk

Resumo

Esta tese é composta por três artigos de investigação sobre os anúncios de rating. O primeiro artigo, no Capítulo 1, analisa os efeitos dos anúncios da Fitch, da Moody's e da S&P sobre a volatilidade idiossincrática da rendibilidade das ações das empresas. O artigo demonstra a existência de aumentos significativos na volatilidade na sequência de revisões em baixa nas notações de crédito, especialmente quando oriundas de várias agências; não foi detetada evidência conclusiva sobre os efeitos associados aos aumentos nas notações. A reação na volatilidade é também mais significativa nas pequenas empresas e nas empresas com baixos níveis de rating. Confirma-se ainda que, quando a revisão em baixa da notação é feita pela S&P, os efeitos são superiores aos das outras agências, revelando que os investidores reagem não só ao tipo de anúncio, mas também à agência que o emite.

O segundo artigo, no Capítulo 2, apresenta evidência sistemática referente a alguns efeitos não intencionais das reduções de notação sobre os incumprimentos futuros de crédito. Com base em metodologias de análise de causalidade e utilizando uma extensa base de dados referente a ratings de longo prazo a empresas, atribuídos pela Moody's, S&P e Fitch, o artigo mostra que reduções de notação de grau de investimento para grau especulativo podem incrementar a probabilidade de incumprimento a 1 ano em, pelo menos, 3%. O aumento da probabilidade parece ser mais acentuado quando as revisões em baixa nas notações de crédito são mais profundas. O efeito esperado poderá igualmente ser intensificado caso as empresas registem uma baixa notação inicial.

O terceiro artigo, no Capítulo 3, incide no papel quase regulatório dos ratings, dependendo este da medida em que as notações são estáveis e refletem uma ótica "through-the-cycle". Propondo um novo indicador sobre a dinâmica dos ratings, que resume todas as migrações por estes registadas, o artigo analisa se os ratings atribuídos pelas três maiores agências a empresas cumprem tal requisito. A evidência encontrada demonstra que as alterações nas notações são mais elevadas durante as recessões económicas, particularmente no caso da S&P. Apesar da sensibilidade que manifestam face aos ciclos económicos, os ratings revelam ser uma medida do risco de crédito menos volátil, mas também potencialmente menos rigorosa, do que os modelos de previsão do incumprimento baseados em indicadores financeiros.

Classificação JEL: D83; G24

Palavras chave: Previsão; Transmissão de informação; Ratings; Risco de incumprimento

To my father

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"If I have seen further it is by standing on ye sholders of Giants."

Sir Isaac Newton

Letter to Robert Hooke (5 February, 1676), in Turnbull, H. W. (Ed.) (1959), *The Correspondence of Isaac Newton*, 1, 1661–1675, Cambridge University Press, p. 416.

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Chapter 1

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1.1 Introduction

Credit rating agencies are considered as information specialists on the creditworthiness of bonds and other debt related securities, therefore influencing the cost of financing. The empirical evidence suggests, however, that announcements of rating changes convey significant information and bring forward financial effects beyond the simple cost of debt of rated firms. The extent to which these announcements add new information to financial markets is an issue explored by a strand of investigation in finance. Many papers analyse the effects of such announcements on the pricing of stocks, bonds, and credit default swaps. Norden and Weber (2004) present a comprehensive overview of this research. Although results vary, most evidence suggests a price overreaction after downgrades. However, the same does not apply to upgrades, revealing that distinct type of ratings changes generate asymmetric effects on securities returns.

Surprisingly, research on the effects of rating announcements has been mostly restricted to the influences on returns. As already underlined by Abad and Robles (2012), the literature of the impact of credit rating announcements on volatility of returns is almost inexistent, especially in the case of idiosyncratic risk. Given the potential destabilizing impact of rating changes on securities price returns, if they affect access to finance or future investment opportunities, it is in fact important to also consider volatility.

There are at least three reasons to expect volatility effects of ratings changes. First, if ratings agencies convey information that is subsequently evaluated and traded on by investors, the increased information flow about the firm should be expected to increase volatility. Second, if ratings downgrades result in restricted access to financing, or otherwise constrain a firm's ability to develop its investment opportunities, then a volatility increase might be expected as the firm's economic activity declines and, consequently, its capacity to generate future earnings becomes restrained. Third, as the downgrade causes some investors to consider the firm to be an inappropriate investment, volatility might increase due to liquidity pressures as these investors search for buyers.

This paper addresses the potential effects of rating announcements on firm's stock return volatility, selecting idiosyncratic volatility as the variable of interest. We analyze both absolute and relative idiosyncratic volatility; the use of complementary approaches to volatility should provide a more complete assessment on the effects of ratings. Earlier research on volatility concentrates on the analysis of absolute volatility. This type of analysis, of which we highlight the EGARCH model of Nelson (1991), incorporates the serial correlation (often observed in absolute volatility) by using autoregressive conditional heteroskedasticity models. On the other hand, relative idiosyncratic volatility is given by firm-specific stock return volatility relative to firm's systematic volatility, therefore allowing us to control for market volatility. The use of such measure of volatility is motivated by works of Roll (1988), Durnev et al. (2004), Ferreira and Laux (2007), among others. Using both absolute and relative volatility, we model idiosyncratic volatility as a function of the rating announcement, controlling for some firm-related information and the macroeconomic conditions observed at the time of announcement.

We base the investigation on exhaustive ratings information covering a period over twenty years, with announcements from the three major agencies: Fitch, Moody's and Standard & Poor's (S&P). The paper documents results relative to announcements concerning at least 1,619 firms with 3,974 announcements. To the best of our knowledge, this is the first paper to address comprehensively the relation between idiosyncratic volatility of a firm's stock return and rating announcements with the backing of a large amount of information.

The findings in the paper reveal that different types of rating announcements stimulate distinct reactions on volatility. Downgrades increase both relative and absolute idiosyncratic volatility; for example, downgrades by S&P intensify absolute volatility by 33.6% and lead to a 30.5% change in relative volatility. Upgrades do not have significant effects on absolute volatility, though reducing somewhat relative idiosyncratic volatility. This means that, similar to earlier findings about the stock's return (e.g., Holthausen and Leftwich, 1986; Hand et al. 1992; Goh and Ederington, 1993; Norden and Weber, 2004), asymmetries also arise in the volatility of a stock's return subsequently to rating announcements.

By documenting that downgrades increase idiosyncratic volatility of returns, we close the triangular relation among rating announcements, future returns and volatility. This relation is reinforced by two additional findings reported in previous literature. One is the negative correlation between returns and idiosyncratic volatility, confirmed by Ang et al. (2006) and Jiang et al. (2009); the effects of downgrades reported in this paper substantiate that correlation. The other is the leverage effect, first proposed by Black (1976) to explain the generally negative correlation between stock prices and volatility; this correlation is stronger as the firms' debt-to-equity ratios increase. Blume et al. (1998), Amato and Furfine (2004), Jorion et al. (2009) and Güttler and Wahrenburg (2007) also demonstrate the negative influence of leverage on credit ratings. Hence, the evidence in this paper corroborates intuition raised by combined effects of leverage on ratings, returns and volatility.

Per agency, and particularly until one month after the announcement date, we find that downgrades by S&P imply more remarkable effects on volatility when compared with the other two agencies. In the case of Fitch, the effects remain insignificant, which is consistent with findings in Norden and Weber (2004). This is an additional important result of our paper, as it implies that it's not only the type of news received by investors that influence volatility of returns; investors may also react depending on the agent issuing the news, meaning that ratings from different agencies do not have necessarily similar informational contents. We interpret the slightly greater effects of downgrades by S&P, when compared to those of Moody's, with the somewhat lower average ratings of S&P in our sample. The relatively low representativeness in the study of Fitch's announcements is an explanation for the generally low significance they reveal.

The paper also shows that higher volatilities of returns emerge in the case of small-size firms. Likewise, the lower is the announced rating level, the more volatile becomes the issuer stock's return. In addition, a positive change in GDP increases the relative idiosyncratic volatility, but absolute idiosyncratic volatility is more likely to decrease, at least up to one month after the announcement. Therefore, cyclicality in relative idiosyncratic volatility is mostly due to absolute idiosyncratic volatility being less countercyclical than systematic volatility.

Extending the analysis to a framework with multiple contemporaneous announcements from different agencies, we detect that downgrades issued consistently by distinct agencies clearly amplify the effect over relative idiosyncratic volatility. When there is a lack of consensus in ratings from different agencies, the effects on volatility remain significant as long as the first agency announces a downgrade. Additionally, also when we allow for multiple rating announcements, the duration between announcements becomes statistically relevant, suggesting a negative relation with the volatility of returns; lower duration between announcements means a higher flow of firm's information generated from ratings and leads to higher return volatility.

Finally, drawing from Nelson's EGARCH (Nelson, 1991), our specification of absolute idiosyncratic volatility encompasses lagged volatility among the explanatory variables. Consistent with the evidence in the literature about volatility of returns (e.g., Bollerslev, 1986; Glosten et al., 1993; Nelson, 1991), the results we obtain show that current volatility depends on the one-period lagged volatility; i.e. volatility clustering is quite significant.

Prior research on the effects of rating announcements on volatility of stock returns generally focus on restricted and small samples. For example, Abad and Robles (2012) also provide empirical evidence suggesting that rating changes affect asymmetrically volatility, but their analysis is confined to the Spanish stock market and to a sample of just 386 rating announcements. The vast majority of such announcements relates to the financial sector, reflecting the idiosyncrasies of Spanish bond issuers. Kliger and Sarig (2000) restrict the analysis to deviations from investors' expectations in ratings of 118 firms. Fulop (2007) finds evidence of influence of downgrades from investment grade to speculative grade in 168 firms, but does not investigate upgrades and other type of downgrades. Hooper et al. (2008) and Brooks et al. (2012) analyze as well the effects of rating announcements on stock volatility, although their study centers only on the effects over systematic volatility.

The remainder of the paper is organized as follows. Section 1.2 reviews the main findings reported in previous literature about the stock price reactions to credit rating announcements. Section 1.3 describes the methodological principles adopted in the study for empirical analysis. The data selected and descriptive statistics are reported in Section 1.4. In Sections 1.5 and 1.6, we present regression results, respectively, for absolute and relative idiosyncratic volatility, and examine their implications. Section 1.7 concludes.

1.2 Related literature

Relevant corporate news is a potential trigger of corporate credit rating announcements. It is not unexpected, therefore, that significant financial effects emerge near the date of the announcement; still, it is not so evident how, when and where these effects take place exactly. The need for evidence concerning the linkage between announcements and financial effects opened an avenue for research dating back from the 1970's. Most of it focuses on the effects on asset price returns, of which we highlight the case of stocks.

Previous literature generally underlines abnormal effects of negative announcements in terms of returns. Usually based on event study methodology that calculates cumulative abnormal returns, results reported to date suggest that stock returns overreact negatively to rating downgrades. However, a symmetric overreaction is not witnessed in upgrades. Striking evidence about this asymmetry is in Pinches and Singleton (1978), Griffin and Sanvicente (1982), Holthausen and Leftwich (1986), Hand et al. (1992), Goh and Ederington (1993), Dichev and Piotroski (2001), Norden and Weber (2004), and in Jorion and Zhang (2007).

Goh and Ederington (1993) complement by adding that downgrades related with deteriorations in the firm's financial prospects lead to negative market reactions, whereas those associated to an increase in leverage generate non-significant reactions. Dichev and Piotroski (2001) also report how the effects vary after the downgrade. The negative abnormal stock returns last at least a year after the downgrade and may be as low as -14 percent during that period, despite being more remarkable in the first months. According to them, abnormal returns associated to a downgrade are also more negative for small and low-credit-quality firms. Comparing rating changes and reviews for rating changes from the three major agencies, Norden and Weber (2004) find that negative announcements from S&P and Moody’s relate to abnormally low returns around the announcement; no significance is detected however relative to announcements by Fitch.

Ederington and Goh (1998) advance two main reasons for the returns overreaction to negative ratings changes. The first is that markets receive valuable new information when agencies release negative announcements about the issuer; they have access to private information that rated firms are typically averse to disclose directly to the market. The second is that, due to reputational concerns, the agencies expend more resources in detecting deterioration in credit quality than improvements. Jorion et al. (2005) additionally interpret the “downgrade effect” and the implicit fall in stock prices as the capitalized value of higher borrowing costs of the issuer. They conclude that, after a SEC regulatory change in 2000, the consequences of rating downgrades became larger than before and that market reaction to upgrades started to be significant.[1]

Consistent with previous literature, Jorion and Zhang (2007) confirm the asymmetric return response to rating announcements. However, they also find some relevant effects following upgrades, despite these are much lower than those from downgrades. They reveal that asymmetry of effects hinges on the rating level prior to announcement, wherein effects of

[1] In 2000, the Regulation Fair Disclosure attributed a favored position to the rating agencies comparatively to other potential sources of information about companies.

downgrades in low-rated issuers are greater. An explanation, suggested by these authors, is that a downgrade by one notch for a low-rated firm implies an absolute greater variation in the implicit probability of default, than what happens in a similar downgrade applied to a high-rated firm. As a reflection of the higher magnitude on the probability of default, larger impacts arise in bond yield spreads and on stock prices.

If the investigation on effects that ratings changes produce on stocks returns is abundant, the same does not happen in what concerns to volatility of returns. Yet, some interesting findings have been already reported. For example, Kliger and Sarig (2000) examine the effects generated by rating deviations from investors' expectations on the volatilities implied by 118 option prices on stocks. Using Moody's announcement of refined ratings on April 26, 1982, and computing implied volatilities on a 5-day window around that date, they find that a decline (rise) on volatilities follows better (worse) than expected refined ratings.[2] Other works include Fulop (2006), which explores the existence of feedback effects of rating downgrades and finds support for an increase in volatility around the announcement of downgrades. Because his sample is composed of 168 U.S. public firms which were downgraded from investment to speculative grade, he does not quantify the impact of upgrades. Focusing on Spanish issuers, Abad and Robles (2012) report evidence of a reduction in both systematic and unsystematic risk following positive rating announcements, which include rating changes, rating watches and rating outlooks. Regarding negative announcements, they reveal a rebalancing of the systematic and unsystematic risk, with systematic risk increasing after the announcement, whereas the reaction in unsystematic risk is not so clear as it might decrease depending on the methodology of analysis they use.

With regard to sovereign ratings, Hooper et al. (2008) determine that downgrades (upgrades) contribute to a significant increase (decrease) in stock index returns volatility, although the effect is again more prominent in the case of downgrades. A similar conclusion is reached by Brooks et al. (2012), who confirm that rating levels have a significant negative relationship with realized volatilities among national stock markets. It seems, therefore, that sovereign ratings announcements have an impact on market and systematic volatility. Overall, these references contribute to the hypothesis that ratings convey relevant information to financial markets, which appears to materialize not only in abnormal returns, but also in volatility patterns of returns.

[2] In this case, the 5-day window compares the volatility on the five trading days prior the announcement with the following five trading days.

1.3 Methodology

Consider a market model adjustment for a stock's return,

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{1.1}$$

where $r_{i,t}$ and $r_{m,t}$ are respectively the stock's return of firm i and the market's return, both observed in time period t; α and β are parameters and ε is an error term. The variation of the firm's stock return may be both market-related as well as firm-specific. Correspondingly, computing volatility as the variance of returns and assuming $\mathrm{COV}(r_m, \varepsilon_i) = 0$, the total volatility of stock i's return, σ_i^2, splits into the non-diversifiable or systematic volatility and the idiosyncratic volatility, as shown below

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_{\varepsilon_i}^2 \tag{1.2}$$

σ_m^2 denotes the market-wide volatility, $\beta_i^2 \sigma_m^2$ expresses firm i's systematic risk, whereas $\sigma_{\varepsilon_i}^2$ is the firm's idiosyncratic volatility. The latter is the variation in the firm's return explained by idiosyncratic factors, such as firm-specific news (e.g. announcements on its ratings). Its calculation is given by the difference between the observed return and the correspondent estimated return, $r_{i,t} - \hat{r}_{i,t}$, which is precisely the residual of a regression applied to equation (1.1). The idiosyncratic volatility of firm i's return is therefore the variance of that residual.

1.3.1 Absolute idiosyncratic volatility

A classical approach to analyze volatility of returns resides in modeling absolute volatility. Numerous approaches use the exponential generalized autoregressive conditionally heteroskedastic (EGARCH) approach, proposed by Nelson (1991). This model reflects evidence of stock return volatility upsurges following bad news and volatility decreases when good news are disclosed (e.g., Braun et al., 1995). Likewise, volatility exponentially modeled adds the appealing property that no parameter restrictions are needed to ensure positiveness of estimated variances. The log transformation of volatility, which emerges in the linearized version of this model, also diminishes the risk of potential heteroskedasticity problems.

Previous literature on absolute volatility of returns points to volatility clustering, confirming a somehow predictable behavior of variance (see, for example, Engle, 1982; Bollerslev, 1986; Glosten et al., 1993; Nelson, 1991). An important predictor of future variance of returns lies, therefore, in past history of returns. Glosten et al. (1993) extend this analysis by showing that other explanatory variables have also significant effects on volatility of stock returns.

Hence, in order to analyze the absolute idiosyncratic volatility, we add the lagged idiosyncratic volatility to an exponential model which measures the effects of rating announcements on stock's return volatility. Denoting t as the day when firm i has been given a rating announcement, and allowing for the impact of ratings through time to be measured in the time window N, we model absolute idiosyncratic volatility as

$$\ln\left(\sigma^2_{\varepsilon_{i,t+N}}\right) = \theta_1 + \theta_2 \ln\left(\sigma^2_{\varepsilon_{i,t}}\right) + \sum_{j=1}^{s} \mu_j Z_{j,i,t} + \nu_{i,t+N} \tag{1.3}$$

$\ln\left(\sigma^2_{\varepsilon_{i,t+N}}\right)$ is the natural logarithm of idiosyncratic volatility estimated in $[t;\ t+N]$. For each N, we compute the idiosyncratic volatility after the announcement $\left(\sigma^2_{\varepsilon_{i,t+N}}\right)$, as well as the lagged idiosyncratic volatility $\left(\sigma^2_{\varepsilon_{i,t}}\right)$; no overlapping and no gap either exist between $\sigma^2_{\varepsilon_{i,t+N}}$ and $\sigma^2_{\varepsilon_{i,t}}$. The idiosyncratic volatility is computed based on equation (1.2) and on the sample variances of the firm's daily return, and the daily return of the Standard & Poor's Composite Index, as reported by CRSP. $Z_{j,i,t}$ stands for each of the s control variables, which include rating covariates. θ_1, θ_2 and μ_j are parameters; $\nu_{i,t+N}$ is the regression error.

To measure the effect of each type of announcement, $Z_{j,i,t}$ includes dummies for upgrades and downgrades; all dummies equal 1 when the variable they refer to is observed and 0 when it is not. In addition, based in Norden and Weber (2004), which underscore the significance of the source of announcement, we evaluate the extent to which the agency making the announcement is relevant to explain stock volatility; specific dummies are accordingly defined. Motivated by the findings of Jorion and Zhang (2007), confirming that lower rated firms reveal a greater negative stock return reaction to downgrades, we add the announced rating level to evaluate the respective effects on volatility.

The analysis also allows for asymmetries of information between issuers and investors. For example, as seen in Behr and Güttler (2008), reactions in the stock market to rating announcements indicate that smaller firms exhibit higher informational opaqueness than larger companies; the opaqueness is more pronounced in some sectors than others. Less precise evidence about a firm's risk in smaller firms and in some sectors explains why the disclosure of new relevant information, especially when it conveys negative news, has a greater impact on volatility. Therefore, we measure size effects and evaluate the relevance of the sector of activity.

The same rationale concerning asymmetric information might be applicable to the frequency of announcements, assuming that, the more often the information is conveyed to investors, the more informed they should remain. Likewise, the lower is the distance or duration between ratings announcements, the more informed investors should be in relation to the firm. In such circumstance, the news disclosed should be less unexpected. However, if ratings announcements wield indeed significant effects on volatility, the conclusion might be too that higher stock return volatility reflects a lower duration between announcements. Consequently, it seems *a priori* relevant to test the extent to which volatility differs due to rating duration. In this case, duration denotes the number of years since the last rating announcement, regardless of the agency concerned. As we endeavour to gauge the effects of rating announcements, and bearing in mind the fact that such announcements are supposed to incorporate already the firm's main idiosyncratic factors, we do not add further firm-specific information to the covariates.

Given the potential influence on ratings brought by changes in Gross Domestic Product (Güttler and Wahrenburg, 2007), and assuming that investors' stock price expectations vary with the economic context, we further allow the effects of ratings announcements on volatility to differ depending on changes in GDP. This assumption is also supported by the relatively long time span of our sample, together with findings from Schwert (1989), revealing that market volatility is higher during recessions. In this regard, we test if the effects of rating announcements change with macroeconomic dynamics, by adding as covariate the quarterly change in real U.S. GDP corresponding to the quarter when the announcement occurs.

Finally, we bear in mind the results in Dichev and Piotroski (2001), highlighting the more pronounced rating effects on returns in the first months after the announcement. Consistent with this, our paper evaluates differences in volatility corresponding to distinct time windows. To draw conclusions about such question, we split the analysis in time windows N of 30 and 90 days, within each window computing the respective volatility, which brings forth separate estimates of the parameters relative to equation (1.3).

1.3.2 Relative idiosyncratic volatility

To obtain a broader perspective on the effects that ratings may exert on volatility, we draw from previous literature to investigate relative idiosyncratic volatility of returns. This line of research is pioneered by Roll (1988). Focusing on the influence of firm's idiosyncratic factors to explain stock price variations, he investigates the extent to which firm-specific news explain divergences in the R^2 of the market model, as described by equation (1.1), when applied to different firms. The higher is $1-R_i^2$, the greater will be the influences of firm i's specific information over its specific stock returns variation. Using the adjusted R_i^2, represented as $\bar{R}_i^2$, we obtain that $1-\bar{R}_i^2=\sigma_{\varepsilon_i}^2/\sigma_i^2$, from where we may assess the relation between $1-\bar{R}_i^2$ and $\bar{R}_i^2$, as

$$\begin{aligned}\frac{1-\bar{R}_i^2}{\bar{R}_i^2} &= \frac{\sigma_{\varepsilon_i}^2}{\beta_i^2\sigma_m^2} \\ &= \frac{\sigma_{\varepsilon_i}^2}{\sigma_i^2-\sigma_{\varepsilon_i}^2}\,, \quad \forall\ \sigma_i > \sigma_{\varepsilon_i} \end{aligned} \tag{1.4}$$

This implies that the previous relation is equivalent to firm-specific stock return volatility, measured relative to systematic volatility. Studying the influence on returns exerted by specific idiosyncratic features of the firm, Morck et al. (2000), Durnev et al. (2004), as well as Ferreira and Laux (2007), select as variable of interest such measure of volatility, which we call the relative idiosyncratic volatility.

We adopt a similar analysis, in order to reinforce the role of firm-specific information as a determinant of idiosyncratic volatility and to control for market volatility. The higher are values of relative idiosyncratic volatility, the smaller will be the proportion of total stock return variation described by market-wide variation, comparatively to what is explained by firm-specific variation.

Given that $1-\bar{R}_i^2$ is bounded within the interval [0; 1], and in line with Morck et al. (2000), Durnev et al. (2004), and Ferreira and Laux (2007), we apply natural logarithms to equation (1.4), obtaining a logistic transformation of $1-\bar{R}_i^2$. By adjusting the dependent variable, we hope as well to obtain skewness and kurtosis closer to a normally distributed variable, and therefore avoid a highly skewed error distribution that may compromise the interpretation of the estimates in the model. In addition, the logarithmic transformation of (1.4) reduces the risk of obtaining heteroskedastic residuals. The resulting dependent variable, identified as the logistic relative idiosyncratic volatility, is thus as follows

$$\Psi_i := \ln\left(\sigma_{\varepsilon_i}^2\right) - \ln\left(\beta_i^2\sigma_m^2\right), \quad \Psi \in \mathbb{R} \tag{1.5}$$

We should note that due to the application of logarithms to relative idiosyncratic volatility, negative values of Ψ_i will arise whenever firm-specific volatility is lower than systematic volatility, i.e. when $\sigma_{\varepsilon_i}^2 < \beta_i^2\sigma_m^2$.

Given the previous definitions, our structure of relative idiosyncratic volatility is

$$\Psi_{i,t+N} = \theta + \sum_{j=1}^{k} \delta_j X_{j,i,t} + \xi_{i,t+N} \tag{1.6}$$

θ and δ_j $(j = 1, \dots, k)$ are parameters, $\Psi_{i,t+N}$ is estimated in $[t;\, t+N]$, t is the announcement date relative to firm i, and $N = \{30; 90\}$. For each N, we estimate the logistic relative idiosyncratic volatility after the announcement (Ψ_{t+N}), and the lagged logistic relative idiosyncratic volatility (Ψ_t). $X_{j,i,t}$ denotes control variables, which include rating covariates, such as dummies for upgrades and downgrades, and ξ_{i,t_i+N} is the regression error.

1.4 Data and descriptive statistics

1.4.1 Data

The empirical analysis in this paper is based on ratings information from Moody's Default & Recovery Database, the database of S&P Capital IQ, and Bloomberg (RATC: Company Credit Rating Changes); the latter is the source used for ratings issued by Fitch. Information on each firm's stock price daily return and on S&P's Composite Index daily return derives from CRSP. To measure the firm's size, we obtain the firm's assets from COMPUSTAT. We also retrieve the quarterly GDP change from the Bureau of Economic Analysis (U.S. Department of Commerce); the information pertains to the seasonally adjusted annual rate based on chained 2005 dollars.

Following previous ratings literature (e.g., Amato and Furfine, 2004; Jorion and Zhang, 2007), we assign to each rating level a score that replicates the order of each rating letter and rating modifier. In this paper, we consider 22 rating classes. The highest rating available for each agency corresponds to 1 (i.e., rating AAA from S&P or Fitch, and rating Aaa from Moody's), the second highest rating matches 2 (i.e., rating AA+ from S&P or Fitch and rating Aa1 from Moody's), and so forth. The worst rating, which stands for default, is the 22nd class.

The sample of ratings refers to U.S. firms with at least one rating assigned by Moody's, S&P or Fitch, between January 1990 and February 2012. This sample encompasses firms listed or which have been listed in this time period in the NYSE, AMEX or NASDAQ, according to CRSP. As in previous literature (e.g., Hull et al., 2004; Jorion and Zhang, 2007; Hooper et al., 2008), we initially restrict the sample to unique rating events within N. Unique announcements are those that have not been preceded or followed by other rating events related with the same firm, in the interval $[t-N;\, t+N]$. The selected cases lead to two subsamples for announcements, one for N = 30 and the other for N = 90. In order to evaluate the effects when more than one agency makes announcements within the same timeframe, we extend subsequently the sample for N = 30 to include all rating announcements observed in that timeframe.

In order to directly evaluate the significance of the potential effects of downgrades and upgrades, we allow for all type of announcements, including situations where rating is left unchanged. Such situations may occur whenever the same issuer has more than one long term rated obligation (with similar seniority) and subsequent ratings announced by one agency for these obligations are equal. An additional explanation for unchanged ratings lies in announcements of rating outlooks, the majority of them "Stable". Accordingly, if an announcement occurs due to a rating outlook, we classify it as rating unchanged.

Consistent with the previous time intervals, the extraction of market information refers to the time windows of 30 and 90 calendar days. Within each window, we calculate the daily volatility of the firm's stock price returns prior and after an announcement. Among the firms in CRSP, some have insufficient market information around the announcement date, because either the oldest date or the most recent one with market information are less distant than 30 or 90 days relative to the announcement date. To overcome this problem, but at the same time avoid losing relevant information, when focusing the analysis on N = 30 we remove from the sample announcements without at least a minimum window size of 10 days for returns; 30 days is the minimum size when dealing with N = 90.

1.4.2 Descriptive statistics of ratings

From a total of 36,337 initially detected rating announcements, issued by the three agencies between January 1990 and February 2012, we restrict the samples to 9,237 rating announcements when considering the 30-day time window; 3,974 is the number of announcements for the 90-day time window. Figure 1.1 displays the yearly distribution of rating announcements in each case. Excluding the first years and 1999, the figure shows relatively well spread distributions of announcements, especially in the 90-day window.

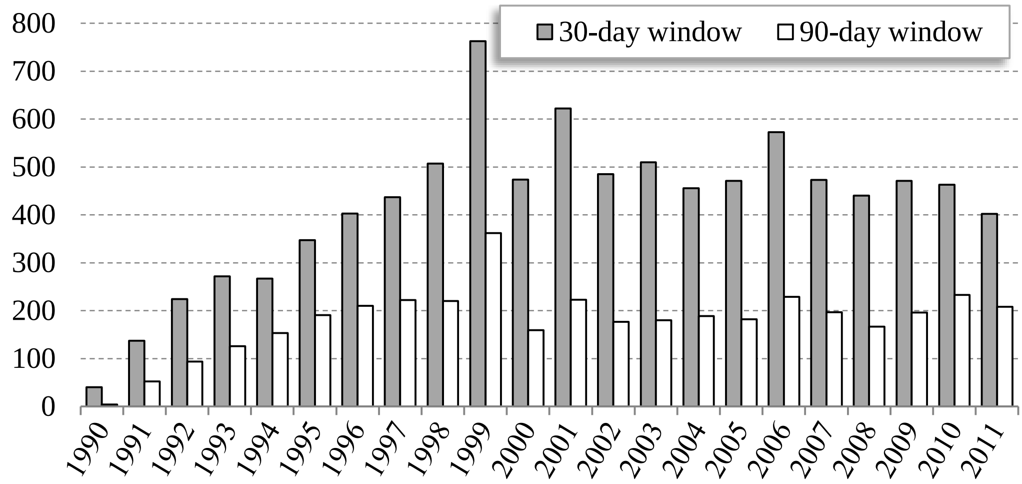

Figure 1.1: Yearly distribution of rating announcements

When we detail the yearly distribution per type of announcement, we find that downgrades prevail when the economy deteriorates; in economic expansions upgrades are prominent. For example, in the mid-nineties, when the economy was booming, the number of upgrades per each downgrade topped 1.45, considering the 30-day window; conversely, during the downturn of 2001 this relation fell to a minimum of 0.34. The representativeness of information, which substantially lowers the risk of biased conclusions, is equally confirmed by the number of firms: the subsample of 30-day time window comprises 1,921 firms, whereas the 90-day window reaches 1,619 firms.

Table 1.1 illustrates the respective distribution per industry, from where we observe a high proportion of firms belonging to Manufacturing.

Table 1.1: Distribution of firms per industry

This table reports the distribution of firms per industry in the 30-day and 90-day samples, with information aggregated at the first two digits of the SIC code.

Industry (SIC code)	30-day window	90-day window
Agriculture, Forestry, and Fishing (SIC: 01-09)	11	10
Mining and Construction (SIC: 10-17)	175	149
Manufacturing (SIC: 20-39)	822	709
Transportation, Communications, and Utilities (SIC: 40-49)	332	266
Wholesale and Retail Trade (SIC: 50-59)	233	199
Finance, Insurance, and Real Estate (SIC: 60-67)	33	28
Service Industries (SIC: 70-89)	306	249
Public Administration (SIC: 91-99)	9	9

Information concerning the distribution of ratings per direction or type of announcement and per rating agency is in Table 1.2. The values reported confirm that downgrades clearly exceed upgrades, especially in the 90-day window sample; the remaining type of announcements includes all situations where rating is left unchanged. The high proportion of downgrades is consistent with descriptive statistics in Norden and Weber (2004); specifically, they analyze ratings from 2000 to 2002 and report a total of downgrades six-fold the number of upgrades. The number of announcements of Moody's largely outweighs those of S&P and, in particular, of Fitch, the latter representing a marginal weight. The representativeness of information from this agency becomes more relevant from 2000 onwards, after the significant corporate reorganization it went through in 1998.

Table 1.2: Distribution of announcements

This table illustrates the percentage of announcements per direction of change and rating agency.

	30-day window	90-day window
Upgrades	26.36%	17.39%
Downgrades	32.65%	58.86%
Moody's	64.19%	67.24%
S&P	33.68%	30.62%
Fitch	2.13%	2.14%

In order to detect patterns in rating announcements, we analyze the distribution of changes between consecutive ratings. Accordingly, we build transition matrices for the 30-day and 90-day time windows, with ratings distributed according to the letters; that is, rating modifiers are grouped. The grouping in the ratings of S&P(Fitch)/Moody's and its correspondence with the score or numeric scale is as follows: AAA/Aaa = 1; AA/Aa = 2-4; A/A = 5-7; BBB/Baa = 8-10; BB/Ba = 11-13; B/B = 14-16; CCC/Caa = 17-19; CC-D/Ca-C = 20-22. Due to the respective small number of cases they contain, the lowest ratings are grouped too. Tables 1.3a and 1.3b display the results, from where we are able to evaluate the level of rating stability.

Reporting relatively similar distributions, both tables place the majority of ratings in the middle of the rating scale, with near 75% of all announcements in the rating interval between levels 8 and 16 (Figure 1.2). Likewise, relative stability is evidenced from the almost inexistent changes far from the main diagonal of the transition matrices; as a reference, around 40% of announcements denote maintenance of the prior rating.

Table 1.3a: Transition matrix for the 30-day window

Tables 1.3a and 1.3b describe the observed rating changes respectively for the 30-day and 90-day samples. Ratings are grouped according to the letters and are represented by their respective score. Except where denoted, values in the matrices are percentages.

Prior rating	Announced rating								Number of ratings
	1	2-4	5-7	8-10	11-13	14-16	17-19	20-22	
1	75.4	11.5	8.2	4.9	-	-	-	-	61
2-4	1.2	79.1	16.2	3.2	0.3	-	-	-	345
5-7	0.1	1.4	79.7	17.1	1.2	0.3	0.1	-	1,557
8-10	0.1	0.0	6.5	78.3	11.6	2.8	0.6	0.1	2,237
11-13	-	-	0.4	12.0	60.8	24.9	1.7	0.2	2,029
14-16	-	-	0.1	0.9	18.1	68.5	10.9	1.5	2,577
17-19	-	-	-	0.3	5.2	38.7	46.3	9.4	382
20-22	-	-	-	-	6.1	32.7	32.7	28.6	49
Number of ratings	55	303	1,458	2,300	2,001	2,500	524	96	9,237

Table 1.3b: Transition matrix for the 90-day window

Prior rating	Announced rating								Number of ratings
	1	2-4	5-7	8-10	11-13	14-16	17-19	20-22	
1	82.1	7.1	7.1	3.6	-	-	-	-	28
2-4	2.2	76.1	17.4	2.9	1.4	-	-	-	138
5-7	0.2	0.8	82.8	14.5	1.2	0.3	0.2	-	647
8-10	0.1	-	5.5	85.6	6.9	1.6	0.2	-	938
11-13	-	-	0.3	8.6	78.8	10.8	1.4	-	858
14-16	-	-	0.1	0.9	10.6	82.6	5.3	0.4	1,198
17-19	-	-	-	1.4	1.4	20.9	74.3	2.0	148
20-22	-	-	-	-	-	10.5	10.5	78.9	19
Number of ratings	28	112	618	989	880	1,133	191	23	3,974

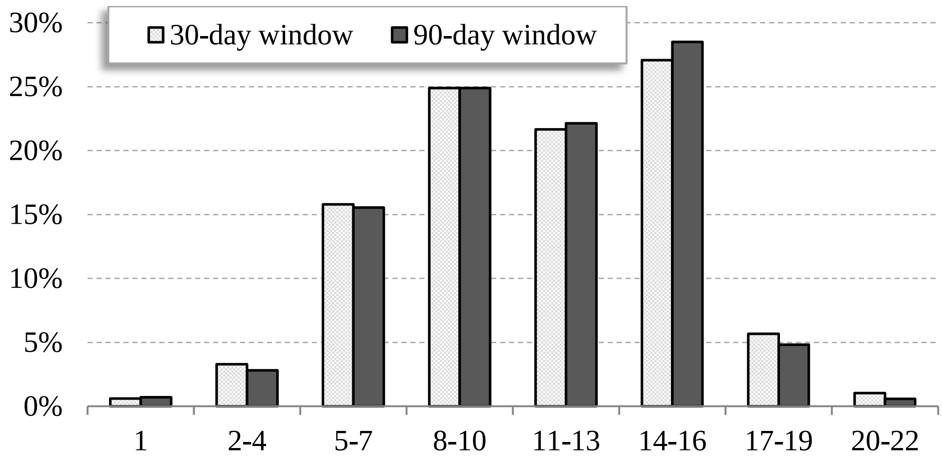

Figure 1.2: Distribution of credit ratings per rating class

The outcomes in the previous transition matrices do not differ much from the empirical evidence towards stability of ratings reported in prior literature for the one-year transition analysis (e.g., Nickell et al., 2000; Altman and Rijken, 2004). Such comparison of results extends to the detection of higher volatility of rating transitions in the lower graded classes. In fact, although not evidenced by the 90-day window, the transition matrix for the 30-day window reveals a reduction in the percentage of cases that remain in the prior class when credit quality declines. Despite the closeness between our results and those of prior research, we should stress that, contrary to such research, there is not a fixed time horizon in our rating matrices. The potential differences that subsequently might emerge are lessened, however, by the relatively similar duration of announcements (average duration near one year; see Table 1.4), at least in the 30-day window.

Table 1.4 provides additional details about announcements per agency. We note that the overall mean of announced ratings is near the transition levels to speculative grade. In addition, on average, S&P seems to apply slightly lower levels (higher score), corresponding to a rating close to BB (Ba2 in Moody's notation), the second level of the speculative grade. In contrast, Fitch's ratings are nearer to BBB- (Baa3 in Moody's notation), the last level of the investment grade. The mean of ratings changes, positive in all cases, points to slight downgrades both in the shortest and longest time windows.

Table 1.4: Descriptive statistics of rating announcements
This table displays the mean and the standard deviation of ratings announced per agency.

	30-day window		90-day window	
	Mean	Std. deviation	Mean	Std. deviation
Rating announced				
Fitch	9.9898	3.4949	9.5529	3.1453
Moody's	10.8133	4.2210	10.9192	4.1022
S&P	12.0765	3.2226	11.9737	3.1434
Rating change				
Fitch	0.1117	1.9000	0.2857	2.0917
Moody's	0.2274	1.6743	0.1459	1.7279
S&P	0.1562	1.6879	0.1383	1.6617
Rating duration (years)	1.0965	1.1477	1.6087	1.2621

1.4.3 Descriptive statistics of volatilities

Selecting as reference the 30-day window, we calculate the monthly average annualized volatilities of daily returns along the observation period. Figure 1.3a displays the evolution of absolute idiosyncratic volatility (σ_{ε}^{2}), the systematic volatility ($\beta^{2}\sigma_{m}^{2}$) and total firm risk (σ^{2}), whereas Figure 1.3b exhibits the evolution of the logistic relative idiosyncratic volatility, $\ln[\sigma_\varepsilon^2/(\beta^2\sigma_m^2)]$. With all values of volatility winsorized at the bottom and top 1% levels, both figures refer to $t+30$.

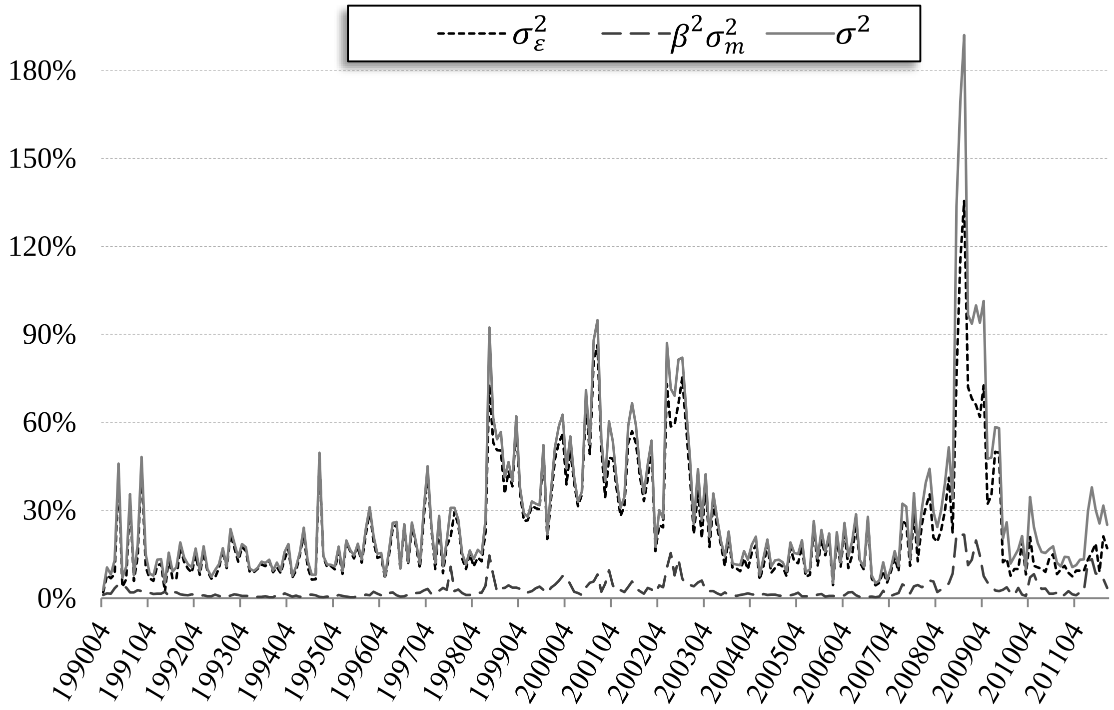

Figure 1.3a: Average absolute annualized volatilities (30-day window)

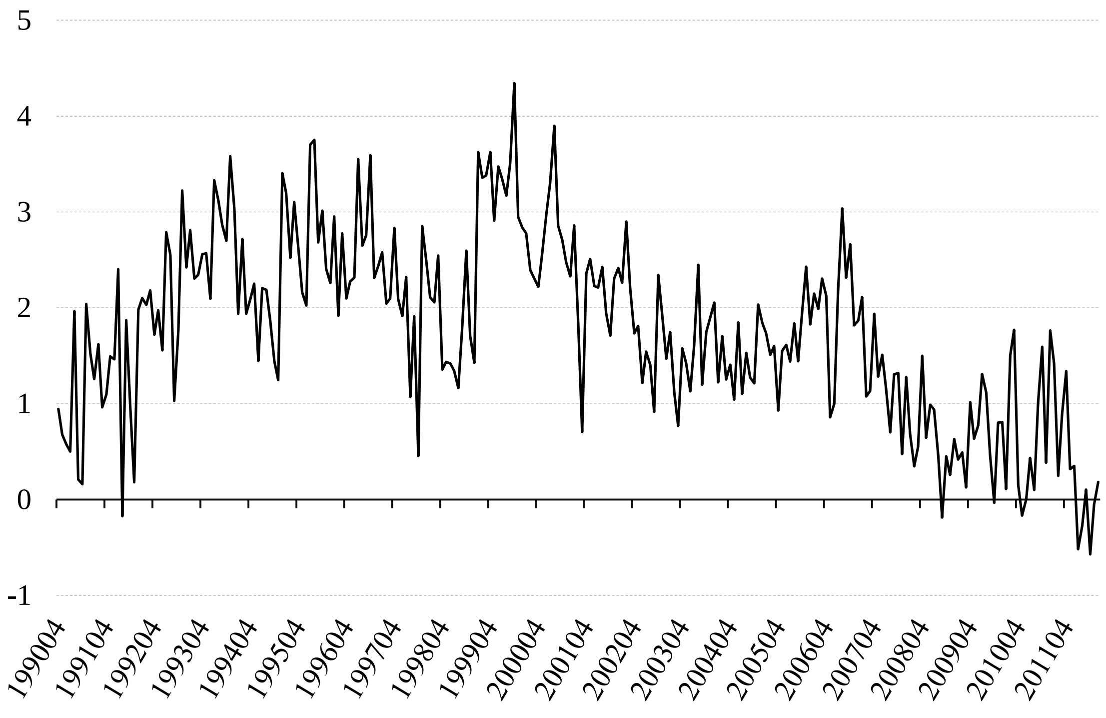

Figure 1.3b: Average logistic relative idiosyncratic volatility (30-day window)

As depicted by Figure 1.3a, there is striking evidence of abnormal volatilities in periods of major economic crises, such as in 2001 and 2007-2008. Also revealing the presence of volatility clustering, this evidence is applicable not only to the systematic risk, but also and especially to the firm's idiosyncratic risk, and consequently to the total firm risk. Moreover, there is some suggestion of rising volatilities even before crises mature. Yet, in what concerns the logistic relative idiosyncratic volatility, the evolution seems to be somewhat unaffected by the occurrence of major crises (Figure 1.3b). This should reflect the fact that, when computing relative idiosyncratic volatility, the effects of such crises are already mostly incorporated in systematic risk. We expect therefore the relative idiosyncratic volatility and the rebalancing of the total risk of the firm to be determined primarily by firm-specific factors, some of which may nonetheless be somewhat influenced by economic cycles.

Table 1.5 includes the volatility levels prior and after ratings announcements. The table shows that total volatility mostly reflects the influence of idiosyncratic volatility; 76% (77%) of the variations in total volatility is explained by idiosyncratic volatility in our 30-day (90-day) sample. The annualized mean idiosyncratic volatility reported in the table (approximately, 26%), is above the 19.4% reported in Ferreira and Laux (2007), mostly due to the distinct periods analysed. For example, our sample covers 2007 and 2008, a period characterized by remarkably high volatilities in the stock markets, not included in their study.

Table 1.5: Descriptive statistics of volatility
This table displays the mean and the standard deviation of volatilities.

	30-day window		90-day window	
	Mean	Std. deviation	Mean	Std. deviation
Total variance (annualized):				
After the announcement (σ^2_{t+N})	0.3101	0.5884	0.2571	0.3832
Prior the announcement (σ^2_t)	0.3100	0.5669	0.2472	0.3539
Idiosyncratic volatility (annualized):				
After the announcement ($\sigma^2_{\varepsilon_{t+N}}$)	0.2624	0.5505	0.2134	0.3591
Prior the announcement ($\sigma^2_{\varepsilon_t}$)	0.2565	0.5055	0.1994	0.3058
Logistic relative idiosyncratic volatility:				
After the announcement (Ψ_{t+N})	1.8622	2.0229	1.9201	2.0300
Prior the announcement (Ψ_t)	1.8819	1.9613	1.9159	1.9565

In what concerns mean volatility prior and after the announcement, the evidence suggests a slightly higher idiosyncratic volatility after the announcement, both in the 30 and 90-day windows. Actually, in the longer term, all indicators of volatility are higher than what the period prior the announcement reflects. However, in the shortest term of 30 days, the relative idiosyncratic volatility is somewhat lower. Note that such results may reflect mixed influences, namely those from upgrades and downgrades. Therefore, to achieve a precise outlook on the distinct reactions in volatilities of returns following rating announcements, we need to take into account the type of announcements and control for other potential determinants of volatility; the next sections report the results of such analysis.

1.5 Analysis of absolute idiosyncratic volatility

We estimate regression equation (1.3) using the 30-day and 90-day samples, and selecting three alternative sets of exogenous variables, so that a more complete understanding of the announcements' impact over absolute volatility comes out. In the first set we choose the following variables: dummies for downgrades, upgrades, S&P and Fitch, as well as the rating level and duration, the firm's size, computed by the natural logarithm of firm's assets, and the annualized quarterly change in real GDP.[3] As we show in Section 1.6, the rating level expands the effect of rating downgrades; i.e., the worse is the rating announced the stronger is the effect of the downgrade. However, this probably means as well that a significant part of the true effect of downgrades is absorbed by the coefficient of the rating level. Therefore, we select a second group of variables by excluding the rating level from the previous set, so that coefficients related to the announcements incorporate all the effects generated by such announcements. For the last set of variables, we split the type of announcements per agency, which replace *Downgrade*, *Upgrade*, *S&P* and *Fitch* in the second set of variables.

Table 1.6 displays the results corresponding to the previous three sets of variables. In each set, the proportion of idiosyncratic volatility explained by the variation in covariates, as exhibited by the respective adjusted *R*-squared, confirms a better fitted regression in the longer time window; non-specified factors in the regressions seem to have lesser influence in the longer time window. We confirm that downgrades are always relevant, both in the shortest and longest time span. In addition, when the rating level is removed we detect a significant rise in the effects of downgrades over volatility, particularly in the 30 days after the announcement. Actually, in that time frame, a firm with a previous annualized idiosyncratic volatility near the average (26%), *ceteris paribus* will see an instantaneous effect on its volatility of $1.1794 \times 26\% = 30.66\%$ if its ratings are downgraded. Yet, the effects of

[3] We also test industry effects by including the sector of activity as potential covariate of volatility, defined according to the first digit of the SIC code. No significant influences stand out however, both in the 30-day and the 90-day windows. Due to the respective very low *t*-ratios, implying no major differences in volatility per industry, we opt not to include that information in the model.

upgrades are not so evident; if we exclude the rating level or split the type of announcement per agency, upgrades actually become always non-significant at the 5% significance level.

The table also substantiates the influence of the agency making the announcement. Indeed, announcements by S&P produce the strongest effects on volatility of returns, namely when such announcements are downgrades. For example, considering the 30 days after announcement, when S&P downgrades an issuer whose annualized idiosyncratic volatility is again 26%, the respective instantaneous effects on volatility of stock returns will increase to 34.74%. This is above the average effect generated by downgrades during the same time span (as seen before, downgrades in general cause an increase in volatility up to 30.66%). The comparatively greater influence of S&P announcements on volatility is to some extent in line with Norden and Weber (2004), who point to announcements by S&P and Moody's showing a greater impact on the stock price return than announcements by Fitch.

From the estimated parameter related with *Size*, we see that larger firms reveal lower volatility, which corroborates the higher informational opaqueness mentioned by Behr and Güttler (2008) for smaller firms. A 1 percentage point increase in a firm's asset size reduces its idiosyncratic volatility of returns subsequent to rating announcements by as much as 23%; moreover, the effect of the asset size tends to diminish as we move away from the date of announcement, i.e. when we move to the 90-day window.

Regarding the influence of GDP change, we find no clear evidence. The coefficients are generally non-significant at the 1% significance level, and in the longest time window their respective signal is counterintuitive; indeed, in line with what we find in the 30-day time window, we expect that economic growth is countercyclical with volatility. The negative signal of the coefficient estimates related to *Duration*, especially in the second and third regressions, where we find statistically significant estimates, imply that more frequent announcements lead to more volatility of returns.

Table 1.6: Absolute idiosyncratic volatility regression estimates

This table reports Ordinary Least Squares estimates of regressions on absolute idiosyncratic volatility using three sets of variables. The explanatory variables comprise the prior idiosyncratic volatility ($ln\, \sigma^2_{\varepsilon_t}$), dummies for rating downgrades and upgrades, dummies for ratings by S&P and Fitch, and for rating downgrades by Moody's (*Downgrade_M*), S&P (*Downgrade_SP*) and Fitch (*Downgrade_F*), as well as for upgrades per agency (*Upgrade_M*, *Upgrade_SP* and *Upgrade_F*). Also included are the announced rating level, the number of years since the last rating (*Rating duration)*, the log of the firm's assets (*Size*), and the annualized quarterly change in real GDP; the latter is entered as decimals, not as percentage points.

	(1)				(2)				(3)			
	30-day time window		90-day time window		30-day time window		90-day time window		30-day time window		90-day time window	
	Estimates	*t*-ratio	Estimates	*t*-ratio	Estimates	*t*-ratio	Estimates	*t*-ratio	Estimates	*t*-ratio	Estimates	*t*-ratio
Intercept	-3.6255 **	-25.63	-2.6020 **	-14.88	-1.7321 **	-18.11	-1.3202 **	-11.41	-1.5433 **	-16.58	-1.2958 **	-11.32
$ln\, \sigma^2_{\varepsilon_t}$	0.5276 **	57.61	0.6549 **	49.90	0.5815 **	66.11	0.7025 **	57.06	0.5866 **	66.65	0.7032 **	57.17
Downgrade	0.0580 *	2.26	0.0801 **	2.61	0.1794 **	7.11	0.1212 **	3.94				
Upgrade	-0.0965 **	-3.69	-0.0056	-0.15	-0.0447	-1.69	0.0236	0.61				
Rating level	0.0629 **	17.92	0.0407 **	9.69								
S&P	0.2312 **	10.22	0.0963 **	3.56	0.2197 **	9.55	0.0878 **	3.21				
Fitch	0.1224	1.71	0.1322	1.60	0.0990	1.36	0.1070	1.28				
Rating duration	-0.0189	-1.90	-0.0092	-0.98	-0.0368 **	-3.65	-0.0194 *	-2.05	-0.0323 **	-3.19	-0.0185	-1.95
Size	-0.1149 **	-9.16	-0.0887 **	-6.10	-0.2181 **	-19.24	-0.1499 **	-11.32	-0.2300 **	-20.33	-0.1505 **	-11.37
GDP	-0.4045	-1.05	1.3567 **	2.93	-0.7580	-1.94	1.1163 *	2.39	-0.8942 *	-2.28	1.0710 *	2.29
Downgrade_M									0.1110 **	3.79	0.1052 **	3.23
Upgrade_M									-0.0531	-1.68	0.0380	0.87
Downgrade_SP									0.3363 **	9.79	0.2030 **	5.40
Upgrade_SP									0.0379	1.04	0.0339	0.60
Downgrade_F									0.2848 *	2.38	0.0945	0.90
Upgrade_F									0.0058	0.05	0.1556	0.93
Adjusted R^2	0.49		0.60		0.48		0.59		0.47		0.59	
F-statistics	999.71		652.86		1,048.19		706.21		828.80		564.23	
Observations	9,237		3,974		9,237		3,974		9,237		3,974	

* indicates significance at the 5% level; ** indicates significance at the 1% level

Finally, analysing volatility clustering, our estimates show a remarkable influence from the lagged idiosyncratic volatility, a result observed either in the 30-day and 90-day windows following the announcement. In the first case, for each additional percentage point in relative volatility prior the announcement, there is an expected 58.7% variation in volatility after announcement. In the second case, the variation can ascend up to 70.3%. The increase in the influence of lagged idiosyncratic volatility as we move away from the date of announcement implies that volatility tends to revert to the volatility mean, as soon as the effect of innovation begins to dissipate.[4]

As reported in Table 1.6, we use the Ordinary Least Squares (OLS) method to estimate coefficients. We also obtain estimates based on a robust regression that excludes outliers with a Cook's (1979) distance higher than 1, followed by Huber and biweight iterations, and the results are consistent with what we achieve using OLS.[5] We estimate as well an alternative model to equation (1.3), by isolating the variation in volatility, which implies changing the endogenous in the regression to $\ln\left(\sigma^2_{\varepsilon_{i,t+N}}\right) - \ln\left(\sigma^2_{\varepsilon_{i,t}}\right)$; i.e., $\theta_2 = 1$. The correspondent results, particularly in the case of downgrades, maintain in general the previous signs, although nonetheless most are statistically non-significant, probably because of the restriction imposed.

Due to the non-linear relation of risk throughout the rating scale, we acknowledge that a simple linear conversion of ratings to an ordered numerical scale, similar to the one used, may raise questions as to the effects of the rating level. Therefore, we assign instead a dummy to each group of ratings, as represented in Subsection 1.4.2. The results follow in Table 1.7.

The results in the table confirm the conclusions we reached before. Downgrades contribute to higher volatility at least until 90 days after the announcement, whereas upgrades seem to stay influent and reduce volatility only during the shorter term of 30 days. Additionally, the rising coefficients as we move downwards the rating scale imply that higher volatility is generally expected for worse rating groups, associated to higher risk. Surprisingly, the statistical significance of announced ratings within investment grade is rather low, suggesting that such ratings do not affect significantly to volatility, contrarily to the highly significant estimates relative to speculative grade announcements. Once again, the lower the announced

[4] The empirical evidence in this study is therefore coherent with relevant literature on volatility (e.g., Bollerslev, 1986; Glosten et al., 1993; Nelson, 1991), which underlines that current volatility of securities depends on the volatilities exhibited in previous time periods.

[5] Huber weighting assigns smaller weights to larger residuals. From iteration to iteration, these weights are applied until convergence is achieved, after which the converged model is weighted using biweights. Because biweights are not sensitive to outlier data, they are considered robust.

rating, the greater tends to be the instantaneous effect on volatility. The remaining variables are mostly in line with the results reported in Table 1.6.

Table 1.7: Absolute idiosyncratic volatility regression estimates with dummies for rating level

This table reports estimates of regressions on absolute idiosyncratic volatility. The covariates include the prior idiosyncratic volatility ($ln\,\sigma^2_{\varepsilon_t}$), dummies for groups of rating, each one indicated by the respective cardinal range, dummies for rating downgrades and upgrades, dummies for ratings by S&P and Fitch. Also included are the number of years since the last rating (*Rating duration)*, the log of the firm's assets (*Size*), and the annualized quarterly change in real GDP; the latter is entered as decimals, not as percentage points.

	30-day time window			90-day time window		
	Estimates	*t*-ratio	*p*-value	Estimates	*t*-ratio	*p*-value
Intercept	-3.3039	-17.91	0.000	-2.5723	-12.10	0.000
$ln\,\sigma^2_{\varepsilon_t}$	0.5240	57.03	0.000	0.6462	49.13	0.000
Downgrade	0.0562	2.18	0.029	0.0739	2.41	0.016
Upgrade	-0.0823	-3.11	0.002	0.0076	0.20	0.842
Rtg 2-4	0.0721	0.50	0.615	0.2583	1.64	0.102
Rtg 5-7	0.1126	0.84	0.403	0.2066	1.43	0.152
Rtg 8-10	0.1966	1.47	0.143	0.2399	1.67	0.095
Rtg 11-13	0.4104	3.03	0.002	0.3734	2.57	0.010
Rtg 14-16	0.6057	4.45	0.000	0.5077	3.47	0.001
Rtg 17-19	0.9230	6.46	0.000	0.8953	5.74	0.000
Rtg 20-22	1.3508	7.90	0.000	1.1621	5.36	0.000
S&P	0.2466	10.75	0.000	0.1167	4.24	0.000
Fitch	0.1391	1.95	0.052	0.1574	1.90	0.057
Rating duration	-0.0178	-1.79	0.074	-0.0072	-0.77	0.443
Size	-0.1205	-9.53	0.000	-0.0925	-6.37	0.000
GDP	-0.4047	-1.05	0.293	1.4300	3.10	0.002
Adjusted R^2	0.4941			0.6000		
F-statistics	602.34			398.38		
Observations	9,237			3,974		

1.6 Analysis of relative idiosyncratic volatility

This section extends the investigation concerning the volatility effects from rating announcements to the analysis of relative idiosyncratic volatility. We analyse effects both in a framework with unique announcements and in a framework where multiple contemporaneous announcements are allowed.

1.6.1 Framework with unique announcements

We summarize the regression estimates of equation (1.6) in Table 1.8. Our estimation method is the OLS, but we test again the robustness of results by using robust regression, whose results once more do not differ much from what we obtain with OLS.

Opposite to our results in Section 1.5, and to the literature about ratings effects on returns (e.g., Holthausen and Leftwich, 1986; Hand et al., 1992; Dichev and Piotroski, 2001), this table suggests that upgrades affect volatilities of returns, at least in the very short term. As expected, negative news conveyed by downgrades add to volatility, while positive news related with upgrades seem to diminish it. Taking into account the definition of the endogenous in this case, as in equation (1.5), a downgrade announcement generates an increase of 21.63% in relative idiosyncratic volatility in the shorter horizon of 30 days, lower than the 29.51% in the longer term of 90 days. Given the mean logistic relative idiosyncratic volatility of 1.86 (relative to the 30-day window), which implies that idiosyncratic volatility is 86.56% of total volatility, an increase of 21.63% in relative idiosyncratic volatility rises the proportion to 90.59%.

Table 1.8: Relative idiosyncratic volatility regression estimates

This table reports estimates of regressions of logistic relative idiosyncratic volatility on a set of covariates. The covariates include dummies for rating downgrades and upgrades, dummies for ratings by S&P and Fitch, the announced rating level, the number of years since the last rating (*Rating duration)*, the log of the firm's assets (*Size*), and the annualized quarterly change in real U.S. Gross Domestic Product (*GDP*); the latter is entered as decimals, not as percentage points.

	30-day time window			90-day time window		
	Estimates	*t*-ratio	*p*-value	Estimates	*t*-ratio	*p*-value
Intercept	6.3043	27.84	0.000	6.9114	20.65	0.000
Downgrade	0.2163	4.61	0.000	0.2951	4.14	0.000
Upgrade	-0.2059	-4.32	0.000	-0.1868	-2.12	0.034
Rating level	0.0357	6.04	0.000	0.0215	2.37	0.018
S&P	0.0822	2.00	0.045	-0.0911	-1.46	0.144
Fitch	-0.1160	-0.89	0.374	-0.2117	-1.10	0.271
Rating duration	0.0056	0.31	0.758	-0.0349	-1.60	0.110
Size	-0.6875	-30.45	0.000	-0.7648	-23.10	0.000
GDP	12.6942	18.16	0.000	14.8672	13.83	0.000
Adjusted R^2	0.22			0.27		
F-statistics	324.21			184.95		
Observations	9,237			3,974		

Although downgrades continue to be rather significant to explain volatilities as we move away from the date of announcement, the evidence on upgrades becomes weaker (the related parameter is non-significant at the significance level of 1%). This evidence on the insignificance of upgrades to volatility is more in line with the seeming irrelevance of such announcements for stock returns, already reported in previous literature.

Given that higher ratings match lower scores, the announced rating displays a positive effect on volatility, suggesting a relevant influence from the rating level. Brooks et al. (2012) report a similar finding relative to sovereign ratings. Our results confirm that low graded firms are in fact relatively more sensitive in terms of the respective volatility of returns, with each level of downgrade bringing an extra 3.57% (2.15%) increase in the relative idiosyncratic volatility in the 30 (90) days that follow the announcement. The lesser effects associated to the rating level, observed in the longer time frame comparatively to the shorter term, counterbalances somewhat the greater impact from the rating downgrade during the same period.

The coefficients estimates related to *GDP* suggest that rating announcements have heightened impacts on the relative idiosyncratic volatility in a more dynamic economic growth context. A percentage point increase in the quarterly change of GDP generates a 12.69% increase in relative idiosyncratic volatility in a time frame of 30 days, below the effect in the 90-day window (14.87%). Though apparently this may seem opposite to the assumption in Kaminsky and Schmukler (1999), stating that negative ratings reinforce a herding behavior in economic crises, it may not really lead to a different perspective. Bearing in mind the definition of our endogenous variable, $\Psi = \ln[\sigma_\varepsilon^2/(\beta^2\sigma_m^2)]$, we easily conclude that what the positive influence of *GDP* on Ψ truly reflects is a change in the proportion of the total stock return variation described by idiosyncratic volatility; it really does not mean that higher economic growth implies an enlargement of the absolute idiosyncratic volatility. Actually, since market volatility is countercyclical (Schwert, 1989), it may happen that, as shown in Section 1.5, idiosyncratic volatility is also countercyclical, but less than market volatility, producing cyclicality in the relative idiosyncratic volatility.

In respect to the influence of rating duration, there is a non-significant relation with stock return volatility; that is, the fact that one issuer is rated more frequently than another does not reflect into significant differences in their respective relative idiosyncratic volatilities. On the contrary, when observing the estimated coefficient of *Size*, we confirm a significant influence; larger firms, normally associated to greater informational transparency, denote lower relative volatility effects after the rating announcement.

Table 1.8 features as well that no major differences seem to derive from the agency assigning the rating, even though S&P is marginally significant in the shorter time window (significant at 5%). In order to clarify the marginal influences of each agency, we subdivide the announcements per type and agency. Using such information to replace the variables *Downgrade*, *Upgrade*, *S&P* and *Fitch*, we regress the logistic relative idiosyncratic volatility on the new set of covariates. Table 1.9 displays the results.

The coefficients estimates of the variables which are common to Table 1.8 do not differ much in both tables. However, concerning the coefficients of the new variables, namely those referring to the type of announcement and agency making the announcement, Table 1.9 clearly substantiates that the agency making the announcement seems to affect relative volatility. In particular, relating to the shorter time horizon, announcements by S&P seem to impact more on volatility than announcements by Moody's; rating upgrades by Fitch also seem to reduce volatility.

In the longer time window, the effects of rating upgrades seem to vanish, as the related coefficients become non-significant, which is more evident in the case of Moody's. Also relative to Moody's, the effect on volatility generated by downgrades in the longer time window is stronger when compared to the shorter time window and to downgrades by S&P.

Table 1.9: Relative idiosyncratic volatility regression estimates (announcements per agency)

This table displays estimates of regressions of relative idiosyncratic volatility on dummies for rating downgrades by Moody's (*Downgrade_M*), S&P (*Downgrade_SP*) and Fitch (*Downgrade_F*), as well as upgrades per agency (*Upgrade_M*, *Upgrade_SP* and *Upgrade_F*). Also included are the announced rating level, the number of years since the last rating (*Rating duration)*, the log of the firm's assets (*Size*), and the annualized quarterly change in real GDP; the latter is entered as decimals, not as percentage points.

	30-day time window			90-day time window		
	Estimates	*t*-ratio	*p*-value	Estimates	*t*-ratio	*p*-value
Intercept	6.3869	28.41	0.000	6.8942	20.64	0.000
Downgrade_M	0.1681	3.09	0.002	0.3067	4.05	0.000
Upgrade_M	-0.1359	-2.38	0.017	-0.1431	-1.43	0.153
Downgrade_SP	0.3048	4.94	0.000	0.2414	2.81	0.005
Upgrade_SP	-0.2673	-4.10	0.000	-0.3204	-2.45	0.014
Downgrade_F	0.2280	1.06	0.288	-0.0100	-0.04	0.967
Upgrade_F	-0.4494	-2.28	0.023	-0.3164	-0.83	0.409
Rating level	0.0366	6.02	0.000	0.0207	2.28	0.023
Rating duration	0.0103	0.56	0.573	-0.0352	-1.61	0.106
Size	-0.6960	-30.98	0.000	-0.7638	-23.09	0.000
GDP	12.6257	18.09	0.000	14.8989	13.87	0.000
Adjusted R^2	0.22			0.27		
F-statistics	259.78			148.00		
Observations	9,237			3,974		

We should add a remark on the seemingly dissimilar effects from distinct agencies, in particular in view of the relatively high effects from downgrades announced by S&P. Such effects emerge in a framework with unique ratings, in which we do not observe simultaneous announcements from distinct agencies. Thus, although remote, there is a possibility that other circumstantial causes are contributing to volatility when S&P announces its ratings, which potentially limits our conclusions. More conclusive evidence is achieved in the next subsection, using a specification allowing for simultaneous announcements.

1.6.2 Multiple announcements

With the purpose of determining the effect of consistent rating announcements on the stock return volatility, we broaden the framework of analysis to a scenario with multiple contemporaneous announcements across rating agencies. In this context, we use the expression *consistent rating announcement* as the direction of the rating announcement, not the rating itself. Hence, there is consistency in rating announcements when an upgrade (downgrade) from one rating agency moves in tandem with at least one upgrade (downgrade) from another agency along the time period selected. There is consistency as well when both agencies announce maintenance of their ratings. All other situations are classified as contradictory.

The time period selected for analysis corresponds to the 30-day window (N = 30). Using such reference, we allow for multiple contemporaneous rating announcements from different agencies in the underlying time period. The previous restriction of unique ratings in the boundary of $2N$ days near the date of the announcement is, therefore, skipped. With the new criteria, we obtain a different sample of 19,658 observations. In the new sample, the distribution of ratings per agency reveals again a greater representativeness of Moody’s, with 55.4% of all announcements, whereas S&P reaches 38.8% and Fitch obtains 5.8%.

Per type of consistency, the sample is subdivided as follows. 2,914 observations stand for rating announcements denoting changes with equal sign as the announcements from other agencies. Of these, 1,766 announcements are downgrades and 531 upgrades; the remaining 617 imply maintenance of ratings. There is contradiction in 1,662 announcements. In 575 of such cases, the first rating is a downgrade and the subsequent rating is an upgrade or a rating maintenance, 397 cases stand for an upgrade followed by downgrade or maintenance, and the 690 remaining are those whose first announcement implies maintenance of rating. 15,082 announcements have insufficient information to tell whether they are consistent or not, either because subsequent announcements belong to the same agency or because they are separated by more than 30 days.

The multiple announcements approach replaces variables *Upgrade* and *Downgrade* (presented in Table 1.6) by dummies for rating consistency and contradiction, both subdivided depending on the first rating being an upgrade or a downgrade. Correspondingly, we define *Consistency_Up*, *Contradiction_Up*, *Consistency_Down* and *Contradiction_Down*; the endogenous is once more the logistic relative idiosyncratic volatility. Table 1.10 summarizes the results.

Table 1.10: Relative idiosyncratic volatility estimates in a multiple announcements scenario

This table shows estimates of a regression of relative idiosyncratic volatility on dummies for rating consistency or contradiction when upgrades (*Consistency_Up* and *Contradiction_Up*) and downgrades (*Consistency_Down* and *Contradiction_Down*) occur. As before, we add dummies for ratings by S&P (*S&P*) and by Fitch (Fitch), as well as the announced rating, the rating duration, the log of the firm's assets (*Size*), the annualized quarterly change in real GDP; the latter is entered as decimals, not as percentage points.

	30-day time window		
	Estimates	t-ratio	p-value
Intercept	0.5916	6.58	0.000
Consistency_Down	0.4223	8.67	0.000
Contradiction_Down	0.2523	3.77	0.000
Consistency_Up	0.0094	0.15	0.880
Contradiction_Up	0.0955	1.39	0.165
Rating level	0.1579	55.99	0.000
S&P	0.2789	14.26	0.000
Fitch	0.1113	2.75	0.006
Rating duration	-0.0627	-6.96	0.000
Size	-0.1181	-15.39	0.000
GDP	5.9148	17.52	0.000
Adjusted R^2	0.29		
F-statistic	806.72		
Observations	19,658		

The table shows that, when we take into account contemporaneous announcements from different agencies, downgrades continue to generate rather strong effects on volatility, regardless of being in consistency or in contradiction with the announcements from different agencies; yet, the effects on volatility are much stronger in the presence of consistency. When one agency downgrades an issuer and, within the following 30 days another agency does the same, the relative idiosyncratic volatility of returns increases by 42.23%, higher than the effect produced when subsequent announcements from other agencies contradict such downgrade (25.23%). Also note that, when announcements of downgrades are consistent, the resulting effect on relative idiosyncratic volatility emerges stronger than the marginal effect previously displayed in Table 1.8 by downgrades alone. In what concerns upgrades, we observe that the related coefficients are non-significant, confirming that, in a more realistic approach where multiple announcements may take place, upgrades may in fact be less relevant for volatility.

Regarding the other coefficients estimates, Table 1.10 illustrates parameters signals relative to the rating level, *Size*, *S&P* and *GDP* consistent with the results shown in Table 1.8. However, while the marginal effects of the rating level and S&P are much higher when we consider multiple ratings, the influences of *Size* and *GDP* are more moderate. This means *Size* and *GDP* absorb some of the influence of ratings when we restrict the analysis to a framework with unique ratings; we should notice that such framework is less accurate than another one with multiple ratings, as seen by the respective adjusted *R*-squared (22% vs. 29%). An additional worth mentioning feature in Table 1.10 is the significance and signals of the coefficients estimates relative to *Fitch* and *Rating duration*. Contrary to the lack of significance detected when we analyze unique announcements, now both variables denote significant effects. In fact, in a framework with multiple announcements, Fitch generates more volatility than Moody's (but less than S&P). Regarding rating duration, the evidence suggests a negative relation with volatility of returns; this confirms a preponderance of the potential volatility effect of rating announcements over the asymmetric information assumption, which reduces volatility, as outlined in Subsection 1.3.1.

1.7 Summary and conclusion

This paper documents evidence about effects of rating information on the firm's stock return volatility. The results reported extend the literature on the factors determining a stock's return volatility and, consequently, the stochastic evolution of stock price through time. Such results have implications for portfolio managers in determining asset pricing, and for regulators in terms of the use of external credit ratings for determining banks capital requirements.

We find that rating downgrades expand the relative and absolute idiosyncratic volatility of stock returns. Nevertheless, the evidence concerning upgrades is less clear, which is in line with the asymmetry of effects already detected in sock returns. The rating announced reinforces the effect of downgrades over volatility, and the informational opaqueness, specifically in smaller firms, is a factor that stimulates higher variance of returns. Likewise, when compared with Fitch and Moody's, announcements of S&P have higher effects on volatility, especially in the short term and when downgrades are announced. A more dynamic economic growth seems to reduce absolute volatility, but amplifies relative volatility effects following the announcement. The positive effect of economic growth on relative volatility reveals a higher countercyclical reaction of systematic volatility relative to the change in GDP, than what is observed in idiosyncratic volatility. Finally, when different agencies downgrade a firm contemporaneously, the relative idiosyncratic volatility of that firm's return increases significantly. Given these findings, models of volatility forecasting should gain significantly from the inclusion of rating-related information. Such information adds to the idiosyncratic factors that characterize the firm, namely those formerly pointed out by Durnev et al. (2004), and Ferreira and Laux (2007), in models that explain relative idiosyncratic stock return volatility.

Some related questions deserve further investigation. In line with prior research of ratings' impact over returns (Norden and Weber, 2004), we underscore the probable effects of rating outlooks and rating watches, not explored in this paper. Future investigation should also focus on the effects of rating announcements on volatility in the long run, for example using longer periods such as the one-year term; this extension of the time horizon might bring too some insights regarding the length needed until volatility effects dissipate. The same applies to other securities and other stock markets besides the U.S. market, where it might be interesting to extend knowledge regarding the respective volatility intricacies as a function of rating announcements. In addition, considering previous findings from Koutmos and Booth (1995), who conclude for the relevance of quantity of news as determinant of volatility, future research should investigate as well how volatility of returns react to the magnitude of the rating change.

As a final remark, it seems noteworthy to underscore that idiosyncratic volatility is recognized as one of the relevant variables determining credit ratings. For example, Jorion et al. (2009), add empirical evidence pointing to better ratings being associated to lower volatility. On the other hand, this study complements by showing that rating downgrades stimulate a firm's relative and absolute idiosyncratic volatility. For that reason, we may ask until what extent rating downgrades lead to a looping of volatilities and new rating downgrades, generating a *snowball* effect that ultimately becomes corrosive for the rated firm.

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Chapter 2

Is There a Self-fulfilling Prophecy in Credit Rating Announcements?

2.1 Introduction

The concept of self-fulfilling prophecy is described by Merton (1968, p. 367) as a situation whereby an incorrect belief or expectation brings forth a new behavior that eventually causes the original false conception to come true. For example, he uses a parable of a bank with a stable financial structure that suddenly faces unfounded rumours of insolvency. As the rumours spread, depositors become increasingly anxious, ultimately leading the bank into bankruptcy.

The relation between credit ratings and credit default is a similar example. Credit ratings are meant to foretell the future payment behaviour of the rated firm and to lessen information asymmetry between that firm and investors. However, rating announcements may as well generate non-negligible effects on the firm concerned, such as its cost of debt, among other impacts.[6] When these announcements are negative and convey substantial bad news about the rated firm, they may generate not just temporarily debt cost effects. Instead, longer lasting consequences that restrain the firm's financial management and stability may emerge. Such announcements are likely to undermine investors' confidence in the firm and strongly stimulate the proportion of investors anticipating a firm's default, so withdrawing credit. The resulting credit restrictions potentially spark liquidity crises that can jeopardize the firm's ability to honor its future financial commitments and push it towards credit default; just like in Merton's parable. Given the widespread use of credit ratings, it is fundamental to investigate this potential effect of ratings on credit default.

The purpose of this paper is to study the hypothesis that rating downgrades increase the probability of default. The obvious difficulty is to disentangle the cause from the effect.

[6] For example, Ederington and Goh (1998) find that equity analysts are likely to adjust earnings forecasts "sharply downward" after a downgrade.

Indeed, as some firms might be so financially fragile that they would have defaulted regardless of having been downgraded or not, it is not trivial to separate the potential causal effects we are investigating from ratings' prediction accuracy. *Ex post*, we realize what happened to firms with negative ratings announcements; however, we do not know what would have happened *ceteris paribus* to the same firms in the absence of such announcements. In other words, we observe the factual outcome but not the counterfactual, which generates a missing data problem, as defined by Holland (1986).

Such problem potentially explains why related literature did not test yet the possibility of some credit rating announcements turning into self-fulfilling prophecies of default. For example, Bannier and Tyrell (2006) admit that a wide early withdrawal of credit access pushes the firm into default. As a result, Kuhner (2001) postulates that some negative credit rating announcements may turn into self-fulfilling prophecies. Inclusively, this hypothesis was already admitted by Moody's (Fons, 2002), which acknowledges "that its ratings can potentially become self-fulfilling forecasts" in the case of negative announcements, where higher capital costs are expected and restrictions to the issuer's access to funding may arise; possibly, these circumstances might even lead to default.

Manso (2013) presents a theoretical framework for feedback effects of credit ratings, which endogenizes default. In such framework, based on performance-sensitive-debt, under increased competition and widespread criticism, a rating agency pursuing an accurate rating policy may face a downward pressure on its ratings, which increases the default frequency. The feedback results from the effects of ratings on interest rates, consequently determining the issuer's optimal default decision, which in turn influences ratings. Small shocks to fundamentals, may thus lead to a credit-cliff dynamic and generate a "death spiral". We extend this line of research by testing conjectures raised in this and previous papers.

The current paper uses a threefold econometric approach. Based on Shumway (2001) and Campbell et al. (2008), the first approach consists in a credit default prediction model which includes rating covariates, controlling for several default-related variables. We acknowledge that this is a naïve approach to causality; as ratings also track the probability of default, endogeneity is not precluded here. However, this analysis helps us to clarify our research hypotheses. In addition, it complements the results obtained using two methods of causality analysis, our second and third approaches. The second approach lies in the propensity score matching technique proposed by Rosenbaum and Rubin (1983). The utilization of this method to analyse causality problems similar to ours proliferates in distinct fields of scientific research, such as biology, medicine, economics and sociology. The third approach, the

Heckman treatment effects approach, or Heckit model (Heckman, 1978, 1979; Maddala, 1983, p. 120), controls for the plausible endogeneity of the rating announcement; it represents therefore a valuable alternative to the credit default prediction model. Interestingly, although the three previous approaches imply distinct methodologies, their outcomes are quite consensual.

Relying on an extensive database of ratings issued by Fitch, Moody's and Standard & Poor's (S&P), between 1990 and 2011, the paper shows evidence suggesting that some rating downgrades may potentially aggravate the risk of default. Such is the case of ratings moving from investment grade to speculative grade, which seems to cause an increase over 3% in the 1-year probability of default when it occurs. The potential effect appears to be even larger when we observe downgrades from a level that is already speculative to another one at best equal to a highly speculative grade; in this case, the 1-year probability of default may increase by at least, 12.13%. In addition, the magnitude of the rating change is found to cause significant effects too. One interpretation for these effects of rating downgrades, in line for example with Gonzalez et al. (2004) and Jorion et al. (2005), is that ratings convey significant information to the markets. In view of the results in the current paper, were seemingly abnormal reactions in the rate of default emerge when rating news are rather negative, another probable explanation is that such news could also add noise that affects the firm's financial performance.

The reputation of rating agencies depends on their ability to anticipate future situations of credit default by assigning them worse rating levels. For example, as stated by Güttler and Wahrenburg (2007), the better the ability of a rating agency to anticipate upcoming defaults, the higher will be its reputation. For not being able to timely anticipate some of the largest credit failures, especially after the financial markets volatility since the end of the 1990's, the three major rating agencies have been the target of some bitter criticism. The most cited examples are the failures of Enron in 2001, Worldcom and Adelphia Communications Corporation in 2002, Parmalat in 2003, Lehman Brothers in 2008, as well as the failures of sovereign issuers (Asian countries in 1997, Russia Federation in 1998, and Argentina in 2001), and of some mortgage-related securities during the subprime crisis of 2007-2008. Indeed, when assessing credit risk, it is rather important to evaluate to what extent the underlying assessment tool is able to anticipate default events. Put in another way, the hit rate or true positives for that tool should remain high and the false negatives or type II error (i.e. defaults predicted as non-defaults) should be kept low.

An implication from our findings, aligned with the disclosure in Manso (2013), that rating agencies should consider "the effects of their ratings on the probability of survival of the borrower", is that it is equally important to evaluate if overly pessimistic ratings do not unduly penalize borrowers.This means that the misclassification rate due to false positives or type I error (i.e. non-defaults predicted as defaults) must also be minimal. Otherwise, with a downward bias in credit decisions, creditors themselves will lose profitable business opportunities. In addition, regardless of the reasoning behind the detected effects, a natural consequence from the evidence in this paper is that rating information, if added to the covariates of statistically-based credit default prediction models, improves the accuracy of these models.

It is relevant to underline potential limitations to our conclusions. The study analyses only public information, but there is also a non-negligible amount of private information that rating agencies may incorporate in their ratings. It may be that, based alone on public information, the firm denotes a low risk of default, but the correspondent rating could already reflect private information that imply an almost unavoidable event of default. Another potential limitation is that we do not control for all public market information, such as bond and CDS spreads. This could be relevant information if some rating downgrades lag market prices in the prediction of incoming defaults.[7] Yet, given the financial effects and information content of ratings, this possibility does not contradict the hypothesis that some downgrades may further aggravate the financial stability of several obligors, and as such enhance their risk of default. Similar limitations are present in other causality problems, given their underlying missing data problems. By using a threefold econometric approach, we hope to mitigate these limitations to some extent.

The rest of the paper is organized as follows. Section 2.2 provides an overview of the main determinants behind the different rating levels, and highlights the already identified financial effects and information content of credit ratings. This section contains as well the results of our credit default prediction model, paving the way to research hypotheses. Section 2.3 describes the data used for analysis, and reports selected descriptive statistics. Section 2.4 contains an overview of the causality methodologies employed to investigate the hypotheses; the results obtained are also detailed and discussed here. Section 2.5 concludes.

[7] In this regard, Vassalou and Xing (2004) show that default risk in equity returns changes prior to changes in the firm's ratings.

2.2 The relation between ratings and default

This section is divided into three subsections. The first describes some of ratings' main features and draws from previous literature to summarize credit ratings' financial and non-financial determinants; financial effects of rating announcements are also outlined here. The second subsection explores a preliminary analysis on the question raised in this paper. This analysis allows us to postulate research hypotheses in the third subsection.

2.2.1 Literature review

2.2.1.1 Credit ratings and their determinants

A credit rating is an independent opinion, whether solicited or unsolicited, on the relative ability and willingness of a party with debt obligations to meet its financial commitments (OECD, 2010).[8] In addition to publicly available information that unsolicited credit ratings reflect, solicited ratings also incorporate private information that otherwise exposed would jeopardize the strategy of the rated company. The research in this paper focuses on the second type of ratings, based on information about the three main agencies: S&P, Moody's and Fitch.[9]

Though private information limits the investigation on some factors weighted to determine credit ratings, namely those obtained by the agencies via private meetings with management, a few papers explore the main observable determinants of ratings. This is the case in Cantor and Packer (1997), Blume et al. (1998), Amato and Furfine (2004), Kisgen (2006), Güttler and Wahrenburg (2007), and Jorion et al. (2009). Given that, as ordinal and qualitative measure of risk, each rating ultimately ranks the level of risk, such papers generally use ordered multinomial probit or logit estimations, from where they identify the main variables or factors determining credit ratings (Table 2.1). Due to the unobservable variables inherent to the rating process, Kamstra et al. (2001) confirm that most related estimation methods tend to correctly forecast, at best, only circa 78% of the observed ratings.

[8] Generally, a credit rating reflects the creditworthiness of the issuer, rather than the credit quality of its debt obligations. As referred by Cantor and Packer (1997), an issuer or an obligation may be rated by more than one agency, a circumstance more likely for large and experienced issuers.

[9] Together, the three agencies dominate the worldwide market: S&P and Moody's hold approximately 80% of the market, while Fitch owns 14% (Langohr and Langohr, 2008, p. 386). Such level of concentration confirms the oligopolistic structure of this market (OECD, 2010), primarily nourished by large barriers to entry. For instance, Bolton et al. (2012) call an "artificial barrier" the creation of the Nationally Recognized Statistical Rating Organizations, the designation adopted by the Securities and Exchange Commission for the agencies whose ratings are valuable for investments decisions.

Presenting a digest of explanatory variables reported in previous literature on credit ratings, Table 2.1 reveals that different references select four accounting ratios:

- *Interest coverage*: Sum of Operating Income After Depreciation and Interest Expense divided by Interest Expense;
- *Operating margin*: Operating Income Before Depreciation divided by Net Sales;
- *Long term debt leverage*: Total Long Term Debt divided by Total Assets;
- *Total debt leverage*: Total Debt divided by Total Assets.

Table 2.1: Relevant variables determining credit ratings

This table summarizes the main covariates of credit ratings, and reports their expected influence on credit ratings, according to the results of previous literature.

Variable	Type of variable	Expected influence	References
Interest Coverage	Accounting	Positive	Blume et al., 1998; Amato and Furfine, 2004; Jorion et al., 2009; Güttler and Wahrenburg, 2007
Operating Margin		Positive	
Long Term Debt Leverage		Negative	
Total Debt Leverage		Negative	
Log of Total Assets		Positive	Kisgen, 2006
Earnings Before Interest, Taxes, Depreciation and Amortization divided by Total Assets		Positive	
Debt divided by Total Capitalization		Negative	
Log Outstanding Debt		Negative	Güttler and Wahrenburg, 2007
Market Value of the Firm	Market	Positive	Jorion et al., 2009
Market Model Beta		Negative	
Residual Volatility		Negative	
Market Value of Equity		Positive	Amato and Furfine, 2004
Change in GDP	Macroeconomic	Positive	Güttler and Wahrenburg, 2007
Year and industry dummies	Other	-	Jorion et al., 2009
Previous ratings		Positive	Güttler and Wahrenburg, 2007

Albeit accounting-type variables predominate, the table also displays other relevant determinants of ratings, being it market or macroeconomic-type information, or even the rating history. Regarding the expected influence exerted by each variable, the table tells us that higher credit ratings tend to appear in firms that are more profitable, have lower market risk (e.g., beta, volatility) and lower leverage. Considering the negative influence leverage exerts on credit ratings, the table underscores one of the main factors reported by Poon and Chan (2010) to motivate the rating level: the debt ratio level of the issuer. Concerning ratings from previous periods, Güttler and Wahrenburg (2007) confirm their relevance particularly to predict future ratings for low graded issuers. In accordance with ratings serial correlation, the positive expected influence of ratings history means that the next rating change most probably will be in the same direction as the last one. Altman and Kao (1992), Dichev and Piotroski (2001), Lando and Skødeberg (2002), among others show striking evidence on this issue, especially in the case of downgrades.[10]

2.2.1.2 Financial effects and information content of ratings

The advantages of credit ratings in terms of informational economies of scale and their role in solving principal-agent problems explain their use as creditworthiness standards by debt issuers, investors and portfolio managers. Moreover, regulators and lawmakers also award a quasi-regulatory role to ratings.[11] The extension of ratings' initial purpose as a mere assessment of credit risk, to true benchmarks of creditworthiness for managing regulation, debt issuance and portfolio management, contributed remarkably to the enhancement of rating effects in the last decades.

Behind this enlargement of scope of credit ratings, underlined by Gonzalez et al. (2004), we find several factors. One of them lies in the regulation that directly and indirectly restricts low rating securities owned by banks, insurers, mutual funds and other portfolio managers. Another factor derives from the determination of capital charges for financial institutions according to the borrowers' credit ratings. The constraints imposed on the quality of eligible assets for monetary policy collateral purposes, when such assets have low credit ratings, enhance as well the ratings scope. Overall, such hardwiring of regulatory rules and investment decisions to ratings may aggravate the effects of negative rating announcements, including the development of serious liquidity problems. Among the potential effects from negative announcements, we underline the following.

Cost of capital

From the issuers' point of view, ratings act as a necessary vehicle to improve the pricing of debt, by incorporating relevant inside information about each company's business, but without uncovering specific details. As stated by Kliger and Sarig (2000), this avoids threats to the

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[10] For example, based on ratings observed between 1970 and 1997, Dichev and Piotroski (2001) report that the ratio of upgrades to downgrades following a downgrade is merely 1:15, and that almost 25% of downgraded firms receive a second downgrade within the 12 months that follow the original downgrade.

[11] An evidence of the perceived benefits of ratings is the huge increase in the number of global rated corporate issuers. Langohr and Langohr (2008, p. 377) report an increase six-fold in the number of corporate issuers, to 6,000, in little more than 35 years, while Moody's mentioned in its website a value of rated securities over $80 trillion.

company's private strategy. Naturally, the motivation of issuers when they solicit ratings is their expectation that news conveyed by ratings will not deteriorate market's expectations, let alone the cost of financing; nevertheless, in many cases this does not verify. Actually, as emphasized by Gonzalez et al. (2004) and Jorion et al. (2005), negative credit rating announcements drive up the rated firm's cost of capital, therefore worsening the position of a company that may be performing poorly.

Securities' returns

The link among credit ratings and the cost of debt fosters the perspective that ratings announcements add new information to the markets, particularly when these announcements are negative. In such circumstance, the market value of the firm's securities is affected. Hand et al. (1992), as well as Steiner and Heinke (2001), investigate the effects of rating changes by Moody's and S&P and find that downgrades generate negative overreaction in bond price returns. Steiner and Heinke (2001) show that effects are more intense when rating downgrades are into speculative grade. Based on refinements introduced in Moody's ratings, Kliger and Sarig (2000) isolate the effects that reflect exclusively rating information, and confirm both positive and negative bond price reactions to rating changes, which are stronger for more levered firms. Daniels and Jensen (2005), Hull et al. (2004), as well as Micu et al. (2006) emphasize reactions that materialize into higher values of credit default swaps spreads when rating downgrades are announced.

Further striking evidence about the financial effects of ratings shows up in studies about stock prices. In particular, Holthausen and Leftwich (1986), Hand et al. (1992), Dichev and Piotroski (2001), and Norden and Weber (2004) confirm that significant negative abnormal stock returns arise following rating downgrades, but detect little evidence of abnormal returns following upgrades. Dichev and Piotroski (2001) add that these asymmetric price reactions to rating changes, where negative abnormal stock returns dominate, last at least one year. Jorion and Zhang (2007) also report effects from positive announcements, although the absolute impact is quite lower than what results from negative announcements. In addition, they point out the influence of the rating prior to the announcement, informing that when prior ratings are below the B level, the absolute magnitude of the rating change of one class is associated to a stock price change of -5.04% (for a downgrade) versus 2.52% (for an upgrade);[12] i.e., more pronounced price effects emerge in lower rated firms.

[12] As detailed below, a rating level equal to B denotes highly speculative credit risk.

Among the explanations for the higher susceptibility of markets to negative rating announcements, Ederington and Goh (1998) underline the reluctance of firms to disclose unfavorable information that ends up being reflected in the downgrade. Another explanation which they discuss is the perception that agencies spend relatively more resources detecting deteriorations in the issuer's credit quality.

Financing access

Graham and Harvey (2001) identify a good credit rating as the second most important concern influencing a firm's debt policy. Kisgen (2006) confirms that the imminence of a rating change, being it an upgrade or a downgrade, inhibits a firm's issuance activity; low-grade issuers may possibly not even be able to raise debt capital during weak economic phases. As a result, profitable investment opportunities will be lost, affecting the firm's long term growth; even worse, the firm's liquidity may become damaged. Hence, whenever credit tightening after a downgrade occurs exactly when financing is needed, the financial position of a company that is already performing poorly most probably will deteriorate.

Indirect costs

In addition to the previous effects, relevant indirect costs from lower ratings may emerge as well. As advocated in Kisgen (2006), these include poorer terms with suppliers, negative influences on employees and customer relationships that may result in lost sales and profits.

Perhaps the best example of the outlined negative effects of downgrades is the case of rating triggers, where such effects enhance to a maximum. Rating triggers restrict the availability of credit to the issuer, because downgrades beyond a certain level specified in the contract gives lenders the right to terminate the credit availability, accelerate credit obligations, or apply other comparable restrictions. Manso (2013) argues that unnecessary financial distress emerges under the feedback effects of ratings based on stress-case scenarios, in which rating triggers are set off. Stumpp (2001) explicitly evokes of the risks raised by such instruments, illustrating with the accelerated debt payments and the repurchase of bonds that Enron had to fulfill as a result of rating triggers included in its trading contracts. Ultimately, according to Jorion et al. (2009), rating triggers "contributed to the fast demise of the company". Another example mentioned in Jorion et al. (2009) is the default of General American Life Insurance, in 1999. In this case, a liquidity crisis emerged following the downgrade of the firm's ratings and the subsequent exercise of a 7-day put option attached to the firm's short-term debt. Thus, although conceived to protect investors, rating triggers may cause a circularity problem which trigger backfire on all investors.

Altogether, the effects of ratings lead us to hypothesize that a moderate decline in the rating level could unintentionally turn into a liquidity crisis, artificially increasing the unavoidability of default. As Bannier and Tyrell (2006) put it, because creditors may decide to divest in the borrower firm when credit is critical to her, especially when fears emerge that other investors are adopting similar policies, an "extensive premature withdrawal of credit may force the firm into default". Such reaction generates what Bannier and Tyrell call self-fulfilling beliefs.

2.2.2 Naïve approach to the relation between the probability of default and ratings

To investigate the potential impacts that rating announcements may wield on default, we include rating information in a credit default model after controlling for the firm's intrinsic characteristics. Given the aforementioned potential effects of downgrades, we restrict the analysis to such type of rating announcements. If downgrades are statistically relevant, we should not rule out the possibility of causal effects on defaults. Nevertheless, we ought not to forget as well that ratings may contain meaningful information not included in statistically-based credit default models. Indeed, regardless of the accuracy of such models, this analysis does not fully ensure the removal of the risk of endogeneity between ratings and default; to a certain extent, it is a naïve approach. Still, if we manage to achieve a highly accurate model, the analysis is essential to restrict our research hypotheses, and simultaneously complement the specific causality approaches which we handle subsequently.

2.2.2.1 Statistically-based credit default models

Previous investigation provides insights on accurate modelling approaches and covariates of credit default. For example, using key financial variables, Altman (1968) pioneers a multiple discriminant analysis to predict a firm's failure, and later Ohlson (1980) extends the approach to a logit model; such model avoids the problems in the multiple discriminant analysis.[13] Relying on hazard models instead of the static models applied until then, Shumway (2001) applies dynamic forecasting models to add time-varying covariates to the analysis.

[13] Previously identified problems involve the requirement of predictors normally distributed, as well as similar group sizes of failed and non-failed firms. Another advantage of a logistic function over a linear function for modelling probabilities is that it avoids predicted values outside the interval [0, 1].

Contrary to a static model, the Shumway hazard model's approach allows a firm's risk of distress to change through time; each firm contributes with different periods of information, as long as it did not default before. Additionally, the model introduces a few market-based measures, such as the idiosyncratic standard deviation of a firm's stock returns. As Chava and Jarrow (2004) demonstrate later, the predictive power of a hazard rate model of bankruptcy prediction improves considerably when it includes market variables.

Hillegeist et al. (2004) extend the analysis by explicitly drawing the attention to the advantages of modelling the probability of bankruptcy with a structural model, namely the Black-Scholes-Merton (BSM) option pricing framework.[14] A major advantage of the BSM framework is that it incorporates market-based measures, one of them being precisely asset volatility, as it describes the probability of the value of the firm's assets falling to a level where liabilities cannot be paid. The Merton distance to default is a special application of structural models. Testing the accuracy of such measure, Bharath and Shumway (2008) find, however, that its forecasting power diminishes when accountancy and market-based explanatory variables are accounted for. Campbell et al. (2008) also draw attention to the predictive power of market-based measures. This is greater in longer forecast horizons and when compared to the predictive power of similar book values; an example is the ratio of total liabilities over the market value of assets.

Other literature examines as well the predictive power of distinct explanatory variables on credit default models. Hilscher and Wilson (2011) use a logit model to estimate the probability of failure, and the explanatory variables selected are the firm's profitability, leverage, past returns and volatility of returns, cash returns, market-to-book ratio, stock price, and size. Löffler and Maurer (2011) investigate the influence of leverage dynamics on credit default. To this end, they use a set of accounting and market covariates (leverage, profitability, coverage, past stock returns, stock return volatility, firm size and a proxy for investment opportunities), to which they add the forecasted future leverage ratio. Finally,

[14] The BSM framework (Black and Scholes, 1973; Merton, 1974) takes into account that equity holders are the residual claimants on the firm's assets, so default occurs at time period T if at that moment the face value of maturing liabilities (B) exceeds the market value of assets (V). The probability of default in t ($t < T$) is given by

$$\mathrm{P}_t = \mathrm{Prob}(V_T \leq B_T)$$

which, based on the BSM properties, results from a standard normal distribution

$$\mathrm{P}_t = \mathrm{N}\left(-\frac{\ln\left(\frac{V_t}{B}\right) + \left(\mu - \delta - \frac{1}{2}\sigma_V^2\right)\,(T-t)}{\sigma_V\sqrt{T-t}}\right)$$

μ, δ and σ_V respectively stand for the continuously compounded expected return on assets, the continuous dividend rate expressed in terms of V, and the standard deviation of asset returns.

using a time varying framework, Giesecke et al. (2011) underscore the relation between corporate defaults and macroeconomic situation. Such perspective derives from the perception that, under economically-stressed scenarios, credit default may become unavoidable to the more financially fragile firms.

The previous references generally substantiate that a firm's probability of default should prominently reflect the firm's financial performance and its intrinsic characteristics, namely accounting-based measures and some firm's market related information. Altogether, the related variables allow us to determine what we call a normal probability of default. The probability is abnormal whenever any exogenous factor causes atypical disturbances to the firm's financial performance, therefore becoming a significant predictor of default. This is the case of macroeconomic variables and it may be the case of rating announcements.

2.2.2.2 Rating downgrades and credit default

Among the previous references, we follow in particular Shumway (2001) and Campbell et al. (2008) to derive a first dynamic panel model and covariates that optimize statistical results for default prediction. Next, in a broader approach, we extend the covariates of our credit default forecasting model to rating variables. Such variables are the occurrence of a rating announcement of type D (Type-D announcements) and the magnitude of the respective rating change; Type-D announcements are defined as

$$\begin{cases} R_{d_i-1} & < K \\ R_{d_i} & \geq K \end{cases}$$

R_{d_i-1} and R_{d_i} stand for subsequent rating levels of firm i, respectively observed at day-firm $d_i - 1$ and day-firm d_i, whereas K ($K > 0$) is a rating threshold; both R_{d_i-1} and R_{d_i} derive from a conversion of ratings into scores, as defined later in Table 2.5. Given that such conversion implies that higher scores denote lower ratings, the type of announcements under consideration is a downgrade.[15] The higher is K, the deeper will be the downgrade. For example, when $K = 11$, Type-D announcements denote a rating change from investment grade to speculative grade (henceforth, IGSG announcements).

[15] Conversely, upgrades imply that

$$\begin{cases} R_{d_i-1} & > K \\ R_{d_i} & \leq K \end{cases}$$

We use separate regressions to estimate the marginal effects of announcements and of the magnitude of change in ratings. The motivation for the second regression stems from Manso (2013), who shows that defaults may occur even in a highly rated firm, if it faces a "credit-cliff dynamic" associated to multi-notch downgrades (Manso, 2013).

To estimate the marginal influence of rating announcements, we adopt the following dynamic logit model

$$\mathrm{P}(D_{i,t} = 1) = \frac{1}{1 + \exp[-(Z_{i,t-1}B + \delta \cdot \Omega_{i,t} + \varepsilon_{i,t})]} \qquad (2.1)$$

$D_{i,t} = 1$ if firm i defaulted in year t ($D_{i,t} = 0$, otherwise), $Z_{i,t-1}$ is a vector of market and financial covariates describing firm i in year $t-1$, and Ω represents a binary that indicates when a Type-D announcement occurs ($\Omega = 1$, if observed; $\Omega = 0$, otherwise).[16] B is a vector of parameters, δ is a scalar, and ε is the vector of regression errors.

We estimate the influence related to the magnitude of changes in ratings using

$$\mathrm{P}(D_{i,t} = 1) = \frac{1}{1 + \exp[-(Z_{i,t-1}B^* + \alpha \cdot \Delta_{i,t} + \varepsilon^*_{i,t})]} \qquad (2.2)$$

Δ ($\Delta \in \mathbb{R}$) is a variable denoting the magnitude of the rating change, defined below in equation (2.3), α is the respective coefficient, B^* is a vector of parameters, ε^* is the new vector of regression errors and Z is similar as before. If δ and α are statistically significant and positive, rating downgrades interact with credit default; eventually, such interaction may reflect causality.

Assumptions

To specify the computation of Ω and Δ in the previous equations, we make two assumptions about the potential financial effects of rating announcements: the effects may extend beyond the year of announcement; the effects develop non-linearly with the rating level. The first assumption stems from the long term approach of credit ratings, which according to Langohr and Langohr (2008, p. 80) focuses on a company's almost long-lasting risk profile. Blume et al. (1998) inclusively model credit ratings as a result of the 3-year averages of some financial variables, in consistency with such long-term perspective of

[16] We consider rating variables as a long-term perspective of credit risk (specifically, 3 years) ending in t. This explains why they are reported as contemporaneous, whereas Z is lagged, reflecting last year's financial and market information. In the case of defaults, ratings are restricted to dates prior to the date of default.

ratings. Therefore, considering the announcements disclosed by each agency, we set $\Omega_{i,t} = 1$ when firm i has at least one Type-D announcement in the 3 years prior to t.

The second assumption is not so trivial as in the case of Ω. On a simple approach, we could measure the change in ratings with the difference between the scores associated to the current and the prior rating. However, due to the nonlinear relation between risks denoted by distinct rating levels, a linear difference between them does not reflect how their change impacts the firm, let alone reflect such rating levels. In addition, we observe that rating levels have a nonlinear relation with the cost of debt. This can be confirmed from Figure 2.1, built with data extracted from Reuters (S&P data) and from the Standard & Poor's investment grade and speculative grade composite spreads reported in three different periods.

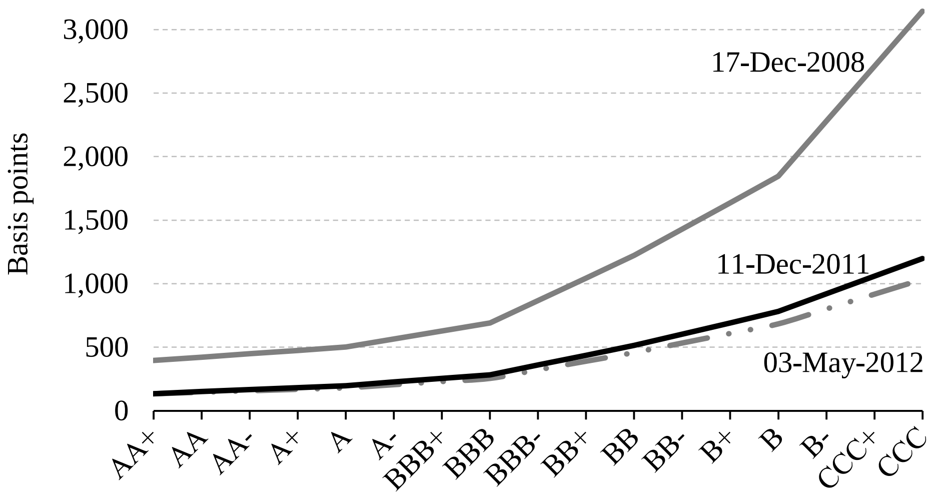

Figure 2.1: Credit ratings and credit spreads

The figure shows that, regardless the stance of economic and credit cycles, lower ratings lead to exponentially greater spreads over the risk free rate. For example, we see that in a relatively stable macroeconomic framework the credit spread for a rating B+ (score equal to 14) is somewhere around 600 basis points. This is almost twice as much as the spread for the lowest investment grade rating level, BBB-, a value unaffordable for most levered firms. To incorporate such evidence in Δ we use an exponential conversion of rating levels, which allows us to distinguish the change in ratings based on the prior and final rating. Hence, Δ is defined as a conversion mimicking the nonlinear evolution of the credit spread along different rating levels

$$\Delta_{i,t} = \underset{\substack{d_i \in t \\ R_{d_i-1} < K \\ R_{d_i} \geq K}}{\text{Max}} \left[\exp\left(\gamma \cdot R_{d_i}\right) - \exp\left(\gamma \cdot R_{d_i-1}\right)\right] \tag{2.3}$$

R_{d_i} and R_{d_i-1} imply, as before, Type-D announcements. γ is a parameter defined such that Δ fairly reflects the link between ratings and spreads. In view of the series in Figure 2.1, we regress exponentially the spread on the rating level, and estimate with an R^2 around 99% that γ is around 0.14. Finally, considering that more than one Type-D announcement may take place per year, Δ is defined as the yearly maximum difference attached to that event in the 3 years prior to t. Also note that rating downgrades occur whenever Δ assumes positive values. For example, let two IGSG ratings announcements be assigned in year t by distinct agencies to firm i; one goes from level BBB (score equal to 9) to level BB+ (score equal to 11) and the other from level BBB- (score equal to 10) to level BB+. In this case, equation (2.3) generates

$$\Delta_{i,t} = \text{Max}\,[(e^{0.14\times 11} - e^{0.14\times 9}); (e^{0.14\times 11} - e^{0.14\times 10})] \cong 1.14$$

Having in mind the formerly defined features of rating variables, for every Type-D announcement we may estimate credit default prediction models as in equations (2.1) and (2.2).

Type-D announcements

To evaluate the influences on default from downgrades with distinct levels of severity and so accommodate the intuition conveyed by Figure 2.1, we consider two kinds of Type-D announcements. The first, occurring when $K = 11$ and denoted by IGSG, is the threshold between investment grade (equal to or higher than BBB-) and speculative grade obligations (equal to or lower than BB+). This threshold is a real landmark for many investors, as a downgrade of their assets to a speculative grade level, calls for an immediate liquidation of those assets. Obligations previously rated as investment grade, when changing to speculative grade, may see their value fall and their yield climb, implying deterioration in the issuers' financing conditions. The resulting significant increase in the firm's cost of capital originates what Jorion and Zhang (2007) among others call the "investment grade effect". Gonzalez et al. (2004) classify the previous threshold as "one of the main thresholds in the world of asset management". Concerning the risk of default, Fulop (2006) analyzes the dynamics of equity prices and concludes that downgrades crossing that threshold seem to generate non-negligible financial distress costs. Note that such threshold is still far from the rating level for an event of default, equal to 22 (see Table 2.5), thus potentially favoring the disentanglement of the aforementioned potential causal effects of ratings relatively to their prediction accuracy.

The second Type-D announcement refers to deeper downgrades, namely those taking place within already speculative rating grades. Specifically, we select $K = 14$ (henceforth denoted as SGSG14), which matches a rating level of B+ (B1 in Moody's notation), precisely where highly speculative rating levels begin. Besides still being far from the level of default, $K = 14$ helps to distinguish between situations where credit default is inevitable, and other situations in which default would be avoided had the rating not been downgraded. We derive this threshold using the cumulative distribution of ratings relative to the subsamples of defaults and non-defaults, each one containing the average rating for each firm-year in the prior 3-year period. Figure 2.2 displays the distributions in these subsamples; values in the Y-axis denote the percentage of firms in the subsample with an equal or higher rating score, i.e. an equal or lower rating.

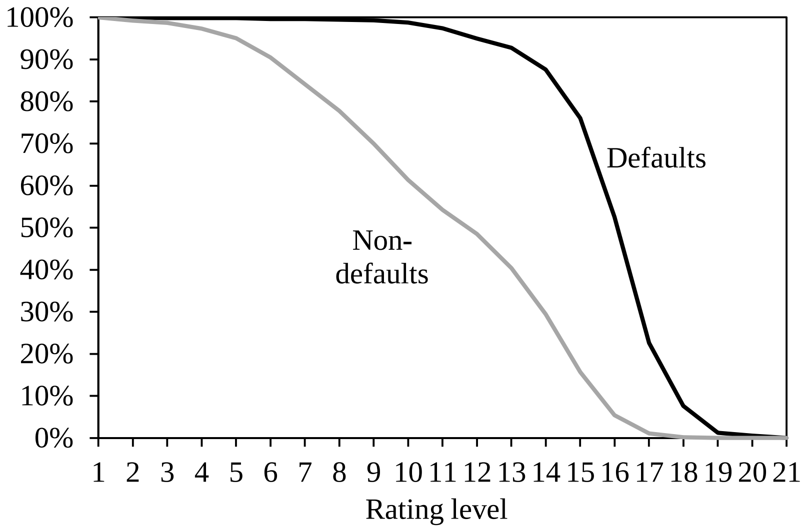

Figure 2.2: Distribution of credit ratings

The difference between the distributions of both subsamples seems pretty evident: defaulted firms reveal a distribution of ratings clearly more biased towards lower ratings (higher rating score) comparatively to non-defaults. Of particular interest is rating level 14, which is the level that best discriminates both distributions, where the Kolmogorov-Smirnov statistic lies. At that level, 88% of defaulted firms have an equal or lower rating (higher score) in the 3 years prior to default, while only 29% of non-defaults are in the same situation.

2.2.2.3 *Influences of IGSG announcements*

In order to select the eligible firm's intrinsic variables that optimize results, we use a manual forward stepwise selection of variables and apply a first regression using only market and financial variables, as presented later. Among other factors, the selection of variables takes into account the economic meaning of estimates obtained for the parameters, as well as the variance inflation factors of covariates, so that potential adverse multicolinearity effects are mitigated. All covariates with high variance inflation factors or whose sign of the related parameter is clearly opposite to what is expected are excluded. Table 2.2 presents the regression results.

As shown by the rather low *p*-values, all exogenous variables are statistically significant and signs of regression coefficients are in line with expectations.[17] We confirm that leverage (*TDLM* and *LTAT*) and in particular volatility (*Sigma*) drive up credit default. Conversely, profitability (*NIATM*), the representativeness of cash available immediately to business (*CHATM*), and market valuation of the firm (*MB*) exert a negative influence on default. Thus, in line with expectations, the probability of default is lower when profitability is greater.

Table 2.2: Credit default prediction

This table reports the estimates of a logistic regression of credit default on the firms' financial and market prior information. The covariates are the natural logarithm of total assets (Size), Total Debt divided by Market Value of Assets (*TDLM*), the firm's standard deviation of the respective daily stock's return (*Sigma*), Net Income divided by Market Value of Assets (*NIATM*), Total Liabilities divided by Total Assets (*LTAT*), cash available immediately to the business (*CHATM*), and market valuation of the firm (*MB*). Heteroskedasticity-consistent standard errors are obtained using Hubber-White estimators.

	Estimates	Robust S.E.	*z*-value	*p*-value
Intercept	-12.3430	0.2355	-52.41	0.000
Size	0.5394	0.0200	26.97	0.000
TDLM	1.7767	0.2373	7.49	0.000
Sigma	46.0312	1.7425	26.42	0.000
NIATM	-5.1717	0.2716	-19.04	0.000
LTAT	3.4114	0.1549	22.02	0.000
CHATM	-1.9941	0.4121	-4.84	0.000
MB	-0.3603	0.0520	-6.93	0.000
Pseudo-R^2	0.4330			
Wald χ^2	4,019.4 (*p*-value = 0.000)			
Observations	109,767			

[17] Note that a positive coefficient in a logistic regression implies that the related variable has a marginal positive influence on the probability being estimated.

The influence of *Size* is not so intuitive. *A priori*, one might be tempted to assume that larger firms are less prone to default, at least due to their greater bargaining power with creditors and investors. Findings in Ohlson (1980), among others, contribute to this expectation. Although we detect a positive effect of *Size* on credit default, other literature also reports similar findings. For example, Campbell et al. (2008) use a measure of size to predict corporate failure and observe the respective coefficient switches signs, becoming positively related with the probability of default, when they adopt a specification with ratios measuring market value of assets, instead of accounting data. We obtain comparable evidence. Another reference is Maffett et al. (2013), who estimate a logit default prediction model by-country and show that the coefficient of size is positive in several countries. Given that we exclude small firms from our sample, it seems therefore that, among relatively large firms, some risks may be triggered by larger size.

Interestingly, most of the variables selected are common to Campbell et al. (2008). Indeed, *Size*, *Sigma*, *NIATM*, *CHATM* and *MB* are mutual to both studies. Though, when looking to the highest value reported in Campbell et al. (2008) for the McFadden's Pseudo-R^2, equal to 31.2%, we observe that the model's overall accuracy reported in the current paper performs better. One conceivable explanation for this difference lies in the fact that, while sources of information are generally the same, the time frame for each study is different. Despite the fact that Campbell et al. (2008) cover a marginally longer period of time than the one we select, our study comprises a more recent period and the time span is reasonably long too. Actually, the results reported here reflect information of defaults observed in the aftermath of the crisis of 2007-2008, not included in their research. Another explanation is that they forecast monthly defaults by analyzing quarterly financial data and monthly and daily market data, while we work with yearly data. We expect that by considering a longer estimation performance period, where structural relations between variables are reinforced, we are able to reduce the forecasting error and as a result obtain more stable forecasts. Complementary, the high level of accuracy revealed by the Pseudo-R^2 reported in Table 2.2 is confirmed by an AUROC of 93.82%.[18] In fact, this is by all standards a very high value.[19]

[18] The Receiver Operating Characteristic is a curve that plots for different thresholds the true positive rate of a specific forecasting tool as a function of the respective false positive rate. The area under that curve (AUROC) is an indicator of particular interest for evaluating the tool's overall accuracy: the higher the AUROC, the more accurate will be the tool. Consequently, the higher will be its power to discriminate binary events.

[19] The value we obtain exceeds by far other models of credit default prediction. For example, Hu and Ansell (2007) compare the relative performance of distinct forecasting models, including the logistic regression, and obtain, at best, an AUROC of 88.6%. However, they use fewer observations in their analysis (246 companies).

Extending the credit default prediction model by including rating variables, namely IGSG announcements, we obtain estimates for the coefficients in equations (2.1) and (2.2), reported in Table 2.3. As seen from estimates relative to the coefficients associated with Ω and Δ, both rating variables are statistically significant. We may conclude, therefore, that IGSG announcements and the respective magnitude of change in ratings have a non-negligible relation with the rated firm's future rate of default.

Table 2.3: Credit default prediction with IGSG announcements

This table contains estimates for equations (2.1) and (2.2). Values reported derive from logistic regressions of credit default on the firms' financial and market prior information, as well as its rating information. In equation (2.1) such information is given by a dummy denoting IGSG announcements (Ω), whereas in equation (2.2) it is given by a continuous variable denoting the magnitude of rating changes in these announcements (Δ). Both rating variables relate to the 3 years prior to t. z-values correspond to heteroskedasticity-consistent standard errors obtained using Hubber-White estimators.

	Equation (2.1)			Equation (2.2)		
	Estimates	*z*-value	*p*-value	Estimates	*z*-value	*p*-value
Intercept	-12.3034	-52.18	0.000	-12.2911	-52.20	0.000
Size	0.5278	26.07	0.000	0.5261	26.24	0.000
TDLM	1.7788	7.48	0.000	1.7801	7.48	0.000
Sigma	46.1423	26.47	0.000	46.1367	26.40	0.000
NIATM	-5.1403	-18.91	0.000	-5.1432	-18.93	0.000
LTAT	3.4073	22.04	0.000	3.3989	21.99	0.000
CHATM	-1.9842	-4.82	0.000	-1.9913	-4.83	0.000
MB	-0.3580	-6.95	0.000	-0.3570	-6.95	0.000
Ω	0.4875	3.01	0.003			
Δ				0.2652	4.92	0.000
Pseudo-R^2	0.4335			0.4344		
Wald χ^2	4,078.60 (*p*-value = 0.000)			4,068.12 (*p*-value = 0.000)		
Observations	109,767					

Although this is not yet conclusive evidence regarding causality effects of ratings on credit default, it is nonetheless a first suggestion that such causality may exist. For example, when computing the average value of the 1-year probability of default for the subsample of firms with an IGSG announcement, we find a difference of 3.59% relatively to the probability of default in the subsample of firms without such announcements. *Ceteris paribus*, this means that out of 28 firms with IGSG announcements one defaults. The evaluation of the estimate of Δ leads to quite similar results.

2.2.2.4 *Influences of deeper downgrades*

Adapting Ω and Δ to SGSG14 announcements, we evaluate the effects of harsher downgrades by re-estimating equations (2.1) and (2.2). Table 2.4 reports the respective values. Once more, the estimates are statistically significant and consistent with economic intuition. Moreover, comparing to the results reported in Table 2.3, we detect improvements in terms of the significance of estimated parameters of Ω and Δ, as well as the global statistical adherence. Further to a high Pseudo-R^2, Table 2.4 also exhibits remarkable AUROCs, respectively 0.9451 and 0.9436, confirming a significant influence of SGSG14 announcements in future credit defaults.

Table 2.4: Credit default prediction with SGSG14 announcements

This table shows estimates for equations (2.1) and (2.2) with SGSG14 announcements. Values reported derive from logistic regressions of credit default on the firms' financial and market prior information, as well as its rating information. In equation (2.1) such information is given by a dummy denoting SGSG14 announcements (Ω), whereas in equation (2.2) it is given by a continuous variable denoting the magnitude of rating changes in these announcements (Δ). Both rating variables relate to the 3 years prior to t. z-values correspond to heteroskedasticity-consistent standard errors obtained using Hubber-White estimators.

	Equation (2.1)			Equation (2.2)		
	Estimates	*z*-value	*p*-value	Estimates	*z*-value	*p*-value
Intercept	-11.7043	-48.71	0.000	-11.8904	-49.98	0.000
Size	0.4297	20.25	0.000	0.4649	22.64	0.000
TDLM	1.3151	5.50	0.000	1.4855	6.23	0.000
Sigma	46.3960	25.69	0.000	46.0403	25.72	0.000
NIATM	-5.0045	-17.97	0.000	-5.0627	-18.36	0.000
LTAT	3.2453	20.81	0.000	3.3119	21.48	0.000
CHATM	-2.2545	-5.20	0.000	-2.1092	-5.00	0.000
MB	-0.3589	-7.12	0.000	-0.3599	-7.13	0.000
Ω	1.8674	19.98	0.000			
Δ				0.4881	14.92	0.000
Pseudo-R^2	0.4581			0.4500		
Wald χ^2	4,052.33 (*p*-value = 0.000)			4,074.99 (*p*-value = 0.000)		
Observations	109,767					

When compared with the results in Table 2.3, estimates in Table 2.4 also display much greater influences from rating variables (Ω and Δ). However, influences of the remaining variables do not change considerably. Likewise, computing the difference in the 1-year probability of default between cases with SGSG14 announcements and those without it, we detect a much higher value than what we get for IGSG announcements. When SGSG14 announcements take place, that difference is 16.59%; this is far above the circa 3% reported before, relative to IGSG announcements. An interpretation for this difference is that, by transmitting worse news, deeper downgrades exacerbate the likely effects on credit default. Note that SGSG14 announcements take place whenever the prior rating level is already a speculative grade. Thus, if SGSG14 announcements determine the probability of default, a prior speculative rating level also contributes to such probability.

2.2.3 Research hypotheses

The results in Tables 2.3 and 2.4 suggest that downgrades to speculative levels relate to an abnormal increase in the rated firm's probability of default. We consider as normal a firm's probability of default that reflects exclusively the intrinsic economic context of that firm, such as its financial performance and demographic characteristics. Abnormal reactions arise in that probability whenever exogenous factors, such as external opinions transmitted by research analysts in general and rating announcements in particular, are significant to the firm's probability of default. For example, Campbell et al. (2008) find that stocks with low analyst coverage reveal stronger financial distress anomaly; however, they do not inform about the effects when analysts deliver negative perspectives. Given the influence of ratings on the firm's credibility, we expect that they generate similar effects as those illustrated by Merton (1968, p. 366) in the bank's parable. Hence, we define the following hypothesis.

H1: *An IGSG announcement generates an overreaction in the firm's probability of default*.

The implications of this hypothesis may be extended. If an IGSG announcement provokes an abnormal increase in the probability of default, it is highly likely that worse announcements also affect that probability. Considering the results in Table 2.4 and in view of higher debt burden due to worse ratings, we postulate that lower rating levels both prior to and after the announcement will exacerbate the probability of default. This hypothesis is consistent with Jorion and Zhang (2007), who find that lower rated firms reveal higher negative reactions to downgrades, namely in their stock prices. Therefore, we define the next hypothesis.

H2: *Deeper downgrades, given by SGSG14 announcements, cause greater effects on the firm's probability of default.*

In order to evaluate whether we should accept any of these hypotheses, our study adopts two well-known causality approaches for the empirical analysis: the propensity score matching approach and the Heckman treatment effects model. The results follow in Section 2.4.

2.3 Data

The empirical investigation in this study derives from a sample of rated and non-rated U.S. firms. With the objective to get a relevant set of comparable firms, we delimit the universe of analysis to public non-financial and non-public administration firms (all SIC codes not comprised between 6000-6999 and not over 9000), the vast majority currently listed or having been listed in NYSE, AMEX or NASDAQ. The time frame considered spans from 1990 to 2012, a length similar to other studies on financial distress; for example, both Altman (1968) and Hillegeist et al. (2004) analyse 20 years. Retrieving data from different sources, we build subsamples for ratings, for several measures of financial and economic performance, and for credit defaults.

Concerning sources of credit ratings information, the paper uses data from Bloomberg's report on Fitch, Moody's and S&P credit ratings (RATC: Company Credit Rating Changes), as well as from the databases of S&P and Moody's. Rating types selected are those that focus on long term obligations, namely: Moody's Issuer Rating; S&P's Issuer Credit Rating and Long Term Local Issuer Credit; Fitch's Long Term Issuer Default Rating and Long Term Local Currency Issuer Default.

The CRSP and COMPUSTAT databases are the sources of information respectively for the firms' market information and the firms' financials, relative to the period from 1990 to 2011. As in Dichev and Piotroski (2001), we exclude cases not covered by COMPUSTAT, considered as small and marginal firms. In order to avoid disturbances from outliers, all financial and market variables are winsorized to the 5^{th} and 95^{th} percentiles of their distributions. Relatively to cases with missing values for any financial variable, we set the omitted value to the respective subsample (default vs. non-default) average for that variable.

Information on corporate defaults from 1991 to 2012 comes from Bloomberg's report on corporate actions (CACT: Capital Change; Bankruptcy Filing), CRSP's delisting code 574, COMPUSTAT's inactivation code 02, UCLA - LoPucki Bankruptcy Research Database, from S&P's database and from Moody's Default and Recovery Database. Credit ratings are another source of information on defaults.

As detailed below, we get a database of 109,767 firm-years, with a default rate of 1.29% and with 31,072 ratings.

2.3.1 Ratings

Among the particulars regarding quantitative analyses of credit ratings, we generally find the need to convert an ordinal and qualitative scale into a numeric scale. This study draws from previous literature (e.g., Jorion and Zhang, 2007; Güttler and Wahrenburg, 2007), and from the numeric correspondence generally accepted by regulators for the different long-term obligations rating scales to define a conversion of rating levels into scores. Table 2.5 exhibits this conversion, with the majority of the reference definitions based on the terminology used by Fitch (2011) and, where applicable, by Moody's (2012) and S&P.[20] The numerical or sign modifier attached to some ratings adds granularity to the scales, further discriminating the risk level inside each rating's main category.

According to Table 2.5, the higher is the score the greater is the risk. Classes that explicitly refer to a possible event of default are all scored 22. For example, beyond a rating level denoting obligations in default, a score equal to 22 includes both RD (Fitch) and SD (S&P), which stand for restrictive and selective default.[21]

Table 2.5: Rating scales of different agencies

This table shows the correspondence between the rating scales of Moody's, S&P and Fitch. A score for each rating level is added.

<table>
<tr><th>Moody's</th><th>S&P</th><th>Fitch</th><th>Score</th><th>Reference definitions</th></tr>
<tr><td colspan="5">Investment grade</td></tr>
<tr><td>Aaa</td><td colspan="2">AAA</td><td>1</td><td>Highest credit quality</td></tr>
<tr><td>Aa1, Aa2, Aa3</td><td colspan="2">AA+, AA, AA-</td><td>2, 3, 4</td><td>Very high credit quality</td></tr>
<tr><td>A1, A2, A3</td><td colspan="2">A+, A, A-</td><td>5, 6, 7</td><td>High credit quality</td></tr>
<tr><td>Baa1, Baa2, Baa3</td><td colspan="2">BBB+, BBB, BBB-</td><td>8, 9, 10</td><td>Good credit quality</td></tr>
<tr><td colspan="5">Speculative grade</td></tr>
<tr><td>Ba1, Ba2, Ba3</td><td colspan="2">BB+, BB, BB-</td><td>11, 12, 13</td><td>Speculative grade</td></tr>
<tr><td>B1, B2, B3</td><td colspan="2">B+, B, B-</td><td>14, 15, 16</td><td>Highly speculative</td></tr>
<tr><td>Caa1, Caa2, Caa3</td><td colspan="2">CCC+, CCC, CCC-</td><td>17, 18, 19</td><td>Substantial credit risk</td></tr>
<tr><td>-</td><td colspan="2">CC</td><td>20</td><td>Very high levels of credit risk</td></tr>
<tr><td>-</td><td colspan="2">C</td><td>21</td><td>Exceptionally high levels of credit risk</td></tr>
<tr><td>Ca</td><td colspan="2">-</td><td rowspan="3">22</td><td>Obligations likely in, or very near, default</td></tr>
<tr><td>-</td><td>SD</td><td>RD</td><td>Selective / Restrictive default</td></tr>
<tr><td>C</td><td colspan="2">D</td><td>Obligations in default</td></tr>
</table>

[20] http://www.standardandpoors.com/ratings/articles/en/us/?articleType=HTML&assetID=1245335682757 (accessed in August 2012).

[21] Restrictive and selective defaults stand for defaults not generalized to all debt obligations of the rated firm.

If an issuer is rated more than once by the same rating agency on the same month, a typical event whenever distinct long term obligations are rated, we select only the worst rating. By doing so, we aim to incorporate in the analysis the potentially stronger rating effects. Similarly, within the last 30 days, if a rating agency announced more than once the same rating for an issuer, we use that rating only once. Likewise, downgrades to default are also kept out from the ratings subsample, given that, when it occurs, a credit default instantly becomes a fact known by all investors concerned. As these downgrades do not bring new information to the market, they are deemed not relevant as potential causes of default. Note, however, that downgrades to default are sources of information on defaults and will be treated as such in our subsample of defaults. Applying all previous criteria, we select 31,072 relevant announcements for analysis. For each firm-year, the rating information is computed for the previous 3 years, given that ratings aim to reflect long term credit risk, and that we want to gauge their long term effects.

2.3.2 Defaults

A corporate credit default is considered here as an event in which firms are unable to fulfil their debt obligations. In particular, similarly to the specifications adopted by Fitch, Moody's and S&P, this definition includes a bankruptcy event (Chapter 7 and Chapter 11 of the U.S. Federal Bankruptcy Code), a failure to timely pay a debt obligation, or any sort of debt restructuring not foreseen in the initial credit agreement. This implies the exclusion of technical defaults.

Besides the previous data sources of defaults, we use credit ratings as a source of information on defaults. Thus, credit ratings that explicitly state that a default event already occurred, despite their differences in the level of severity, are classified as default and feed the information on corporate defaults. This is the case of rating D or RD published by Fitch, C and Ca published by Moody's, and D or SD published by S&P. As some firms defaulted more than once, we select the first event observed as reference.

We remove from the sample all defaults without any financial information in the three years preceding the default event. The same applies to observations for the years following a default; once a default is observed, all subsequent information is considered as not significant for the purpose of the investigation.

2.3.3 Summary statistics

Following the application of the above selection criteria, we obtain a database with a total of 11,215 firms, 9,799 of which without any default during the period selected and 1,416 with at least one default. Using a dynamic panel modelling approach, as in Shumway (2001) and Campbell et al. (2008), we also classify all firms that defaulted as non-defaults in the years that precede the respective default event. The final sample is thus composed by 109,767 firm-years, and consequently the corresponding default rate for the whole period is 1.29%.[22]

We identify 2,536 firms (12,328 firm-years) with at least one rating during the period of analysis, of which 580 defaulted at least once. This shows a proportionately higher fraction of rated firms in the subsample of defaults. Considering the prior 3-year rating information for each firm-year, the number of ratings expands to 58,564 announcements of which 3,332 belong to the subsample of defaults, and the remaining referring to non-defaulted firms in subsequent years. Table 2.6 summarizes the distribution of the sample of firms, with the number of ratings in terms of firm-years between brackets.

Table 2.6: Distribution of the sample of firm-years and ratings

This table reports the aggregate distribution of the sample of firm-years and ratings (in brackets) used for analysis, according to cases with or without default and cases with or without ratings. The sample analyzed includes observations from 1990 to 2012.

	Defaults	Non-defaults
With rating	580 (3,322)	11,748 (55,242)
Without rating	836	96,603

Table 2.7 shows the yearly distribution of the previous information; the year of analysis for each firm is denoted as the reference year. In the case of defaulted firms, the reference year represents the time when credit default occurs. The information concerning the number of ratings indicates announcements observed in the 3-year period prior to the reference year. As expected, there is a higher prevalence of defaults around major U.S. economic crises, such as the sharp economic slowdown of 2001 and the pronounced recession of 2009. In other words, the overall risk of default is, as expected, significantly influenced by macroeconomic conditions.

[22] Note that, due to the information restriction we apply to firms that defaulted more than once, our estimate of the default rate should be lower than the respective true value.

Table 2.7: Yearly distribution of the sample

This table displays the distribution of data along the sample period. Per reference year, it includes the number of defaulted and non-defaulted firms, the rate of default, the number of rating announcements in the 3-year period prior to the reference year, respectively for defaulted and non-defaulted firms, as well as the 3-year prior IGSG-type of rating announcements.

Reference year	Firms			Number of announcements		IGSG announcements	
	Subsample of defaults	Subsample of non-defaults	Rate of default	Subsample of defaults	Subsample of non-defaults	Total	% of ratings
1991	57	4,693	1.2%	23	713	13	1.7%
1992	53	4,912	1.1%	13	1,221	15	1.2%
1993	63	5,277	1.2%	28	1,608	29	1.8%
1994	37	5,577	0.7%	14	1,596	26	1.6%
1995	49	5,876	0.8%	35	1,861	40	2.1%
1996	39	6,542	0.6%	24	2,053	38	1.8%
1997	42	6,621	0.6%	37	2,247	39	1.7%
1998	77	6,411	1.2%	92	2,674	52	1.9%
1999	100	6,413	1.5%	249	3,407	65	1.7%
2000	131	5,992	2.1%	347	2,862	67	2.0%
2001	195	5,505	3.4%	644	3,658	103	2.3%
2002	124	5,065	2.4%	414	3,414	103	2.6%
2003	71	4,816	1.5%	227	3,655	111	2.8%
2004	35	4,651	0.7%	117	3,389	84	2.4%
2005	29	4,533	0.6%	90	3,324	80	2.3%
2006	32	4,378	0.7%	76	3,422	80	2.3%
2007	31	4,073	0.8%	71	2,826	53	1.8%
2008	68	3,824	1.7%	259	2,703	65	2.2%
2009	125	3,625	3.3%	457	3,025	77	2.1%
2010	31	3,435	0.9%	52	2,872	54	1.8%
2011	21	3,203	0.7%	33	2,602	46	1.7%
2012	6	2,929	0.2%	20	110	1	0.8%

The last two columns of Table 2.7 represent the number of IGSG-type of announcements observed in the 3-year period prior to the year of reference and the respective proportion of number of ratings observed in the same period. As in the case of the rate of default, we find that the percentage of IGSG announcements rises when the state of the economy goes through significant declines. It seems interesting to note as well in Figure 2.3 that, in addition to triggering a higher intensity of rating announcements, economic downturns originate a higher preponderance of ratings observed in the subsample of defaults.

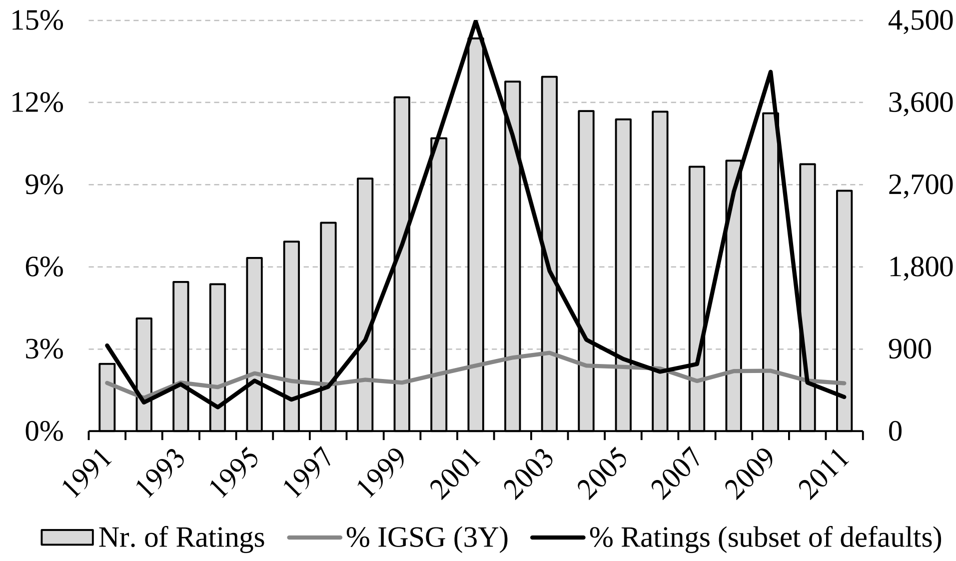

Figure 2.3: Yearly distribution of the prior 3-year announcements

From a univariate analysis perspective, the relation between the rate of default and the previously observed type of rating announcements (Table 2.8) is derived from the 31,072 announcements selected initially.[23] The table tells us that rates of default tend to be higher when ratings announcements are harsher: in general, upgrades are followed by lower rates of default than downgrades, and within the latter the worse rating changes precede the highest rates of default. For example, the rate of default corresponding to an IGSG announcement exceeds an impressive 12% within three years from the date of announcement, specifically when the inherent downgrade is by two or more classes.

In line with the results in Subsection 2.2.2, Table 2.8 also confirms that deeper downgrades precede much stronger rates of default. Although such information could be regarded as an indication of the predictive power of ratings, the fact is that it also does not preclude the possibility of an influence of ratings on the variable they are trying to predict.

Complementary, if we position ourselves in each reference year and look at prior rating information, a substantiation of differences between defaulted and non-defaulted firms emerges, as displayed in Table 2.9. As in Güttler and Wahrenburg (2007), the evidence shows that, the closer is the default event, the worse is correspondingly the firm's average rating. Moreover, when compared to the subsample of non-defaults, defaults constantly reveal lower ratings (higher scores) and a slightly higher number of announcements. In addition, although

[23] By focusing on rating announcements, Table 2.8 provides different information relative to what credit rating agencies typically disclose, namely the relation between the rating level (which may have been announced way before) and the subsequently observed rate of default.

both type of firms denote a continuous downtrend of ratings (i.e. higher consecutive scores) along the last three years, in the case of defaulted firms that trend is much more remarkable.

Table 2.8: Rate of default per type of prior rating announcements

This table shows how the rate of default evolves according to the type of rating announcement, the initial and final rating levels (classified as investment grade, IG, or speculative grade, SG) and the magnitude of the rating change. The 1-year and 3-year time frames following the announcements are selected for analysis. The last column contains the number of ratings per type of announcement.

Type of rating announcement		Rate of default		Total
		… within 1 year	… within 3 years	
Downgrades				
• IG to IG	1 class	0.93%	2.18%	1,926
	> 1 class	1.55%	3.26%	582
• IG to SG	1 class	3.17%	9.80%	347
	> 1 class	6.95%	12.43%	547
• SG to SG	1 class	16.40%	31.44%	3,524
	> 1 class	36.94%	47.57%	2,098
Upgrades				
• IG to IG		0.06%	0.98%	1,641
• SG to IG		0.44%	1.56%	1,604
• SG to SG		2.24%	10.00%	5,391
Unchanged & New ratings		n.a.		13,412

In order to get a better understanding of the financial performance within the two subsamples, we also compute the averages of some financial ratios and variables in the year prior to the reference year in each subsample. The selection of such variables derives from previous literature on financial distress forecasting, in particular Campbell et al. (2008), as well as the accounting-type and market variables already specified in Table 2.1.

Table 2.9: Prior rating information

This table reports the average for selected rating information observed in the 3-year period prior to the reference year, which in the case of defaults corresponds to the year of default. The results of the defaulted firms are compared to those of non-defaulted firms.

	Defaults	Non-defaults
Rating in *t*-1	15.18	10.65
Rating in *t*-2	14.45	10.43
Rating in *t*-3	13.83	10.14
Nr. of ratings in *t*-1	2.44	2.05
Nr. of ratings in *t*-2	2.12	2.07
Nr. of ratings in *t*-3	2.29	2.13

Hence, using annual data and in line with definitions presented in Subsection 2.2.1, we compute the following variables: Interest Coverage (*IC*), Operating Margin (*OM*), Long Term Debt Leverage (*LTDL*), Total Debt Leverage (*TDL*), Total Debt divided by Market Value of Assets (*TDLM*). We analyze as well other variables previously mentioned, namely Operating Income Before Depreciation divided by Total Assets (*OAT*), natural logarithm of Total Assets (*Size*), natural logarithm of Total Debt (*Debt*), firm's stock beta (*Beta*), annual standard deviation of the firm's daily stock return (*Sigma*), and the natural logarithm of the firm's stock price at the close of each year's last trading session (*Price*). Following Campbell et al. (2008), this study also examines Net Income divided by Total Assets (*NIAT*), Net Income divided by the Market Value of Assets (*NIATM*), Total Liabilities divided by Total Assets (*LTAT*), Total Liabilities divided by the Market Value of Assets (*LTATM*), Cash and Short Term Investments divided by the Market Value of Assets (*CHTAM*), and Market to Book Ratio (*MB*).

Table 2.10 summarizes the results obtained. As expected, the table complements the results shown in Table 2.2. On average, defaulted firms reveal high leverage (greater *LTDL*, *TDL*, *TDLM*, *LTAT* and *LTATM*) and poorer profitability (smaller *IC*, *OM*, *OAT*, *NIAT* and *NIATM*). Such firms also signal lower market valuation (smaller *Price* and *MB*), as well as higher risk, as reflected in their stock's return volatility (higher *Sigma*). Comparing the subsamples of rated and non-rated firms, one can see that firms in the first subsample have higher size, debt and systematic risk, as measured by their *Beta*. Besides, rated firms have higher leverage and their profitability is greater too.

Remarkably, weak profitability as an indicator that anticipates credit default has a much more subtle difference in the subsample of ratings when compared to the subsample without ratings. For example, the *IC* of defaulted non-rated firms is considerably lower than the one in defaulted rated firms, the latter being inclusively positive. The higher values of *OM* and *OAT* in the defaulted rated firms, when compared to the non-defaulted non-rated firms, are even more striking. This suggests that less profitable firms are not as much prone to solicit credit ratings, which is in line with findings from Poon and Chan (2010). As for leverage of defaulted firms, ratios for the subsample of ratings always exceed levels of firms without ratings, except in the case of *LTAT*. With a larger debt burden, it seems thus natural that rated firms are more exposed to increases in the firm's cost of funding.

Table 2.10: Financial indicators

This table reports within the different subsamples the average for each financial variable observed in the year prior to the reference year. Variables are selected in line with Table 2.1, as well as additional covariates tested in Campbell et al. (2008) to predict financial distress.

	Defaults		Non-defaults	
	Rated	Non-rated	Rated	Non-rated
IC	0.4850	-4.1486	7.7716	6.4165
OM	-0.0264	-0.3164	0.1550	-0.1583
LTDL	0.5217	0.2344	0.3161	0.1374
TDL	0.6762	0.4618	0.3610	0.2055
TDLM	0.4912	0.3235	0.2370	0.1389
OAT	0.0367	-0.1597	0.1337	0.0131
Size	6.5382	4.4017	7.4642	4.2554
Debt	6.0568	3.3952	6.2947	2.2169
Beta	0.9430	0.7165	0.9969	0.7688
Sigma	0.0653	0.0827	0.0294	0.0446
Price	0.9844	0.1880	2.9944	1.8153
NIAT	-0.1713	-0.4040	0.0237	-0.0887
NIATM	-0.1519	-0.2358	0.0082	-0.0325
LTAT	0.9805	0.9654	0.6608	0.4821
LTATM	0.7551	0.6637	0.4407	0.3169
CHATM	0.0568	0.0670	0.0573	0.1088
MB	1.3187	1.6766	1.7381	2.1926

2.4 Causality analysis

2.4.1 Literature review on causality methods

2.4.1.1 Propensity score matching

We can look at a Type-D announcement as the "treatment" that a number of firms have to tackle, and hypothesize that upcoming events of credit default ($D = 1$) are among the outcomes generated by such treatment. Let $\Omega = 1$ denote a firm with a Type-D announcement, and $\Omega = 0$ otherwise. $\mathrm{E}(D_\Omega)$ denotes the expectation of default in each situation; $\mathrm{E}(D_1)$ is the expected default frequency related to the announcement and $\mathrm{E}(D_0)$ is the expected default frequency related to its absence.

What effectively happened to firms with downgrades is commonly denoted as the factual of downgrades, whereas the correspondent counterfactual specifies what would have happened to the same firms if such downgrades did not occur. We may compare factual and counterfactual outcomes at the population level, by computing the average treatment effect.

Such effect corresponds to the difference in the expected default frequency of firms with a Type-D announcement (treated cases) relative to a scenario where they had not been rated as such (untreated). Formally, as discussed in Imbens (2004), the average treatment effect is given by $\mathrm{E}(D_1 - D_0)$; this measure requires that, for each firm, we were able to observe simultaneously mutually exclusive events. As parallel universes do not exist, we cannot witness a firm at the same time with and without a Type-D announcement. Thus, we compute instead the average treatment effect of the announcement only on the subgroup which had treatment (i.e., the treated cases), as

$$\mathrm{ATT} = \mathrm{E}(D_1 - D_0|\Omega = 1) = \mathrm{E}(D_1|\Omega = 1) - \mathrm{E}(D_0|\Omega = 1) \tag{2.4}$$

ATT is therefore the average effect of a Type-D announcement computed on firms that actually had such announcement. Note that $\mathrm{E}(D_0|\Omega = 1)$ is the counterfactual relative to firms with a Type-D announcement. As this is not an observable variable, it should be estimated by an adequate method, after which we may estimate ATT.

A way to estimate ATT lies in experimental evaluation, based in a random assignment to treatment. However, due to limitations inherent to observational studies, where treatment selection is often determined by subject characteristics, it is not always feasible to use randomness compliant with this method. Therefore, Rosenbaum and Rubin (1983) propose an alternative solution for non-experimental data: the propensity score matching (PSM).

The utilization of PSM techniques abounds in different fields of investigation dealing with causality problems. For example, Dehejia and Wahba (2002) use PSM to investigate the expected effect of a job training program on individuals' earnings. Also based on PSM, Gilligan and Hoddinott (2007) analyse data from Ethiopia to confirm the benefits of an emergency food aid in terms of welfare, access to food, and food security for many households after the peak of the drought in 2002. In the medical literature, Williamson et al. (2011) apply PSM to estimate the effect of maternal choice to give breast milk on the infant's consequent neurodevelopment. Another example of PSM, applied to psychology, is in McCormick et al. (2013), who evaluate the effect of the teacher-child relationship in kindergarten on the children's later academic math and reading achievement. Many more examples could be presented, revealing the widespread acceptance of PSM.

When applied to the problem under analysis, PSM finds firms without a Type-D announcement but with similar characteristics to those with such announcement; this mitigates the previous potential selection bias. Instead of looking at each observable characteristic or covariate separately, which ultimately turns out to be unmanageable, the information for similarity comparison is captured by one single metric: the propensity score.

The propensity score provides therefore the conditional probability of a firm receiving Type-D announcements, given a set of observed covariates X that identify each firm. Formally, this score is defined as

$$\mathrm{P}(X) := \mathrm{P}(\Omega = 1|X) \tag{2.5}$$

According to Rosenbaum and Rubin (1983), treatment assignment is strongly ignorable and identical treated and untreated cases can be unbiasedly matched based on the propensity score alone, if two main assumptions hold. The first is a conditional independence assumption, also called the unconfoundedness assumption. It states that, after controlling for the set of covariates X, treatment assignment Ω (e.g., the announcement) produces similar outcomes as a random process, i.e.

$$(D_1, D_0) \perp \Omega|X \tag{2.6}$$

In our study, this statistical independence implies that a Type-D announcement depends only on the covariates that influence it. The rationale behind this assumption is that, in the presence of enough information on the factors determining the type of rating announcement, we can remove the correlation between (D_1, D_0) and Ω by conditioning on X. As demonstrated in the seminal paper of Rosenbaum and Rubin (1983), the correlation can also be removed by conditioning on $\mathrm{P}(X)$

$$(D_1, D_0) \perp \Omega|\mathrm{P}(X) \tag{2.7}$$

The second assumption is a common support condition that admits a positive probability for both treatment and non-treatment, as represented by

$$0 < \mathrm{P}(\Omega = 1|X) < 1 \tag{2.8}$$

This assumption is essential to ensure that we find matches for $\Omega = 1$ and $\Omega = 0$ in the region of common support, which requires that a balancing property needs to hold; i.e., firms with the same propensity score have similar distributions of covariates, regardless of the announcement status. Firms with and without a Type-D announcement may therefore be matched according to their propensity score. As a consequence, we need to identify cases whose predicted probability of treatment (the announcement) is similar, i.e. $\widehat{\mathrm{P}}(X|\Omega = 1) = \widehat{\mathrm{P}}(X|\Omega = 0)$. This means the matching procedure and the estimates of the propensity score need to balance the distributions of covariates between both groups, rather than being concerned with the most accurate estimate for the true propensity score. Hence, considering (2.8), ATT remains valid only for those firms with announcements which are comparable to other firms without announcements, i.e. where common support remains.

As long as the previous assumptions hold and taking into account (2.7), we may estimate ATT using the unconditional effect over the predicted probability of having a Type-D announcement. The announcement effect for firm i is

$$\begin{aligned}\tau_i &= D_{1,i} - D_{0,i} \\ &= D_{1,i} - \mathrm{E}[D_0 | \Omega = 0, \mathrm{P}(X) = \mathrm{P}(X_i)] \\ &= D_{1,i} - \sum_{j \in \{\Omega = 0\}} \omega(i,j) D_{0,i}\end{aligned} \tag{2.9}$$

where $\omega(i,j)$ is the weight assigned to matched firm j to aggregate outcomes in the control group. $\mathrm{E}[D_0 | \Omega = 0, \mathrm{P}(X) = \mathrm{P}(X_i)]$ is the counterfactual for firm i, which can be estimated as a weighted average of outcomes in the control group ($\Omega = 0$). Aggregating (2.9) for all N_1 firms with the announcement, we obtain an estimator of (2.4) by averaging the effect, as in Heckman et al. (1998)

$$\widehat{\mathrm{ATT}} = \frac{1}{N_1} \sum_{i \in \{\Omega = 1\}} \left[D_{1,i} - \sum_{j \in \{\Omega = 0\}} \omega(i,j) D_{0,i} \right] \tag{2.10}$$

Note that, albeit the balancing property may have been reached, as $\mathrm{P}(X)$ is a continuous variable there is a null probability of obtaining two cases with exactly the same propensity score. To overcome this problem, we need to apply appropriate matching methods and choose accordingly the weights to apply. This study estimates equation (2.10) using the Nearest-Neighbor Matching (NNM), one of the most popular matching methods. For each treated case in the sample, NNM selects the untreated observation with the closest propensity score; this observation is given a weight equal to one, and all others are set to zero. Using this procedure, we estimate the counterfactual treatment outcome.

In order to apply the propensity scoring methodology and to estimate ATT, we follow the process proposed by Abadie et al. (2004). The variables determining credit ratings, as outlined in Subsection 2.2.1, are then selected as potential covariates for the propensity to have a Type-D announcement. Here, we allow for the advantages of including only those variables that determine treatment assignment, as highlighted by Austin et al. (2007).

2.4.1.2 The Heckman treatment effects

Heckman (2008) underlines the potential benefits of "explicitly formulated econometric models" to causal inference, given their virtue in providing insights about the dependencies between the distinct variables involved. In equation (2.1), we use an econometric approach to measure the effects that Type-D announcements might have on credit default, considering as exogenous the treatment dummy variable Ω. Yet, given that such rating announcements may depend on common factors determining credit default, it seems appropriate to take care of an endogeneity issue in Ω.

In order to deal with such issue, and as an alternative to the causality approach in PSM, we now use the evaluation of treatment effectiveness as proposed by Maddala (1983, p. 120); this is an extension to the sample selection model developed by Heckman (1978, 1979). This model, often called as the *Heckman treatment effects approach*, or Heckit model, is useful when we want to control for the conceivable endogeneity of receiving Type-D announcements. An example of the application of the Heckit model to the context of credit ratings is in An and Chan (2008), who investigate the effects of credit ratings on the pricing of initial public offerings. The use of this type of analysis to investigate causality extends similarly to other research areas, with examples found in the research of child welfare (Guo and Fraser, 2009), and of farm productivity (Elias et al., 2013).

Based on the Heckit model, a selection equation embedding a probit model is defined as

$$\Omega_{i,t}^{*} = X_{i,t-1}\mu + u_i \tag{2.11}$$

$$\Omega_{i,t} = \begin{cases} 1 & \text{iff } \Omega_{\mathrm{i,t}}^{*} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Ω^* is a latent endogenous variable related with Ω, the binary variable that indicates treatment (i.e., Type-D announcement), $X_{i,t-1}$ represents, as before, the vector of exogenous variables determining the selection of firm i for treatment, and μ are regression coefficients; u is an error term assumed normal. The selection equation and the probit model interact, as $\mathrm{P}(\Omega_i = 1|X_i) = \Phi(X_i\mu)$, where $\Phi(\cdot)$ is the distribution function of a standard normal random variable.

The outcome equation is

$$\begin{aligned} Y_i &= \mathrm{P}\big(D_{i,t} = 1\big) \\ &= f(Z_{i,t-1}B + \delta \cdot \Omega_{i,t} + \varepsilon_{i,t}) \end{aligned} \tag{2.12}$$

B, $Z_{i,t-1}$, δ and $\varepsilon_{i,t}$ have the same meaning as in equation (2.1). $\varepsilon_{i,t}$ is additionally assumed to be normally distributed, as well as $u \sim \mathrm{N}(0,1)$ and $\varepsilon \sim \mathrm{N}(0, \sigma_\varepsilon^2)$.

Equation (2.12) is expressed by a functional form f which may be nonlinear, as in equation (2.1), or linear. We adopt the response or outcome function in the original framework of the Heckit model, which is linear. Actually, when the outcome is a probability, a nonlinear function (e.g., logit or probit) seems more appropriate, but its use is nontrivial, as discussed in Angrist (2001) and in Freedman and Sekhon (2010). As we are mostly concerned with the variation in the probability of default due to Type-D announcements, instead of the true value of the probability, a linear function may not be inappropriate; the variation in this case is directly provided by δ. Also, when using a linear function, we may interpret the estimate of δ as a valuation of ATT, thus providing a comparison between the outcomes from both models.

Finally, a special concern must be paid to the correlation coefficient between error terms of equations (2.11) and (2.12), denoted by ρ. If ρ is statistically different from zero, u and consequently Ω are correlated with ε; then, the direct estimation of equation (2.12) will generate an endogeneity problem, materialized in biased and inconsistent estimators. The bias may be overthrown estimating Ω simultaneously with the outcome variable Y, using either a maximum likelihood or a two-step consistent estimator.

2.4.2 Results of the propensity score matching approach

In order to predict the occurrence of Type-D announcements, specifically IGSG and SGSG14 announcements, we use indicators of profitability, leverage, size and market. According to the through-the-cycle perspective of ratings, in line with previous research (e.g., Blume et al., 1998), and consistent with the dependent variable (defined as a 3-year event), we compute the 3-year averages of financial and market indicators as potential covariates. As the dependent variable is binary (announcement vs. absence of announcement), we apply a logistic regression instead of ordered logit or ordered probit approaches.[24] Denoting $AvI_{j,i,t-1}$ as the 3-year average of each j covariate ($j = 1, \dots, N$) prior to the reference year, equation (2.13) provides the propensity of a Type-D announcement in firm i and time period t

[24] In spite of probit or logit being the most common econometric techniques used, there are exceptions. For example, Kisgen (2006) uses ordinary least squares to regress credit ratings on a few covariates. However, an overall agreement on the inappropriateness of the least squares method and of methods that ignore the ordinal nature of bond ratings has already been reported in Kamstra et al. (2001).

$$P(\Omega_{i,t} = 1) = \frac{1}{1 + \exp\left[-\left(\alpha + \sum_{j=1}^{N} \beta_j AvI_{j,i,t-1} + V_{i,t}\right)\right]} \quad (2.13)$$

α and β_j are parameters and $V_{i,t}$ is an error term.

Note that all observations, rated and unrated, are inputs to estimate the regression. Therefore, the probability of a Type-D announcement reflects the simultaneous occurrence of two events: the firm is rated and has a Type-D announcement. The first event is actually a requirement for the second, since a firm cannot have a Type-D announcement without being rated. Table 2.11 exhibits the results.

The AUROC in the case of IGSG announcements is 0.9323, higher than the 0.9086 we get in the regression for SGSG14 announcements; this is consistent with the difference in the Pseudo-R^2 for both regressions. In any circumstance, these indicators imply, once again, high accuracy and statistical relevance. The results suggest as well a low multicolinearity level, given all near zero p-values, and in view of signs of parameters generally in line with expectations.

Table 2.11: Prediction of Type-D announcements

This table reports the estimates of two logistic regressions that predict Type-D announcements, respectively IGSG and SGSG14, based on the firms' financial and market prior information. The covariates, denoted with prefix *Av* for each variable, refer to the 3-year average of that variable.

	IGSG announcements			SGSG14 announcements		
	Estimates	z-value	p-value	Estimates	z-value	p-value
Intercept	-11.6276	-43.78	0.000	-8.1028	-56.17	0.000
AvLTDL	1.6197	8.92	0.000	5.4635	42.33	0.000
AvSize	1.1762	37.86	0.000	0.5421	31.46	0.000
AvBeta	0.1586	2.17	0.030	0.4980	8.90	0.000
AvNIATM	-3.5296	-6.55	0.000	-4.6610	-13.56	0.000
AvMB	-0.7892	-13.05	0.000	-0.7088	-16.16	0.000
Pseudo-R^2	0.3024			0.2698		
Likelihood Ratio χ^2	4,110.05 (p-value = 0.000)			5,645.70 (p-value = 0.000)		
Observations	109,767					

We may conclude that IGSG events are more likely in firms with higher long term debt leverage, size and market model beta. Conversely, IGSG events are less probable in firms with higher market value valuation and profitability, here given by net income divided by total assets. Except in the case of size, these results are consistent with the expected influence reported in previous literature, as shown in Table 2.1. In what concerns size, the results suggest a negative influence on ratings, implying a greater likelihood of downgrades of IGSG type in larger firms, which is somewhat contrary to the findings in Kisgen (2006). A conceivable explanation for dissimilarities relative to his results lies in the already mentioned fact that our model predicts the occurrence of two events, namely a firm being rated and the type of rating assigned. Indeed, Table 2.7 confirms the expectation that largest companies are more likely to be rated. Three of the previous types of covariates (size of firms, profitability and market value) are also common to the regression that predicts credit default; we stress, however, that such covariates are measured differently in both regressions. The same happens in relation to leverage: *TDLM* and *LTAT* adjust better to forecast credit default, whereas *AvLTDL* is better to predict IGSG and SGSG14 announcements.

Comparing the estimates in the regressions for both Type-*D* announcements, it is noteworthy to underline that both leverage and market risk have significantly higher marginal effects on SGSG14 announcements, when compared to the results obtained for IGSG announcements; the same applies to the respective *z*-values. Hence, such variables seem to have a higher influence on deeper downgrades.

Based on the previous selection of covariates, we apply the propensity score methodology and estimate the average treatment effect on the treated, ATT. As described in Subsection 2.4.1.1, we select the nearest-neighbor matching method, whence the estimates of ATT, reported in Table 2.12, are obtained. This table also contains the associated standard errors, fundamental to know if the estimated average treatment effect is significantly different from zero; the estimation of standard errors use bootstrapping.[25] The extremely low *p*-values confirm that both announcements are statistically significant and positive. This means that downgrades equal to (or worse than) a change from investment grade to speculative grade have causality effects on the probability of default, confirming hypothesis H1.

[25] This estimation method of standard errors consists in drawing new samples with replacement from the existing sample, from where the model and propensity scores are re-estimated several times; the standard error is derived from the different results obtained.

Table 2.12: ATT estimations when IGSG or SGSG14 announcements are selected as treatment

This table reports estimates of average treatment effect on the treated, when the treatment variable is the occurrence of IGSG or SGSG14 announcements. Selecting as covariates of propensity score the variables in Table 2.11, the estimation of ATT derives from nearest-neighbor matching methods.

	Estimate	Standard Error	*z*-value	*p*-value
ATT (IGSG)	0.0306	0.0072	4.23	0.000
ATT (SGSG14)	0.1213	0.0084	14.51	0.000

We observe that when downgrades are IGSG-type, ATT equals 3.06%. This is the estimated effect in the 1-year probability of default due to a downgrade of IGSG-type. Interestingly, this estimate is quite near the 3.59% shown in Subsection 2.2.2.4, when we estimate a credit default prediction model with IGSG announcements. In contrast, the effect of SGSG14 announcements, equal to 12.13%, is way above the value detected in the case of IGSG, although nonetheless below the 16.59% derived in Subsection 2.2.2.5. The much larger effect in the case of SGSG14 is relevant to corroborate hypothesis H2. Therefore, we show that greater effects on the firm's probability of default emerge as a result of deeper downgrades, given by SGSG14 announcements. As these announcements denote prior ratings which are already speculative grade, the influence of SGSG14 also means that low prior rating levels contribute to the probability of default. In order to confirm the consistency of these results, we now extend the analysis to the Heckman treatment effects approach.

2.4.3 Results of the Heckman treatment effects approach

The estimation of a Heckit model requires that we first define the variables both in the selection equation (2.11) and in the regression equation (2.12). Given the high accuracy revealed by our previous estimations, we use the variables selected for estimating credit default (Table 2.2) and credit announcements (Table 2.11); the maximum likelihood method allows us to estimate regressions parameters. As in the case of the propensity score matching, we estimate effects of both type of announcements, IGSG and SGSG14. However, when estimating the effects of IGSG announcements using the Heckit model, the outcomes show a statistically significant estimate of ρ; in a test of correlation between error terms, we reject the null hypothesis, H_0: $\rho = 0$ (p-value equal to 0.007). This means that this estimation method does not fully remove the threat of endogeneity bias in equation (2.1). Anyhow, the estimate of ρ is actually quite low ($\hat{\rho} = 0.0332$), suggesting therefore that the level of correlation between the two error terms, ε and u, is similarly low. Hence, as this model adds little to findings from previous methodologies, we do not consider the Heckit model's results in the case of IGSG announcements.

Outputs from the Heckit model relative to SGSG14 announcements follow in Table 2.13. With a p-value of 0.765, H_0: $\rho = 0$ is not rejected, implying that the risk of endogeneity bias in equation (2.1) remains remote in this case. Accordingly, the estimate of ρ indicates once more a negligible value ($\hat{\rho} =$ -0.002), supporting the remoteness of such risk.

Table 2.13: Treatment effects model estimates for SGSG14 announcements

This table reports estimates of the Heckman treatment effects model, when SGSG14 announcements are selected as treatment variable. Ω, the endogenous in the selection equation, is simultaneously a covariate in the regression equation that predicts credit default. The related parameter estimate indicates the direction of the effect.

	Estimate	Standard Error	z-value	p-value
Regression equation (Y)				
Constant	-0.0846	0.0019	-44.79	0.000
Size	0.0061	0.0002	32.11	0.000
TDLM	0.0334	0.0029	11.33	0.000
Sigma	0.9232	0.0197	46.93	0.000
NIATM	-0.1186	0.0036	-33.14	0.000
LTAT	0.0365	0.0015	24.26	0.000
CHATM	-0.0085	0.0036	-2.33	0.020
MB	-0.0001	0.0003	-0.26	0.793
Ω	0.1335	0.0028	48.04	0.000
Selection equation (Ω)				
Constant	-4.0181	0.0640	-62.74	0.000
AvLTDL	2.5224	0.0603	41.81	0.000
AvSize	0.2452	0.0079	30.96	0.000
AvBeta	0.2532	0.0264	9.58	0.000
AvNIATM	-2.2951	0.1641	-13.98	0.000
AvMB	-0.2895	0.0187	-15.50	0.000
ρ	-0.0020	0.0066		
σ_ε	0.1063	0.0002		
λ	-0.0002	0.0007		
Wald χ^2	13,010.48 (p-value = 0.000)			
Observations	109,767			
Likelihood Ratio test of independent equations (ρ = 0):	χ^2 (1) = 0.09 (p-value = 0.765)			

In what concerns the direction of influence of each covariate, the signs of parameters are consistent with economic intuition, though *MB* reveals a low z-value. Of particular interest to the analysis in this study, is the estimate of the parameter associated to Ω. As mentioned at the end of Subsection 2.4.1, the regression equation of the outcome variable (in our case, the probability of default Y) in the Heckit model is linear. Hence, δ, the parameter associated to Ω, gives the direct effect of the occurrence of an SGSG14 announcement, which compares to the ATT. The respective estimate is positive and statistically significant at the 5% significance level. The effect is therefore estimated in 13.35%, a value between the estimate derived from the ATT and the direct estimation of credit default, accounting for SGSG14 announcements.

2.4.4 Interpretation and implication

Despite using different methods to estimate the potential effects caused by negative ratings announcements on subsequent credit defaults, we detect relatively similar results when selecting two types of announcements (Table 2.14). All estimates of these potential effects are relevant at the 1% significance level, except in the case of the Heckman treatment effects method applied to IGSG announcements.

Notwithstanding the relative similarity of results, a careful interpretation is recommended. These results suggest that some negative rating announcements cause an increase in the rated firm's default. We interpret this effect as being a reflection of undermined investors' confidence, following the negative news conveyed by ratings. Moreover, the worse is the information in ratings announcements, in particular when deeper downgrades are disclosed, the more affected becomes investors' confidence; therefore, the stronger seems to be the impact on the issuer financial performance and on its risk of default.

Table 2.14: Estimated effects caused by IGSG and SGSG14 announcements on credit default
This table summarizes the results achieved using the methodologies discussed in Sections 2.5 and 2.6.

Estimation method	IGSG effects	SGSG14 effects
Credit default prediction model	3.59%	16.59%
Propensity score matching	3.06%	12.13%
Heckman treatment effects	n.a. *	13.35%

* Non-significant estimate at the 5% significance level.

These results should not however discourage issuers looking to be rated. Indeed, credit ratings remain doubtless a very powerful and essential market instrument for most firms to obtain funding at a relatively low cost. What our findings really seem to imply is that, prior to soliciting ratings, issuers should first evaluate the extent to which they are economically sound enough to avoid future deeper downgrades. The trade-off for some firms is between an immediate potential benefit of lower cost of funding and a probably higher cost of financial distress in the future. On the other hand, in line with Manso (2013), our findings suggest that, when announcing deeper downgrades, rating agencies should be fully aware of the respective potential negative feedback effects.

Finally, these results also bring a powerful insight for credit default prediction models, namely in what concerns the covariates of those models. In fact, due to the causal effects of rating announcements, specifically when they convey negative news, the inclusion of rating information as a covariate of such models is expected to add to the accuracy of prediction already given by the firm's intrinsic details. Löffler and Maurer (2011) reinforce such perspective, by finding that current rating is a significant explanatory variable in their default prediction model.

2.5 Summary and concluding remarks

Credit ratings convey information to the markets. In what concerns a firm's risk of default, this paper confirms that some negative rating announcements are relevant enough to generate additional pressures for a default in the rated firm's obligations. The pervasive effects that such announcements seem to generate reinforce the perception that, to a certain extent, rating agencies are powerful enough to determine the unfolding outcomes of the markets. In the words of Langohr and Langohr (2008, p. 473), they are considered "among the more powerful and less understood financial institutions on the planet".

Benefiting from an extensive database of rating announcements and supported by complementary methodologies for causality analysis, the evidence in this paper suggests that rating downgrades from an investment grade to a speculative grade have a non-trivial effect in the firm's probability of default. The effect seems to be substantially amplified when levels of rating prior and after announcement are lower, namely when we observe downgrades for an already speculative grade level to a level at best highly speculative. Consistent with these findings and corroborating Manso's (2013) framework, the probability of default also seems to worsen with the magnitude of rating downgrade. By confirming effects of rating announcements on a firm's future performance, we also confirm and mainly provide an explanation for the finding in Löffler and Maurer (2011), that ratings provide valuable information for default prediction.

Future related empirical investigation should consider the effects of multiple Type-D announcements, namely when issued by different agencies, and include firms from different geographies in the analysis. Additional conceivable extensions of this line of research remain in the analysis of other rating-related information as covariates of credit default models, as well as in the inclusion of information regarding the state of the business cycle. For example, relative to the latter, we might conjecture that the potential causal effects of negative credit ratings on credit default will be heightened particularly under recession periods, when firms are financially more vulnerable. This is particularly relevant if we consider that reputation cycles in ratings relate, to some degree, with business cycles fluctuations.

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Chapter 3

Assessing the stability of credit ratings

3.1 Introduction

In the last four decades the role of ratings expanded remarkably, after the introduction in 1975 of the Nationally Recognized Statistical Rating Organizations. Under such recognition by the Securities and Exchange Commission, some credit rating agencies have been accepted for indirectly regulating the quality of investments of banks and other financial institutions.

Further to the conservatism (Bannier et al., 2010) and accuracy (Cantor and Mann, 2003) advocated for ratings, relative stability is considered to be a major requirement for this quasi-regulatory role of ratings. As underlined in Altman and Rijken (2006), stability in ratings is valued from a regulatory point of view, as it helps to prevent procyclical effects and lessens to a certain extent the consequences of credit crunches. Likewise, long term investors request a degree of rating stability to have the least possible adjustments in their portfolios, in order to avoid high transaction costs and hurdles to portfolio management. Such costs, Löffler (2005) points out, are likely to be larger for downgrades as a result of forced sale of bonds and the activation of restrictions due to covenants.

It is relatively clear, however, that stability somewhat conflicts with another requirement of ratings: accuracy. Actually, higher accuracy demands faster rating adjustments to prevailing events, which implies lower rating stability. On the other hand, a more stable rating system means a greater difficulty in timely anticipate credit default. Given the conflicts underlying rating stability and rating accurateness, for example Gonzalez et al. (2004) suggest that it would be interesting to investigate whether rating agencies are effectively becoming more concerned with short term accuracy, in detriment of stability.

This paper addresses the extent to which the requirement of relative stability of ratings is fulfilled in the case of the three major agencies, Fitch, Moody's and Standard & Poor's (S&P), contributing to the ongoing debate about the use of ratings for regulatory purposes

(Hanley and Nikolova, 2014). Motivated by the influence of reputation cycles in ratings (Zhou, 2001; Mathis et al., 2009; Rablen, 2013), the effects of increased competition between rating agencies (Manso, 2013), the evidence of drifts in rating changes (Altman and Kao, 1992; Amato and Furfine, 2004; Jorion et al., 2009), and the countercyclical accuracy of ratings (Bar-Isaax and Shapiro, 2013), the paper specifically answers two questions: Is countercyclicality present in the dynamics of rating announcements? How do stability and accuracy of ratings compare to alternative measures of credit risk? To that end, the paper analyses the frequency of corporate rating changes based on a novel indicator of rating dynamics, which aggregates information from the rating transition matrix; statistics on rating reversals and on large rating changes complement findings from this indicator. Having in mind the potential conflicts between stability and accuracy in ratings, we also assess the level of success of the agencies in pursuing simultaneously these goals.

Drawn from an extensive sample of corporate rating announcements covering almost 2,900 U.S. firms and spanning over 20 years, the results confirm that abnormal reactions in rating changes are generally seen after major economic crises and when rates of default peak. For example, a variation of +1% in the global rate of default leads up to one out of ten issuers to see ratings change by one level in a 3-month period. Our findings suggest that S&P's ratings are more susceptible to rising rates of default comparatively to Moody's and Fitch, and that higher rating volatilities come together with lower rating grades. Nevertheless, we detect that ratings from Moody's reveal greater variability of changes. This is consistent with the perception, presented in Güttler and Raupach (2010) and in Güttler and Wahrenburg (2007), that Moody's adjusts its ratings to default risk in a timelier fashion than S&P. The findings reported in the paper also suggest that criticisms to rating agencies following major failures in their predictions do have effects in rating policies. By verifying that rating dynamics are indeed countercyclical and negatively correlated with rating levels, the paper reinforces the perspective of procyclicality in ratings, previously investigated in Ferri et al. (1999), Amato and Furfine (2004), and Parnes (2007).

Stability in ratings should derive from their forward-looking reflection of the fundamental credit risk relative to each issuer. Accordingly, the agencies are supposed to apply a long term through-the-cycle approach, centering on more than one business cycle, instead of reproducing a picture of the issuer´s current situation or its near future.[26] This means that ratings should exhibit independence from business cycles, hence lowering the effects of credit crunches. To some extent, our findings question the perception of ratings providing a view completely through-the-cycle. In this regard, the paper is close to Feng et al. (2008), which analyze data from annual transition matrices reported by S&P. Using a dynamic latent factor model to account for influences of business cycles on rating migrations, they find effects from the business cycle and conclude that ratings are closer to a point-in-time approach.

Despite the evidence reported in the current paper confirming that ratings are susceptible to business cycles changes, we also document that they are indeed more stable, but potentially less accurate (at least in the 1-year horizon) for measuring credit risk, when compared to accounting-based models of default prediction. In that sense, the paper supports conclusions from Hilscher and Wilson (2013), showing that ratings provide only feeble forecasts of corporate failure across firms and across time.

The remaining of the paper is organized as follows. Section 3.2 focuses on credit rating dynamics and trends, highlighting the reputation cycles in ratings, as well as shifts in credit ratings. Section 3.3 deals with the methodology of investigation, and describes the data. Section 3.4 examines the empirical results reached, and analyses their implications. Section 3.5 summarizes and concludes.

3.2 Credit rating dynamics and trends

The potential conflict between stability and accuracy in ratings is ultimately reflected in patterns of rating changes across issuers and across time. Especially in the issuer-paying model of credit ratings, this conflict stimulates reputation concerns in the agencies, considering that their widely acceptance depends on how successfully they manage the conflict. Aware of these concerns, a course of investigation on credit ratings addresses the subject of reputation cycles, and its repercussion on rating dynamics. Other studies specifically analyze rating dynamics and conclude for the existence of momentum and serial correlation in ratings. This section reviews the main findings around these issues.

[26] As claimed by Moody's (Cantor and Mann, 2003), being a measure of "relative fundamental creditworthiness, ratings are expected to change slowly and gradually over time" and reversals are avoided. Similarly, the meaning of ratings "should be highly consistent over time"; modifications are expected only as a result of long-term shifts in "relative fundamental creditworthiness". Moody's commitment with stability is further reinforced by the case of downgrades, where "the potentially self-fulfilling nature of ratings requires that Moody's particularly endeavor to avoid "false" negative predictions" (Fons, 2002).

3.2.1 The conflict between stability and accuracy

Although there is not a specific time horizon in risk assessment from ratings, there is evidence that they are a better reflection of credit risk in the long term. Löffler (2013) confirms that ratings anticipate up to 3 years the evolution in market-based estimates of the 1-year probability of default. Similarly, Altman and Rijken (2004) find that a model of default probability mostly resembles a model of credit ratings when its prediction horizon is 6 years.

According to Langhor and Langhor (2008, p. 80), ratings are expected to rely on the inner characteristics of the firm and reflect an almost permanent risk profile, instead of being determined by short term information about credit quality and the state of the business cycle. Cantor and Mann (2003) refer that Moody's normally undertakes a rating action when it is unlikely to be reversed shortly afterwards. They show that about 25% of issuers experience a rating action along a 12-month period, and only 1% undergoes a rating reversal, promoting a consistent interpretation of each rating level through time.

The natural consequence of relative stability in credit ratings is that they tend to lag market implied ratings. For example, Altman and Rijken (2004) confirm that ratings primarily concentrate on a firm's long term default risk. Still, Altman and Rijken (2006) find as well that such long term perspective comes at the expense of ratings' accuracy for predicting default, at least in the short term. Using risk neutral default probabilities derived from diffusion models, Delianedis and Geske (2003) report downgrades (upgrades) occurring only several months after default probabilities rise (fall). This lag of ratings relative to default risk, probably reflecting significant informational deficit, is explained by Löffler (2005) as a result of the avoidance of rating reversals. Löffler (2013) confirms that ratings underperform relative to alternative measures of default risk, namely Moody's KMV Expected Default Frequency (EDF). Tichy et al. (2011) discuss the case of ratings to governments, describing forecasting errors of ratings as reflecting an "underestimation of changes and incapacity to deal with surprizes".

Most investors see rating agencies as being too slow in adjusting their ratings to changes in corporate creditworthiness. Examples lie in the multiple criticisms following the bankruptcies of major companies (e.g., Enron, Lehman Brothers), demanding higher frequency in ratings announcements.[27] Ultimately, this pressure on the agencies promoted higher volatility in their ratings, such as the quicker downgrades of issuers; it's not strange, thus, that as shown in Ferri

[27] See, for example, The Economist (December 1997; February 2011; August 2011; February 2013).

et al. (1999), Nickell et al. (2000) and Amato and Furfine (2004) rating downgrades predominate in recessions. Cantor and Mann (2003) show evidence of transitory higher volatility, with periods of abnormal volatility in rating actions taking place more frequently around recessions. Moody's admits inclusively the presence of higher historical volatility of rating changes when credit stress is intensified (Fons, 2002), which seems to question the alleged through-the-cycle perspective of ratings.

3.2.2 Reputation cycles in ratings

The use of ratings by regulators and investors clearly depends on the reputation endorsed to rating agencies, perhaps their most valuable asset. As claimed by Mathis et al. (2009), Bolton et al. (2012), Bar-Isaac and Shapiro (2013) and Rablen (2013), it is likely that reputation concerns of rating agencies determine fluctuations in the patterns of rating changes. Covitz and Harrison (2003) take into consideration the potential financial incentives to delay downgrades, and conclude that agencies' concerns about their independence and objectivity dominate the adjustments in their ratings. According to Altman and Rijken (2006), the through-the-cycle perspective of ratings bolsters the avoidance of rating reversals, thus contributing to the reputation of rating agencies.

In view of cyclical modifications throughout time in the importance assigned to reputation concerns, Zhou (2001) describes a reputation cycles perspective in the issuer-paying model of ratings. Under this perspective, diminishing reputational losses favoured by the issuers' shopping around weaken the motivations to deliver accurate credit assessments, explaining the relaxation and inflation in ratings.[28] Periods of tightened rating standards characterized by a drop of default rates per rating level tend to follow long term periods of relaxation in ratings. Bolton et al. (2012) show that more competition among the agencies encourages ratings shopping by issuers, inflates rating levels when reputation risks are lower, and market efficiency is distorted by rating complex products.[29] Considering the evidence of inflation in rating levels developing due to an increase in competition, Becker and Milbourn (2011) detect that lower rated firms shop for a third potentially better rating.

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[28] Promoted by increasing competition between rating agencies, the phenomenon of issuers shopping for the best rating is pointed out by Zhou (2001) as one conceivable explanation for a decline in rating standards, as reflected in a general increase in default rates per rating level not explained by business cycles fluctuations.

[29] Tichy et al. (2011) also highlight the potential conflicts of interest in the issuer paying model, where strictness of criteria in ratings assignment may find obstacles before the agencies' commercial interests.

Mathis et al. (2009) also investigate “confidence cycles” in ratings, which are intensified by rating structured finance products.[30] Here, reputation building starts when agencies apply strictness of criteria in order to increase their reputation; in this situation investors are wary, credit spreads are high and issuing activity is low. Cashing on reputation is the next stage, wherein investors turn out to be more confident and reputation improves, credit spreads fall and issuing activity increases. Stimulated by greater confidence of investors, rating standards are then relaxed and the risk of a credit crunch intensifies. The cycle resumes when a crisis of confidence settles in, with emerging increasing defaults, opportunistic agencies being detected, and their reputation falling dramatically; credit spreads also rise again and the issuance volume decreases.

A similar perspective is presented in Bar-Isaac and Shapiro (2013), who add that ratings accuracy is countercyclical. Less accurate ratings emerge in booms, when issuers are less likely to default, income from rating fees is high, and competition for skilled analysts is hard. When the agency’s reputation costs arise, normally observed when well-rated obligations default, the incentives to provide more accurate ratings expand.

Rablen (2013) also investigates the reputational concerns of rating agencies. He focuses on the divergent rating behaviour between the corporate debt market and the markets of structured products, such as mortgage-backed securities and collateralized debt obligations. The findings are that agencies apply more conservative ratings in the first market, where monitoring is perfect, in order to compensate lax rating standards in the less informative markets of structured products. We might question, therefore, to what extent this compensation effect implies overly conservativeness in corporate ratings, particularly in the presence of economic downturns, and as such determine the level of rating stability.

3.2.3 Changes in rating dynamics

Eventually reflecting the conflicting goals of accuracy and stability, as well as the conservatism of rating agencies, changes in rating dynamics are expressed in well-defined trends in ratings and in rating momentum.[31] Relative to rating trends, early evidence shows

[30] Ashcraft et al. (2010) report evidence of a declining performance of ratings accuracy on opaque mortgage-backed securities between 2005 and mid-2007, while the issuance volume of such products was peaking. Further details of flexible rating standards prior to the outbreak of the 2007 subprime crisis is reported in Griffin and Tang (2012), with 98.6% of the AAA rated collateralized debt obligations failing to meet the agencies’ stated AAA standards.

[31] Regarding conservatism, Gonzalez et al. (2004) underline that rating agencies spend more efforts on detecting deteriorations in a company’s financial performance than to its improvement.

that a downward trend seems to have been developing throughout the last decades. The occurrence of drifts in rating changes is reported in Altman and Kao (1992), and is subsequently confirmed in Blume et al. (1998), in Amato and Furfine (2004), as well as in Jorion et al. (2009). An example is the continuous growth between 1985 and 2002 in the proportion of issuers graded as speculative by S&P, from 26% to 46% (Jorion et al., 2009). Blume et al. (1998) to some degree explain the downward trend in credit ratings with a change of rating standards in the direction of strictness of criteria, but do not preclude a decline in the credit quality. Indeed, in the opinion of Jorion et al. (2009), a tightening of credit standards would have implications in terms of higher debt costs and distortion of capital requirements.

In relation to rating momentum, it is important to refer that, instead of following a random walk, fluctuations in ratings reveal serial correlation, generating momentum (see, for example, Altman and Kao, 1992; Nickell et al., 2000; Güttler and Wahrenburg, 2007). Güttler and Wahrenburg (2007) inclusively report evidence of serial cross correlation and momentum amid rating changes from distinct agencies. As reported in Altman and Rijken (2004), this has a strong implication on future ratings being foreseeable from past rating changes, with investors anticipating the serial correlation particularly in the case of downgrades. Actually, in harmony with their conservatism, rating agencies reveal to be more sensitive to bad news than to good news. Comparing the rating changes of both Moody's and S&P applied to a data set of near to default issuers, Güttler and Wahrenburg (2007) conclude that when one of these agencies downgrades an issuer further downgrades of higher level from the other agency tend to follow in the short term (up to 90 days). Additionally, they note that higher accuracy is achieved at the cost of less stability.

3.3 Methodology and data

3.3.1 Methodology

To assess the stability level of ratings we use a three-fold methodology. First, we analyse the sensitivity of ratings to changes in business cycles. Second, we contrast the stability of ratings with the one generated by alternative models of credit risk assessment. Finally, selected descriptive statistics of rating changes and rating reversals are also analysed.

Our approach to assess stability of credit ratings draws from methodologies applied to similar situations. For example, according to Moody's (Cantor and Mann, 2003), the stability of a rating system may be assessed by the frequency of rating changes, especially when such changes are large or correspond to reversals. In this regard, Moody's keeps tracking of three types of rating changes taking place over the past 12 months: a) the percentage of issuers with rating actions; b) the percentage of rating changes of 3 or more rating notches; c) the frequency of rating reversals. The last indicator reflects cases with upgrades followed by downgrades or vice versa. With each statistic summarizing information about a specific feature of ratings changes, these indicators may nevertheless miss the whole picture of rating changes and rating volatility.

The dynamics of credit ratings may be further described by Markov chain transition matrices, regarded as alternative descriptive statistics from which it is conceivable to estimate, within a determined timeframe, the probability of each credit rating being upgraded or downgraded. Examples may be found in Altman and Kao (1992), Nickell et al. (2000), Parnes (2007), Güttler and Raupach (2010). Notice that, despite its advantages for providing a global perspective about ratings stability, such approach gives information on two points in time but does not reflect changes that may have occurred in the interim period; thus, it may lose out the effects of exogenous influences, such as macroeconomic pressures. A sequence of transition matrices could help overcome this potential limitation.

An alternative approach for describing rating dynamics lies in regression analysis. For example, Blume et al. (1998) employ an ordered probit model that relates rating categories with selected exogenous variables. In their approach, slope coefficients are constrained to be constant over time, with variations in the intercept being interpreted as changes in standards of ratings. A similar technique is employed by Amato and Furfine (2004), who incorporate measures of the business cycle to the exogenous variables in order to assess how decisions of the agencies are influenced, after accounting for firm-specific factors. Güttler and Wahrenburg (2007) also use an ordered probit model to investigate serial correlation among rating changes from different agencies, although they conclude that qualitatively similar results emerge when they utilize instead an Ordinary Least Squares (OLS) approach.

3.3.1.1 Sensitivity of ratings to changes in business cycles

We use an econometric approach according to which an indicator of the dynamics of credit ratings implied from transition matrices is regressed on a set of macroeconomic variables, including historic rates of default. If the agencies are unresponsive to external pressures and to the stage of the business cycle, these exogenous variables should be statistically not significant.

In order to calculate the aforesaid indicator of rating dynamics, we define a transition matrix M relative to each time interval as reflecting, per row, the redistribution through time of the total number of firms belonging to every initial rating. If all ratings remain unaltered, the transition matrix is a diagonal matrix.[32] Accordingly, in row s and column r of M, we find the number of firms with a rating equal to s in $t-1$ and a rating equal to r in t; we denote this information as $m(t)_{sr}$. Aggregating firms in all k rating classes, the total number of ratings assigned both in $t-1$ and in t becomes $\sum_{s=1}^{k}\sum_{r=1}^{k} m_{sr}$. Relatively high values far from the main diagonal of the matrix reveal less smooth rating changes, therefore denoting less stable ratings. As a result, the more representative is the number of firms far from the main diagonal the more unstable and volatile will be the rating system.

Regardless of how interesting it may be the transition matrix, its interpretation is nonetheless mostly limited to an analysis similar to before. A holistic, but concise approach, of rating stability supports the adoption of a single indicator that summarizes the information contained in the matrix.

Hence, based on the transition matrix, we derive an indicator of rating dynamics for each time interval by summing up all standardized $m(t)_{sr}$ multiplied by the squared difference between the initial and final rating class; this means the most pronounced changes are weighed more heavily. For a matter of convenience, we skip the time reference t from $m(t)_{sr}$; in addition, we compute the respective standardized value as

$$m_{sr}^{*} = \frac{m_{sr}}{\sum_{s=1}^{k}\sum_{r=1}^{k} m_{sr}} \equiv \mathrm{P}_{sr} \tag{3.1}$$

P_{sr} may be interpreted as the unconditional probability of a change in ratings from s to r.[33] $\mathrm{P}_{sr} \times (s-r)^2$ is the probability weighted rating difference squared. The particular case of this probability being equal to zero corresponds to the expected value of the difference when

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[32] For k rating classes, the matrix is $k \times k$, given that only companies with initial and final ratings are included; i.e. the matrix excludes cases that became non-rated.

[33] Note that this is different from the typical stationary Markov chain process, according to which the probability of transition from rating level s at time period $t-1$ to rating r at time period t is given by

$$\mathrm{P}'_{sr} \equiv \mathrm{P}\{R(t) = r | R(t-1) = s\} = \frac{m_{sr}}{\sum_{r=1}^{k} m_{sr}}$$

where $R(t)$ and $R(t-1)$ denote the rating levels respectively at time periods t and $t-1$.

ratings are stable, i.e. when $s = r$. As $(s - r)^2$ may also be interpreted as the squared deviation relative to zero, the following indicator of rating volatility is calculated

$$\vartheta^2 \equiv \sum_{s=1}^{k} \sum_{r=1}^{k} \mathrm{P}_{sr} \times (s - r)^2 \tag{3.2}$$

Stability peaks when ratings are unaltered, i.e. when $\vartheta^2 = 0$, implying that M is a diagonal matrix; likewise, the higher is ϑ^2 the more unstable and volatile becomes the rating system. Hence, with the set of ratings observed in each two consecutive periods $t - 1$ and t, we quantify the series of rating volatility as the square root of ϑ^2, henceforth denoted as ϑ_t. Afterwards, we are able to regress this indicator according to the following structure

$$\vartheta_t = \alpha + \beta_1 IR_t + \beta_2 GDP_t + \beta_3 RD_t + \varepsilon_t \tag{3.3}$$

where IR, GDP and RD refer respectively to the interest rate, the Gross Domestic Product change and the rate of default in each moment, as indicators reflecting the stance of the business cycle. A business cycle peak (trough) is described by high (low) GDP rates, as well as high (low) interest rates and low (high) rates of default. Previous literature on credit ratings (e.g., Nickell et al., 2000) uses as well the GDP growth rate to describe the business cycle. If ratings follow the alleged through-the-cycle approach, rating changes should be relatively insensitive to the prevailing business cycle; correspondingly, β_1, β_2 and β_3 should be statistically insignificant.

3.3.1.2 Benchmarking the stability of ratings

To complement the previous methodology, we assess the relative stability of ratings using as benchmark the predicted rate of default derived from an accounting-based model of default prediction. In order to do this, we graphically compare trends of the yearly averages of ratings and of the predicted rates of default. If ratings are more stable than the selected benchmark, then a line chart should reflect a more regular evolution in ratings. Likewise, the respective relative standard deviation should also be lower, when compared with the result of the benchmark; therefore, we also examine relative standard deviations.

As underlined in Altman and Rijken (2006), potential conflicts exist between stability and accuracy in a risk assessment system. Therefore, given this potential conflict, we evaluate as well the relative accuracy of ratings, by comparing the observed yearly rates of default with the 1-year prior ratings and predicted rates of default. This analysis is complemented with the calculation of the 1-year accuracy ratios (Gini coefficients) of both forecasting alternatives of credit risk. Similar to Cantor and Mann (2003), we compute such ratio from the cumulative accuracy profiles curve (CAP).[34]

3.3.1.3 Rating changes and rating reversals

The third methodology evaluates the extent to which ratings truly change gradually over time and rating reversals are avoided. For the sake of comparability, we use two indicators tailed by Moody's (Cantor and Mann, 2003): large rating changes and the frequency of rating reversals. Our selection of cases with large rating changes is consistent with Moody's, which track large rating changes as the percentage of three or more rating notches over the total ratings assigned each year.

3.3.2 Data

We obtain data about North American firms and macroeconomic indicators from the following sources: Moody's, S&P, Bloomberg, CRSP, COMPUSTAT, UCLA, the U.S. Department of Commerce and the Federal Reserve Bank Reports. Details on each of these sources and their uses follow below.

Announcements by the three major agencies of long term corporate credit ratings and corporate issuer ratings, relative to the period between 1990 and 2011, are obtained directly from Moody's Default & Recovery Database and the database of S&P Capital IQ; we retrieve additional information on ratings, namely those of Fitch, indirectly from Bloomberg (RATC: Company Credit Rating Changes).

Likewise, we retrieve information on credit defaults from the databases of Moody's, S&P, Bloomberg (CACT: Capital Change; Bankruptcy Filing), as well as from CRSP (delisting code 574), COMPUSTAT (inactivation code 02), and from UCLA - LoPucki Bankruptcy Research Database. To derive estimates of probabilities of default and achieve a benchmark to ratings stability, we extract financial and market information about each firm, respectively, from COMPUSTAT and from CRSP.

In order to estimate equation (3.3), we also need information on GDP changes and on the interest rate. Hence, the quarterly GDP change, measured as the seasonally adjusted annual

[34] Cantor and Mann (2003) define the CAP as a plot for each rating category of the proportion of all firms with an equal or lower rating against the proportion of defaults accounted for by firms with an equal or a lower rating. The accuracy ratio is a summary measure of this curve, expressing the ratio of the area between the CAP curve and the 45-degree line to 0.5 (this is the maximum possible area above the 45-degree line).

rate based on chained 2005 dollars, is retrieved from the Bureau of Economic Analysis (U.S. Department of Commerce). Regarding the interest rate, we extract the federal funds effective rate from the Federal Reserve Bank Reports databases in WRDS. This measure is selected for two reasons. On one hand, being a tool of monetary policy, the federal funds rate reflects not only the current state of the economy, but is also an important leading indicator to anticipate future developments in economic cycles. On the other hand, that rate provides a consistent and stable outlook about the true state of the economy, given that the quarterly GDP change is more volatile and susceptible to circumstantial events.

Based on these sources, we compile an initial sample of 35,570 rating announcements pertaining to 2,898 firms. 15,073 announcements relative to 2,708 firms belong to S&P, 18,731 announcements concerning 2,199 firms are from Moody's, and Fitch assigned 1,766 ratings about 400 firms. In order to ease the analysis, we convert rating letters with modifiers to a score that reflects the rating order (Fitch-S&P/Moody's: AAA/Aaa = 1; …; D/C = 22). In line with this conversion a higher score denotes a lower rating level and, thus, more risk.

3.4 Empirical analysis

This section reports results of a three-part analysis on the stability of ratings issued by the three main rating agencies. First, based on equation (3.3), we examine the different dynamics of each rating agency and the effects of business cycles on ratings. Second, we assess the relative stability of ratings using as benchmark a model that estimates the probability of default. Third, complementing previous approaches and in line with the evaluation applied by Moody's (Cantor and Mann, 2003), we calculate and examine a set of descriptive statistics.

3.4.1 Business cycles effects

Using quarterly observations about ratings, we obtain a series of rating matrices from where the indicator of volatility based on equation (3.2) is derived. Instead of the normally used 1-year transition matrices, the option goes for higher frequency matrices for three reasons. First, the selection of only one transition matrix per year requires a very large period of time to achieve a relevant series of ratings announcements; we believe this requires more than twenty one years, the length of our sample. However, we should note that the remoter we dig information from the past, the scarcer becomes the information on ratings. Second, with a shorter time frame between two consecutive observations, less information is lost in the interim period between them. Third, if the attribute of stability is required for relatively long time horizons, then it should also be required for shorter horizons. Actually, the level of stability is supposed to be high especially in shorter time frames.

Under the previous frequency of transition matrices, ϑ is calculated based on quarterly data of ratings, with ϑ_t providing an overall picture of ratings stability between quarter $t-1$ and quarter t. The estimation of ϑ not only enables the estimation of equation (3.3), but also allows us to compare the stability implied by ratings provided by different agencies.

3.4.1.1 Regression analysis

Based on quarterly data about ϑ, the interest rate (*IR*), the GDP change (*GDPQ*) and the rate of default (*RD*) in the year that corresponds to each quarter, we estimate the parameters of equation (3.3) concerning ratings from the three agencies. Our estimation method is the OLS (Table 3.1), whose results are compared with alternative methods that explicitly address the non-negativity of the endogenous variable. In particular, by using a Tobit regression, we find that the respective estimates are rather similar to what OLS provides, hence supporting our main conclusions.

Table 3.1: Rating volatility regression estimates

This table reports coefficients and *t*-ratios from an OLS regression of an indicator of rating volatility on the Federal Funds Effective Rate (*IR*), the quarterly GDP change (*GDPQ*), and the rate of default of the corresponding year (*RD*).

	Moody's			S&P			Fitch		
	Estim.	*t*-ratio	*p*-value	Estim.	*t*-ratio	*p*-value	Estim.	*t*-ratio	*p*-value
Intercept	0.893	13.81	0.000	0.917	13.08	0.000	0.776	8.18	0.000
IR	-3.113	-3.24	0.002	-6.739	-6.46	0.000	-4.030	-2.85	0.005
GDPQ	-2.507	-3.02	0.003	-2.360	-2.62	0.010	-4.970	-4.08	0.000
RD	8.243	3.01	0.003	9.609	3.24	0.002	-1.300	-0.32	0.747
Adjusted R^2	0.34			0.50			0.24		
F-statistics	15.72			29.15			10.20		
Observations	87			87			87		

The evidence in the table confirms statistically significant marginal effects of *GDPQ* and *IR* on the rating dynamics of every agency; therefore, it seems that stability is to some extent affected by the state of the economy. Still, the differences in the adjusted R^2 expose distinct reactions among the agencies. For example, S&P seems to be more sensitive to the business cycles conditions than Moody's and Fitch; such conditions explain half of the dynamics of ratings by S&P's. What is more, the negative signs of the respective estimates confirm that higher values of the exogenous variables, normally observed when the economy is expanding and higher business activity prevail, bring more stability (i.e., less volatility) to rating changes. Taking as example the case of S&P, when both the interest rate and the GDP increase by 1%, ratings change by more than 0.09 classes. This means that out of 100 firms, 9 will see their ratings change by one class along the quarter in which such increase takes place.

In relation to *RD*, we detect significant influences in the case of Moody's and S&P, but not in Fitch. Such differences may possibly originate from the fewer number of observations in the case of Fitch, or because its announcements are indeed more insensitive to some exogenous influences. Concerning Moody's and S&P, we observe that higher rates of default pressure both agencies to change more their ratings. An increase of 1% in the rate of default, for example in the case of S&P, means that ratings will tend to vary more 0.096 classes than before. This is the same as changing ratings by one class in 1 firm out of 10.

Given the criticisms to the agencies and in line with the reputation cycles perspective, it seems interesting to complement the estimation of equation (3.3), as reported in Table 3.1, with an analysis on the existence of eventual structural breaks. Following Langohr and Langohr (2008, p. 356), we select three specific events where the agencies remained particularly vulnerable to criticisms: the 1997-1998 Asian financial crisis; the 2000-2003 Western equity crisis; and the 2007-2008 subprime credit crisis. Accordingly, a Chow test is applied to equation (3.3), with breaks set for 1998, 2002 and 2008, i.e. 1 or 2 years after the economic crises erupted. We report the respective *F*-statistics in Table 3.2.

Table 3.2: Structural break analysis

The values in this table refer to *F*-statistics of a Chow test applied to rating volatility, with three alternative structural breaks: 1998, 2002 and 2008.

		Moody's	S&P	Fitch
Year:	1998	10.25	6.33	5.41
	2002	9.68	8.69	6.57
	2008	5.68	14.12	4.91

With all *p*-values under 1%, Table 3.2 suggests the presence of structural breaks in the intensity of ratings changes in the wake of more severe criticisms to the agencies. However, the reaction is not uniform: for example, the higher *F*-statistic of S&P in 2008 indicates a stronger reaction to the subprime credit crisis, comparatively to Moody's and Fitch, which is consistent with results shown in Table 3.1. Despite differences in intensities of their reactions and in the variables determining such reactions, this evidence implies that rating agencies seem to be responsive to changes in the business cycle.

Motivated by findings reported in previous literature, this paper investigates additionally the link between rating stability and the level of ratings. In that sense, we measure the respective correlation coefficients and report the results in Table 3.3. Correlation estimates, all statistically significant, suggest that a reduction in stability comes along with lower ratings (higher score). This result is consistent with Nickell et al. (2000), who stress that as we move downward the rating scale a sharp increase in the volatility of rating transitions is observed. From Table 3.3, we can see that the association between the rating level and the respective instability is more intense in the case of S&P. Given the suggestion of procyclicality of ratings, the higher correlation of S&P reinforces the conclusion reported before, that this agency is more reactive to the business cycle than Moody's and Fitch.

Table 3.3: Correlations between volatility and level of ratings

This table shows the Pearson's correlation coefficients between the quarterly rating volatility and the quarterly average rating score. Positive correlations mean that higher rating volatility is associated to higher scores, i.e. lower rating levels.

	Moody's	S&P	Fitch
Correlation	0.460	0.658	0.417
t-ratio	4.776	8.056	4.230
p-value	0.000	0.000	0.000

Generally speaking, the preceding outcomes seem to confirm that rating changes dynamics are countercyclical in the case of the three main rating agencies: a depressed economic setting stimulates greater rating dynamics, while a booming economy brings more stable modifications in ratings. This finding supports the perspective in previous literature, that ratings move procyclically with the state of the economy, where higher frequency of downgrades is observed in recessions, and upgrades prevail in expansions. Our results are in line with Amato and Furfine (2004), who document that the agencies denote excessive influence from the prevailing economic conditions. Likewise, findings in this paper corroborate conclusions in Parnes (2007), which point to influences on the dynamics of ratings driven by changes in the Gross Domestic Product, business cycles and market risk.

3.4.1.2 Comparative analysis of ϑ

In order to detect the extent to which differences exist in rating dynamics among the three agencies, the next three figures provide a comparative analysis of ϑ relative to each agency. Accordingly, Figure 3.1 shows the evolution of the quarterly difference in dynamics between rating changes from Moody's and those from S&P. A positive value implies that rating changes from Moody's are less stable than changes made by S&P during the same time period; a negative value means the reverse.

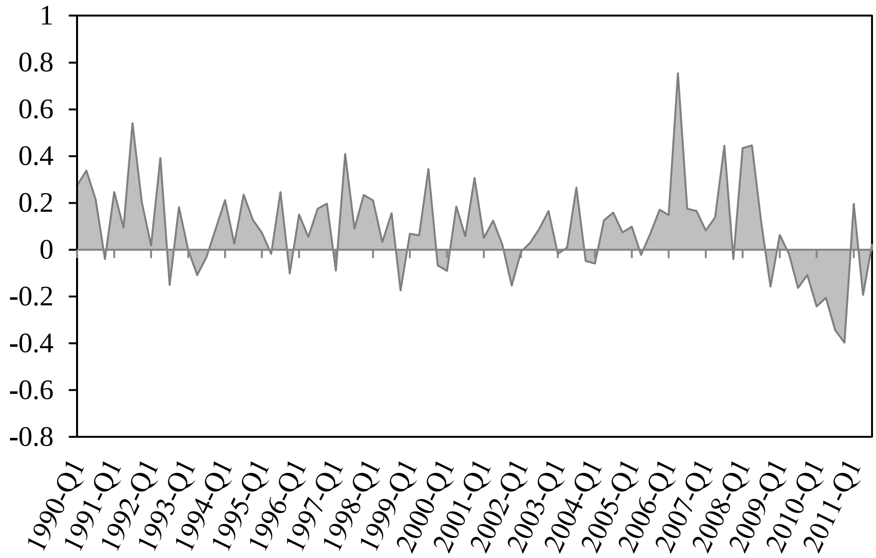

Figure 3.1: Difference of rating volatility between Moody's and S&P

As seen by the higher estimates of the respective parameters and R^2 as reported in Table 3.1, S&P's announcements seem to be more susceptible to the state of the economy. Yet, taking into account the series in Figure 3.1, it is nonetheless interesting to note that Moody's announcements are indeed less stable. This figure confirms the dynamics of Moody's ratings to be generally higher when compared with the same indicator for S&P's ratings. The marginally higher variability of changes in ratings by Moody's is in harmony with evidence in Güttler and Raupach (2010) and in Güttler and Wahrenburg (2007), suggesting that Moody's is more opportune than S&P in adjusting its ratings to increasing default risk.

The average quarterly deviation in ratings along the whole period ascends to 0.09, which means that Moody's changes more its ratings than S&P in every 9 out of 100 issuers, considering a change by one rating level. In 2009 and 2010, after the subprime crisis outbreak, the difference in volatility became negative, meaning that S&P's rating changes actually turned out to be more volatile, and suggesting that these changes are more reactive to the state of economy.

Concerning Figure 3.2, we detect that the variability of rating changes by S&P clearly exceeds almost systematically what Fitch reveals; the difference in the average quarterly deviation in ratings reaches 0.25.

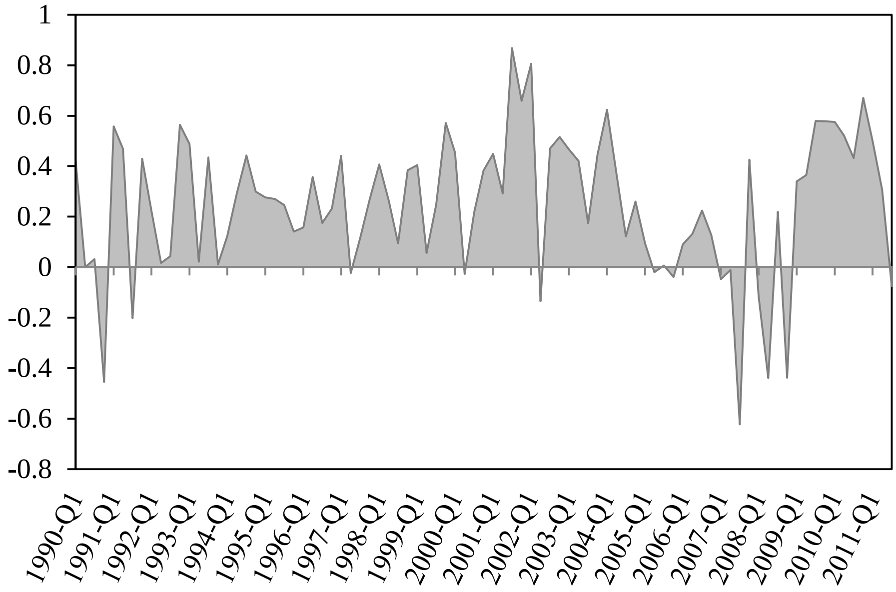

Figure 3.2: Difference of rating volatility between S&P and Fitch

Also in harmony with the data in the previous charts, Figure 3.3 shows that, among the big three agencies, Moody's applies the most profound changes in its ratings, perhaps adjusting them in a more timelier manner than the other two, visibly in contrast with Fitch's rating policy, apparently the most stable. Overall, Moody's changes more its ratings in 0.34 classes than Fitch does. This is the same as saying that, allowing for a change by one level, Moody's changes ratings in more 34 out of 100 issuers than what Fitch does.

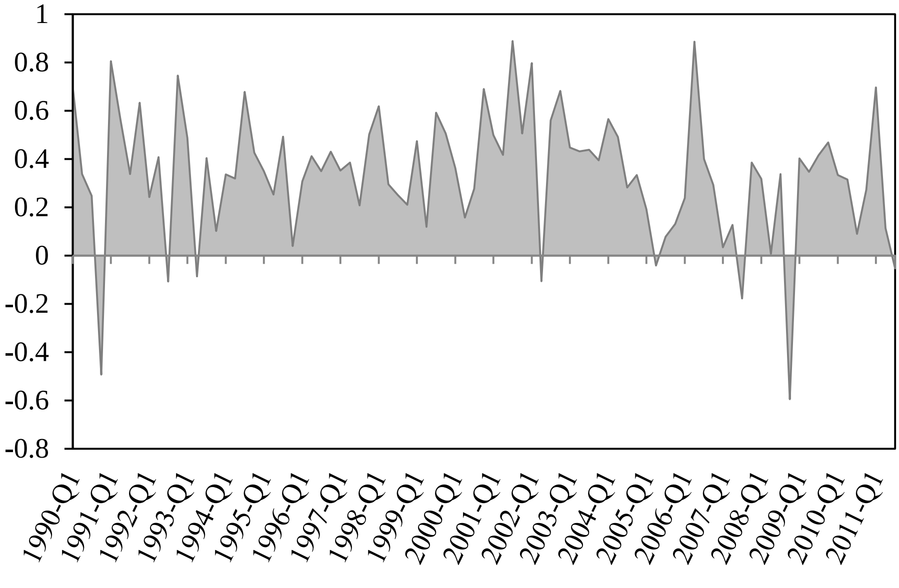

Figure 3.3: Difference of rating volatility between Moody's and Fitch

3.4.2 Benchmarking ratings stability

Our benchmark to ratings is the 1-year probability of default. The approaches for modelling default prediction may be subdivided in the structural models, the reduced-form models and the accounting-based models. Falling in the third category, the method selected in this paper corresponds to the model of default prediction estimated in Carvalho (2013). According to such model, credit default is predicted for each firm based on the respective prior financial and market information.

Based on a database composed by 109,767 firm-years and applying a dynamic panel modelling approach, as in Shumway (2001) and Campbell et al. (2008), Carvalho (2013) regresses a firm's default on the following variables: log of Total Assets (*Size*), Total Debt divided by Market Value of Assets (*TDLM*), the company's annual standard deviation of the respective daily stock's return (*Sigma*), Net Income divided by the Market Value of Assets (*NIATM*), Total Liabilities divided by Total Assets (*LTAT*), Cash and Short Term Investments divided by the Market Value of Assets (*CHATM*), and the Market to Book Ratio (*MB*).

The estimated regression applied to firm i in time period t is as follows

$$\widehat{\ln\left(\frac{P_{it}}{1-P_{it}}\right)} = -12.34 + 0.54\,Size_{it} + 1.78\,TDLM_{it} + 46.03\,Sigma_{it} \\ -5.17\,NIATM_{it} + 3.41\,LTAT_{it} - 1.99\,CHATM_{it} - 0.36\,MB_{it} \tag{3.4}$$

where e_{it} denotes the residual. According to equation (3.4) and consistent with economic intuition, firms are more likely to default when they are more indebted, are less profitable, have lower liquidity and relative market value, and their stock's return is more volatile. Though less anticipated than the influences from other variables, there is also a positive relation between the probability of default and a firm's market value of assets.

Taking into account the observations on the previous explanatory variables for each firm-year, we estimate the respective probability of default for the next 12 months, thus obtaining a yearly series, as represented in Figure 3.4. The figure shows the observed rates of default from 1991 to 2011 and the correspondent yearly average probability of default. Both allow us to assess the relative stability and accuracy of the yearly average ratings provided by Fitch, Moody's and S&P. Several insights may be drawn from here. First, it seems rather obvious that ratings are indeed more stable than the estimates of probability of default derived from a model based on a point-in-time approach. This is reinforced by the relative yearly standard deviations of each series: while the model of probability of default reaches 65% of the respective average, ratings match a rather lower value, 9%. A similar conclusion, pointing to more stability in ratings, is obtained by Löffler (2013) who claims that ratings reflect primarily a long-term trend of credit risk. Indeed, when compared with Moody's KMV Expected Default Frequencies, as market-based estimates of the 1-year default probabilities, or with other estimates of the short-term probability of default, ratings are far more stable.

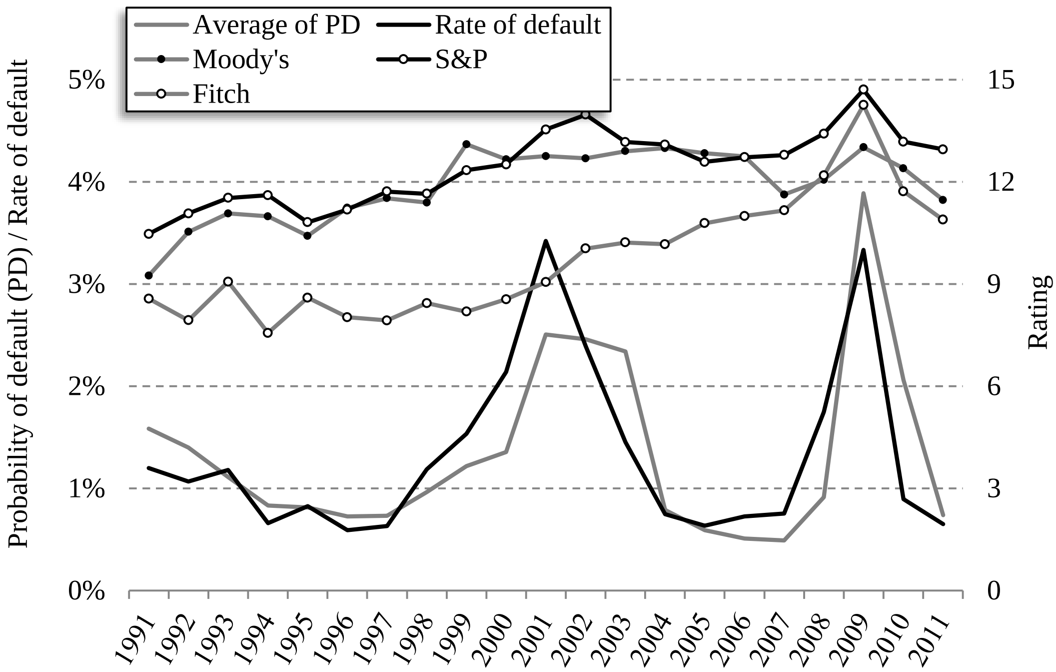

Figure 3.4: Yearly evolution of ratings, probability of default and rate of default

As a result of their higher relative stability, the second insight we draw from Figure 3.4 is that ratings' accuracy becomes penalized when compared with the one from the model of probability of default. The evolution in the latter seems to be more responsive to short term influences, but then again seems to better predict the rises and falls of defaults, namely the peaks reached in 2001 and 2009. This is in line with the evidence already reported in Altman and Rijken (2006). Hilscher and Wilson (2013) show that at least, until a 24-month horizon, the probabilities of default based on accounting and stock market information outperform ratings, although credit ratings offer a good measure of systematic risk. Nevertheless, they conclude that a good measure of systematic risk cannot be at the same time an accurate predictor of default.

We extend the analysis by comparing accuracy ratios (AR). The forecasting ability implied by the 1-year default probability corresponds to an AR of 87.64%, which is above the value implied by the 1-year prior ratings, 76.70%. Concerning the latter, we do not calculate the AR per agency, but instead evaluate ratings together to provide an overall AR. Cantor and Mann (2003) report the Moody's ratings annual average AR, pertaining to pooled cohorts and to the

1-year ahead horizon, as being 82.6%; this is slightly above our estimate of ratings' AR, generally applied to the three agencies. To some extent, the higher AR of Moody's reinforces the perspective that Moody's adjusts its ratings in a timelier manner than S&P and Fitch, as suggested by Güttler and Wahrenburg (2007).

The final insight we draw is that an overall downward trend of ratings (i.e. higher rating scores) develops along the period of investigation. This supports previous findings pointing to ratings deteriorating through time (Altman and Kao, 1992; Blume et al., 1998; Jorion et al., 2009). Nevertheless, after the rating dip of 2009, following the crisis of 2007-2008, the downward trend of corporate ratings appears to invert.

3.4.3 Rating changes and rating reversals

This subsection reports descriptive statistics, in line with Moody's criteria (Cantor and Mann, 2003). The chart in Figure 3.5 uncovers a rising uptrend of volatility behind ratings announced by the three agencies, with a striking difference between the periods before and after 1998. Until that year, only 5.2% of all rating announcements correspond to large rating changes, contrasting with 11.6% after 1998. It seems that criticisms addressed to rating agencies for failing to timely predict the Asian financial crises that emerged in 1997, and the Russian defaults occurring in 1998 did have a widespread effect on their rating policies (see, for example, Langohr and Langohr, 2008, p.381). For instance, Ferri et al. (1999) analyze the East Asian financial crisis of 1997 and 1998 and demonstrate that procyclicality in ratings actually worsened it.

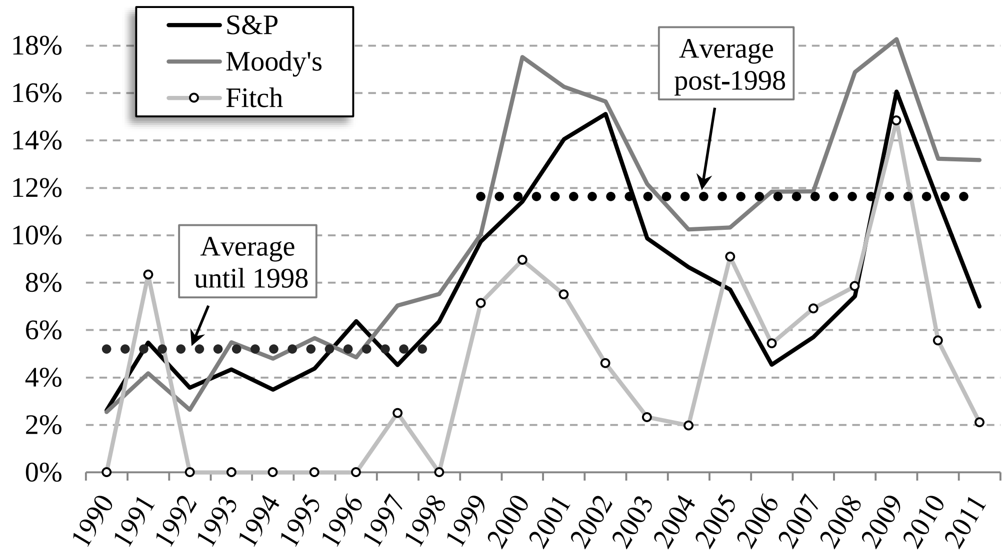

Figure 3.5: Percentage of rating changes of 3 or more notches per rating agency

Figure 3.5 suggests as well that large rating changes tend to be more remarkable next to, or after, major economic crises, which is consistent with the results shown in Subsection 3.4.1. In addition, Moody's ratings seem to reveal higher instability than those from S&P and Fitch. In what concerns Fitch's rating changes, the aforementioned metric reveals an almost irregular evolution, a reflection of the fewer observations in this case, particularly during the 1990's.

In line with the evidence exhibited before, the evolution of the frequency of rating reversals, shown in Figure 3.6, confirms that Moody's rating volatility almost systematically surpasses the volatilities of other agencies. This is more noticeable from 2000 onwards. Analysing ratings of Moody's relatively to the period between January 1999 and January 2002, Cantor and Mann (2003) report an estimate of only 1% for rating reversals. The estimates shown in this paper differ considerably from that value. Potential explanations for such differences reside not only in the databases used (we only analyze corporates), in the total number of issuers considered, as well in the time period analyzed. Equally consistent is the suggestion of volatility peaking in more recent years, particularly evident in the cases of S&P and Fitch, reflecting the impact of the 2007-2008 economic crisis.

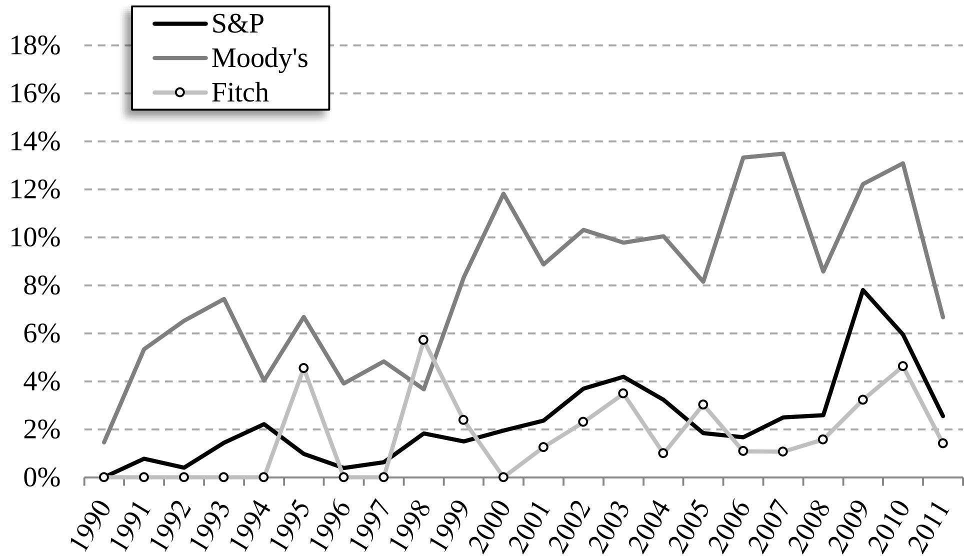

Figure 3.6: Frequency of rating reversals per rating agency

3.5 Summary and conclusion

In order to prevent procyclical effects as well as credit crunches, the quasi-regulatory role of ratings requires stability in rating changes. Long term investors also expect ratings to remain stable, so that high transaction costs derived from adjustments in their portfolios are avoided. An underlying through-the-cycle approach is consequently demanded for ratings, instead of ratings too sensitive to the current business conditions.

Based on the analysis of a new measure of rating volatility, this paper shows that variables reflecting the business cycles account for significant influences on rating volatility. Likewise, the existence of structural breaks relative to the influence of economic variables on volatility is found significant after periods of major criticisms to the agencies. The paper documents as well evidence that higher volatilities are normally associated to lower ratings, and that the volatilities of different agencies have been dissimilar, presumably according to the specific policy adopted by each rating agency. Despite S&P being more reactive to business cycle fluctuations, Moody's ratings reveal more frequent changes, in line with the evidence in Güttler and Raupach (2010) suggesting a relatively higher concern with accuracy in Moody's.

Overall, these results are contrary to the alleged independence between the state of the economy and ratings as an ordinal classification of default risk; this appears to question the potential lessening effect of ratings relative to the occurrence of credit crunches in recessions. Actually, given the aforementioned outcomes, we may ask if ratings truly look through-the-cycle or if, on the other hand, their underlying assessment is generally biased by current conditions and permissive to criticisms. The fact is, though, ratings are nevertheless relatively stable when compared with alternative measures of credit risk.

Previous references (Bolton et al., 2012) have proposed to eliminate the conflicts of interest of credit rating agencies and the shopping of ratings, as a way to prevent rating inflation and alleviate the effects of the agencies' reputation cycles. Based on the findings now reported, additional proposals to inhibit abnormal volatility in recessions may include a more proactive intervention of rating agencies, with more frequent rating announcements. The increased frequency of rating announcements is expected to dilute the potential disruptive effects associated with an extraordinary concentration of large negative rating announcements derived from crises, or as reactions to criticisms. This is the same as delivering bad news in small doses. After all, provided that the agencies are truly capable to focus on long term trends and do not stay overly caught in current events, an increasing frequency of rating announcements, if properly used, has the power to enhance the benefits of using ratings as barometers of the economy and lessen the effects of incoming crises.

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