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

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Abstract

Although credit ratings are meant to foretell a firm's risk of default, anecdotal evidence suggests that they actually influence the firm's probability of default. This paper provides systematic evidence on this unintended effect of rating downgrades on future credit defaults. Based on complementary causality methodologies and using an exhaustive database of long-term corporate obligation ratings issued by Moody's, S&P and Fitch, from 1990 to 2011, the paper shows that downgrades crossing the threshold between investment grade and speculative grade cause an increase of at least 3% in the 1-year probability of default. Naturally, the increase in the probability of default is stronger for deeper rating downgrades. The effect is also stronger for firms that already have a low initial rating.

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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.[1] 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. 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).

It is not strange therefore that related literature does not test the possibility of credit rating announcements turning into self-fulfilling prophecies of default. For example, Bannier and

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

Tyrell (2006) admit that a wide early withdrawal of credit access pushes the firm into default. As a result, Kuhner (2001) postulate that some negative credit rating announcements may turn into self-fulfilling prophecies. This hypothesis is even 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. We extend this line of research by testing the conjectures raised in these papers.

This paper uses a threefold econometric approach. Based on Shumway (2001), 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 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 answer 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 results are quite consensual.

Relying on an extensive database of ratings issued by Fitch, Moody's and Standard & Poor's, between 1990 and 2011, the paper confirms that some rating downgrades aggravate the risk of default. Such is the case of ratings moving from investment grade to speculative grade, which causes an increase over 3% in the 1-year probability of default when it occurs. The effect is even larger when we observe downgrades from a level that is already speculative to another one at best equal to a highly speculative grade; the causality effect in the 1-year probability of default strengthens in this case to, at least, 12.13%. In addition, the magnitude of the rating change is found to cause significant effects too. One interpretation for these significant 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 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 higher 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 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 appears to be 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 a potential limitation 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. Similar limitations are present in other causality problems, given their underlying missing data problems. By using a threefold econometric approach, we hope to mitigate this limitation to some extent.

The rest of the paper is organized as follows. Section 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 3 describes the data used for analysis, and reports selected descriptive statistics. Section 4 contains an overview of the causality methodologies employed to investigate the hypotheses; the results obtained are also detailed and discussed here. Section 5 concludes.

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.

2.1. Literature review

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). Based on public and, in some cases, private information, ratings are assigned by credit analysts as an ordinal and qualitative measure of risk that in most cases reflects the long-term credit strength of the rated party. Rating agencies assign corporate credit ratings either to debt issuers or to particular debt obligations undertaken by those issuers.[2]

In addition to the 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, Standard & Poor's Credit Market Services (S&P), Moody's Investor Services (Moody's) and Fitch, Inc. (Fitch).[3] Dealing with both public and private information, Standard & Poor's (2011) groups in two categories the factors weighed to determine credit ratings: the business risk and the financial risk. Examples

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

[3] 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.

of such factors are the country risk, industry characteristics, company position, risk tolerance, profitability, governance, capital structure and financial policy.

Though private information limits the investigation of a few of these factors, namely those obtained by the agencies via private meetings with management, some papers explore the main observable variables that influence credit 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, ultimately, each rating level denotes a rank relative to other rating levels, such papers generally use ordered multinomial probit or logit estimations, from where they identify the main variables or factors determining credit ratings, as presented in Table 1. Due to the unobservable variables inherent to the rating process, Kamstra et al. (2001) confirm that these estimation methods tend to correctly forecast, at best, only circa 78% of the observed ratings.

Table 1 shows a digest of explanatory variables reported in previous literature on credit ratings. The table reveals that different references select four accounting ratios, commonly computed as:

- 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.

Albeit accounting-type variables predominate, the table also shows 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 and a rating announcement: 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.[4]

Table 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

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. An evidence of the perceived benefits of ratings is the huge increase in the number of global rated corporate issuers.[5]

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 equally to the enhancement of rating effects in the last decades.

[4] 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.

[5] 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.

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. In the U.S. and in other countries, for example, the investment in low rated debt securities, namely those whose classification does not reach at least a "good credit quality", finds limitations and interdictions. 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 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. As ratings reflect fundamental changes in the issuer's credit risk, Kliger and Sarig (2000) underline that it is appropriate to examine only effects that reflect exclusively rating information. Based on refinements introduced in Moody's ratings, their findings confirm both positive and negative bond price reactions following 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 many studies that report relevant influences on stock prices, especially when rating information is negative. 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, displaying an overreaction to the rating announcement; in what concerns rating upgrades, they detect little evidence of abnormal returns. 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, but the absolute impact is lower than what results from negative announcements. In addition, they inform that asymmetries between the informativeness of downgrades and upgrades relate to the rating prior to the announcement; more pronounced price effects concerning to rating changes emerge in lower rated firms. Specifically, they show 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).[6]

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, also discussed in Ederington and Goh (1998), 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.

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

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 the poorer terms with suppliers and the 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. 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 incitement for 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. 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.

2.2.1. 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.[7] 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. 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

[7] Such 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, unlike the former, the latter does not avoid predicted values outside the interval [0, 1].

Black-Scholes-Merton (BSM) option pricing framework.[8] 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, 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 intrinsic characteristics. This is the case of accounting-based measures, as well as some firm's market related information. Altogether, these variables allow us to determine what we call a normal probability of default.

[8] 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

$$P_t = Prob(V_t \leq B_T)$$

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

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

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.

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. Rating downgrades and credit default

Among the previous references, we follow in particular Shumway (2001) and Campbell et al. (2008) to derive a first 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 A (Type-A announcements) and the magnitude of the respective rating change; Type-A 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 5. Given that such conversion implies that higher scores denote lower ratings, the type of announcements under consideration is a downgrade.[9] The higher is K, the deeper will be the downgrade. For example, when $K = 11$, Type-A announcements denote a rating change from investment grade to speculative grade (henceforth, IGSG announcements).

We use separate regressions to estimate the effects of announcements and of the magnitude of change in ratings, in order to minimize the risk of multicolinearity. The marginal influence of rating announcements is estimated with the following logit model

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

$D_{i,t} = 1$ 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

[9] Conversely, upgrades imply that

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

when a Type-A announcement occurs (Ω = 1, if observed; Ω = 0, otherwise).[10] B is a vector of parameters, δ is a scalar, and ε is a vector of residuals.

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

$$P\left(D_{i,t}=1\right)=\frac{1}{1+exp\left[-\left(Z_{i,t-1}B^{*}+\alpha\cdot\Delta_{i,t}+\varepsilon_{i,t}^{*}\right)\right]} \tag{2}$$

where Δ (Δ ∈ ℝ) is a variable denoting the magnitude of the rating change, defined below in equation (3), α is the respective coefficient, B^{*} is a vector of parameters, ε^{*} is the new vector of residuals and Z is similar as before. If δ or 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 ratings. Therefore, considering the announcements disclosed by each agency, we set $\Omega_{i,t}$ = 1 when firm i has at least one Type-A 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 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.

[10] 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.

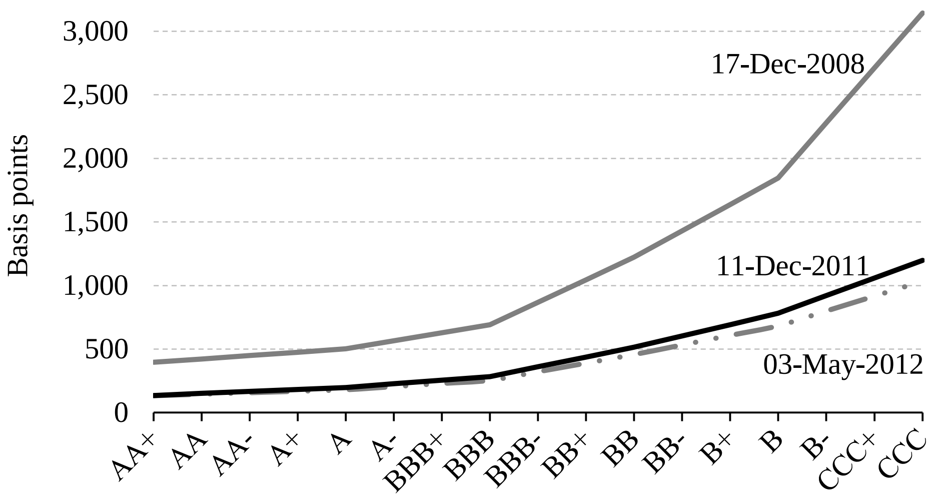

Figure 1: Credit ratings and credit spreads

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 the different rating levels

$$\Delta_{i,t} = \underset{\substack{d_i \in t \\ R_{d_i-1} < K \\ R_{d_i} \geq K}}{Max} \left[\exp\left(\gamma \cdot R_{d_i}\right) - \exp\left(\gamma \cdot R_{d_i-1}\right)\right] \tag{3}$$

R_{d_i} and R_{d_i-1} are, as before, rating announcements of Type A. γ is a parameter defined such that Δ fairly reflects the link between ratings and spreads. In view of the series in Figure 1, we regress exponentially the spread on the rating level and estimate that γ is around 0.14. Finally, considering that more than one Type-A 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 (3) generates

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

Having in mind the formerly defined features of rating variables, for every Type-A announcement we may estimate credit default prediction models as in equations (1) and (2).

Announcements of type A

To evaluate the influences on default from downgrades with distinct level of severity and so accommodate the intuition conveyed by Figure 1, we consider two kinds of Type-A 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 5), thus potentially favoring the disentanglement of the aforementioned potential causal effects of ratings relatively to their prediction accuracy.

The second Type-A announcement A refers to deeper downgrades, namely those taking place within already speculative rating grades. Specifically, we select K=14 (henceforth denoted as SGSG14), which denotes 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 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.

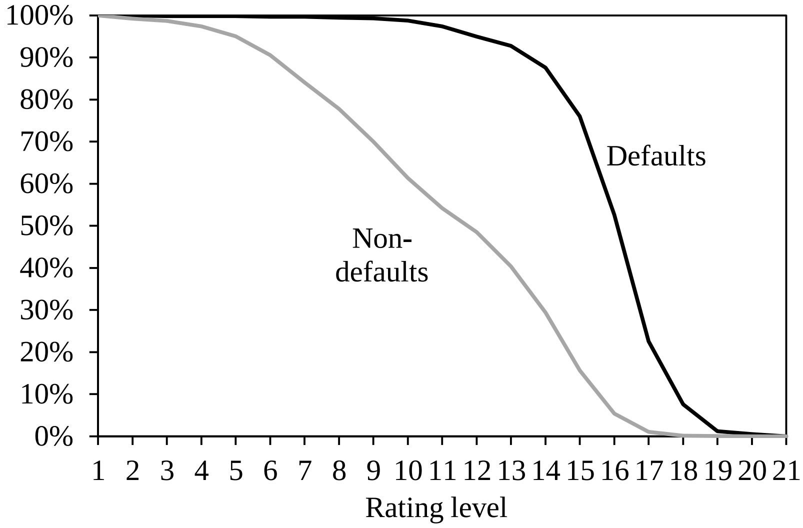

Figure 2: Distribution of credit ratings

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, 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.

2.2.3. Influences of IGSG announcements

In order to select the eligible firm's intrinsic variables that optimize results, we apply a first regression using only market and financial variables, as presented later. The selection of variables takes into account the economic meaning of estimates obtained for the parameters, as well as the correlation coefficients among covariates, so that potential adverse multicolinearity effects are mitigated. As a rule of thumb, we exclude all covariates whose correlation coefficients with other covariates exceed 0.5, or whose sign of the related parameter is opposite to what is expected. Table 2 presents the regression results.

As shown by the almost null *p*-values, all exogenous variables are statistically significant and signs of regression coefficients are in line with what is financially expected.[11] 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

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

influence on default. Thus, in line with expectations, the probability of default is lower when profitability is greater.

Table 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*).

	Estimates	Standard Error	*z*-value	*p*-value
Intercept	-12.3430	0.2243	-55.04	0.000
Size	0.5394	0.0198	27.21	0.000
TDLM	1.7767	0.2122	8.37	0.000
Sigma	46.0312	1.5016	30.65	0.000
NIATM	-5.1717	0.2386	-21.68	0.000
LTAT	3.4114	0.1349	25.29	0.000
CHATM	-1.9941	0.4421	-4.51	0.000
MB	-0.3603	0.0495	-7.28	0.000
Pseudo-R^2	0.4330			
Likelihood Ratio χ^2	6,552.5 (*p*-value = 0.000)			
Observations	109,767			

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. However, 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 model's overall accuracy reported in the current paper performs better. One conceivable explanation for this difference lies in the fact that, although sources of information are generally the same, the time frame for each study is different. While Campbell et al. (2008) cover a marginally longer period of time than the one in our sample, the current study comprises a more recent period and 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 the study of Campbell et al. (2008). 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 forecasting 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 is confirmed by an AUROC of 93.82%.[12] In fact, this is by all standards a very high value.[13]

Extending the credit default prediction model by including rating variables, namely IGSG announcements, we obtain estimates for the parameters in equations (1) and (2). Such estimates, of which are of particular relevance the values for the parameters associated with Ω and Δ, are in Table 3. Looking at values on the table, we detect that both rating variables are statistically relevant, as shown by the respective very low *p*-values. 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.

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.

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[12] The Receiver Operating Characteristic (ROC) 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, commonly denoted as 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.

[13] 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%. They use fewer observations in their analysis (246 companies).

Table 3: Credit default prediction with IGSG announcements

This table shows estimates for equations (1) and (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 (1) such information is given by a dummy denoting IGSG announcements (Ω), whereas in equation (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.

	Equation (1)			Equation (2)		
	Estimates	*z*-value	*p*-value	Estimates	*z*-value	*p*-value
Intercept	-12.3034	-54.83	0.000	-12.2911	-54.82	0.000
Size	0.5278	26.11	0.000	0.5261	26.30	0.000
TDLM	1.7788	8.38	0.000	1.7801	8.38	0.000
Sigma	46.1423	30.70	0.000	46.1367	30.68	0.000
NIATM	-5.1403	-21.55	0.000	-5.1432	-21.57	0.000
LTAT	3.4073	25.27	0.000	3.3989	25.22	0.000
CHATM	-1.9842	-4.49	0.000	-1.9913	-4.50	0.000
MB	-0.3580	-7.27	0.000	-0.3570	-7.26	0.000
Ω	0.4875	3.03	0.002			
Δ				0.2652	5.13	0.000
Pseudo-R^2	0.4335			0.4344		
Likelihood Ratio χ^2	6,560.98 (*p*-value = 0.000)			6,574.13 (*p*-value = 0.000)		
Observations	109,767					

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 (1) and (2). Table 4 reports the respective values. Once more, the estimates are statistically significant and consistent with economic intuition. Moreover, when comparing to results reported in Table 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 4 also exhibits remarkable AUROCs, respectively 0.9451 and 0.9436, confirming a significant influence of SGSG14 announcements in future credit defaults.

When compared with results in Table 3, the estimates in Table 4 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 in IGSG announcements. When SGSG14 announcements take place, that difference is 16.59%; this is far above than the circa 3% reported before, relative to

IGSG announcements. This seems to suggest 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.

Table 4: Credit default prediction with SGSG14 announcements

This table shows estimates for equations (1) and (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 (1) such information is given by a dummy denoting SGSG14 announcements (Ω), whereas in equation (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.

	Equation (1)			Equation (2)		
	Estimates	*z*-value	*p*-value	Estimates	*z*-value	*p*-value
Intercept	-11.7043	-51.69	0.000	-11.8904	-52.75	0.000
Size	0.4297	20.46	0.000	0.4649	22.64	0.000
TDLM	1.3151	6.10	0.000	1.4855	6.92	0.000
Sigma	46.3960	30.21	0.000	46.0403	30.18	0.000
NIATM	-5.0045	-20.71	0.000	-5.0627	-21.03	0.000
LTAT	3.2453	23.99	0.000	3.3119	24.58	0.000
CHATM	-2.2545	-4.97	0.000	-2.1092	-4.70	0.000
MB	-0.3589	-7.35	0.000	-0.3599	-7.38	0.000
Ω	1.8674	20.44	0.000			
Δ				0.4881	16.77	0.000
Pseudo-R^2	0.4581			0.4500		
Likelihood Ratio χ^2	6,932.96 (*p*-value = 0.000)			6,809.90 (*p*-value = 0.000)		
Observations	109,767					

2.3. Research hypotheses

The results in Tables 3 and 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 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, the 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 4.

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.

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 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.[14] 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 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

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

denoting obligations in default, a score equal to 22 includes both RD (Fitch) and SD (S&P), which stand for restrictive and selective default.[15]

Table 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>

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. 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.

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

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), 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.

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 hazard modelling approach, as in Shumway (2001), 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%.[16]

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 6 summarizes the distribution of the sample of firms, with the number of ratings in terms of firm-years between brackets.

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

Table 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 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.

Table 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 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 and of the default rate 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.

The last two columns of Table 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 the 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 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.

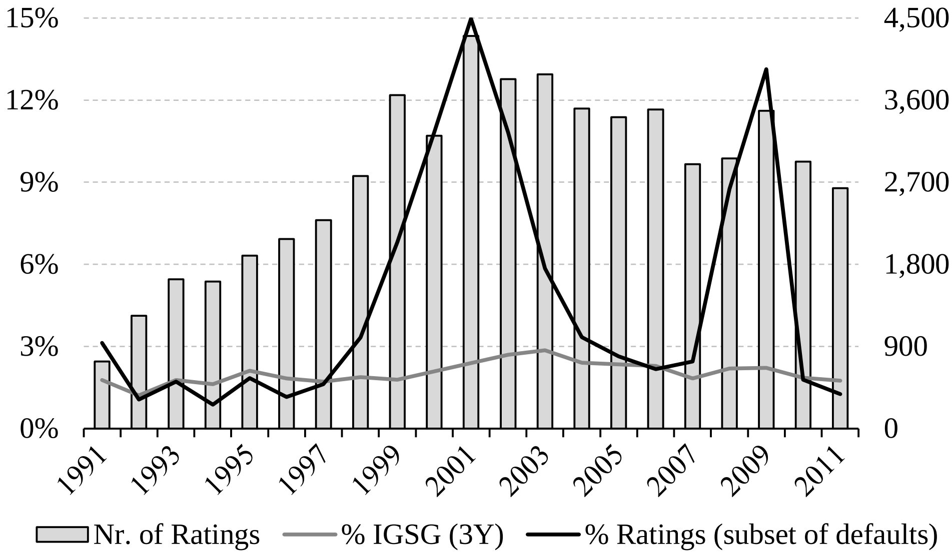

Figure 3: Yearly distribution of the prior 3-year announcements

From a univariate analysis perspective, the relation between the rate of default and the previously observed type of rating announcements, reflected in Table 8, is derived from the 31,072 announcements selected initially.[17] 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.

[17] By focusing on rating announcements, Table 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.

Table 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 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 line with the results in Subsection 2.2, Table 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 shown in Table 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 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.

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 1.

Table 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 Section 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 10 summarizes the results obtained. As expected, the table complements the results shown in Table 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 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 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

4. Causality analysis

4.1. Literature review of causality methods

4.1.1. Propensity score matching

We can look at a Type-A 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 $\Omega = 1$ if a firm has a Type-A announcement, and $\Omega = 0$ otherwise. $E(D_\Omega)$ denotes the expectation of default in each situation; $E(D_1)$ is the expected level of default related to the announcement and $E(D_0)$ is the expected level of default related to its absence.

To compare the factual and counterfactual outcomes, we would need to know the average treatment effect at the population level.[18] Such effect corresponds to the difference in expected default of firms with a Type-A 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 $E(D_1 - D_0)$; this measure requires that, for each firm, we were able to observe simultaneously mutually exclusive events. As parallel universes do not exist, we cannot observe at the same time a firm with and without a Type-A announcement. Thus, we compute instead the average treatment effect of the announcement only on the subgroup of cases with that treatment (the treated cases), as

$$\mathrm{ATT} = E(D_1 - D_0|\Omega = 1) = E(D_1|\Omega = 1) - E(D_0|\Omega = 1) \qquad (4)$$

In our case, ATT is the average effect of the Type-A announcement computed on those firms that actually had such announcement. As the counterfactual for firms with a Type-A announcements, i.e. $E(D_0|\Omega = 1)$, is not observed, 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

[18] As before, the factual of downgrades denote what effectively happened to firms with downgrades, while the counterfactual means what would have happened to the same firms if such downgrades did not occur.

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 in this paper, PSM finds firms without a Type-A announcement 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, something that ultimately turns out to be unmanageable, the information for similarity comparison is captured by one single metric: the propensity score.

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

$$P\ (X) := P(\Omega = 1|X) \tag{5}$$

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.

$$(D_1, D_0) \perp \Omega|X \tag{6}$$

In our study, this statistical independence implies that a Type-A 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 $P(X)$

$$(D_1, D_0) \perp \Omega|P(X) \tag{7}$$

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

$$0 < P(\Omega = 1|X) < 1 \tag{8}$$

This assumption is essential to ensure that we find matches for $\Omega = 1$ and $\Omega = 0$ in the region of common support, which implies 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-A 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. $\hat{P}(X|\Omega = 1) = \hat{P}(X|\Omega = 0)$. 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 (8), ATT remains valid only for those firms with announcements which are comparable to the firms without announcements, i.e. where common support remains.

As long as the previous assumptions hold and taking into account (7), we may estimate ATT using the unconditional effect over the predicted probability of having a Type-A announcement. The announcement effect for firm i is

$$\begin{aligned}\tau_i &= D_{1,i} - D_{0,i} \\ &= D_{1,i} - E[D_0|\Omega = 0, P(X) = P(X_i)] \\ &= D_{1,i} - \sum_{j\in\{\Omega=0\}} \omega(i,j) D_{0,i} \end{aligned} \tag{9}$$

where $\omega(i,j)$ is the weight assigned to matched firm j to aggregate outcomes in the control group. $E[D_0|\Omega = 0, P(X) = P(X_i)]$ is the counterfactual for firm i, which can be estimated as a weighted average of outcomes in the control group ($\Omega = 0$). Aggregating (9) for all N_1 firms with the announcement, we obtain an estimator of (4) by averaging the effect, as in Heckman et al. (1998)

$$\widehat{\mathrm{ATT}} = \frac{1}{N_1} \sum_{i\in\{\Omega=1\}} \left[D_{1,i} - \sum_{j\in\{\Omega=0\}} \omega(i,j) D_{0,i} \right] \tag{10}$$

Note that, albeit the balancing property may have been reached, as $P(X)$ 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 (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 2.1, are then selected as potential covariates for the propensity to have a Type-A announcement. Here, we allow for the advantages of including only those variables that determine treatment assignment, as highlighted by Austin et al. (2007).

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 (1), we use an econometric approach to measure the effects that Type-A 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 the decision to have credit ratings. 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.

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

$$\Omega_{i,t}^{*} = X_{i,t-1}\mu + u_i \tag{11}$$

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

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

The outcome equation is

$$
\begin{aligned}
Y_i &= P(D_{i,t} = 1) \\
&= f(Z_{i,t-1}B + \delta \cdot \Omega_{i,t} + \varepsilon_{i,t})
\end{aligned}
\tag{12}
$$

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

Equation (12) is expressed by a functional form f which may be nonlinear, as in equation (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 such as the logit or probit functions 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-A 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 both models.

Finally, a special concern must be paid to the correlation coefficient between error terms of equation (11) and (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 (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 two-step consistent estimator or maximum likelihood.

4.2. Results of the propensity score matching approach

In order to predict the occurrence of Type-A 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. The prefix *Av* is added to each covariate to denote the respective 3-year average prior to the reference year. As the dependent variable is binary (announcement vs. absence of announcement), we apply a logistic regression instead of ordered logit or ordered probit approaches.[19] Denoting $AvI_{j,i,t-1}$ as the 3-year average of each j covariate ($j = 1, \ldots, N$), equation (12) provides the propensity of a Type-A announcement in firm i and time period t

$$P(\Omega_{i,t} = 1) = \frac{1}{1 + exp\left[-\left(\alpha + \sum_{j=1}^{N} \beta_j AvI_{j,i,t-1} + V_{i,t}\right)\right]} \tag{13}$$

α and β_j are parameters and $V_{i,t}$ is a residual variable.

Note that all observations, rated and unrated, are inputs to estimate the regression; therefore, the probability of a type A announcement reflects the simultaneous occurrence of two events: the firm is rated and has a type-A announcement. The first event is actually a requirement for the second, since a firm cannot have a Type-A announcement without being rated. Table 11 exhibits the results.

Table 11: Prediction of Type-A announcements

This table reports the estimates of two logistic regressions that predict Type-A 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					

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, the correlation between covariates mostly well below 0.5, and in view of signs of parameters generally in line with expectations.

[19] 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).

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 1. In what concerns size, the findings suggest a negative influence on ratings, which results in a greater likelihood of downgrades of IGSG type in larger firms. This is somewhat contrary to the findings in Kisgen (2006). Besides potential differences in the samples, another conceivable explanation for dissimilarities in results lies in the fact that our model predicts the occurrence of two events, which include the likelihood of being rated, in addition to the type of rating assigned. Indeed, Table 7 confirms the expectation that largest companies are more likely to be rated. Three of the previous types of covariates are also common to the regression that predicts credit default: size of firms, profitability and market value. Although leverage belongs to both regressions, we measure it differently in each of them. *TDLM* and *LTAT* adjust better to forecast credit default, whereas *AvLTDL* is better to predict IGSG and SGSG14 announcements.

In relation to SGSG14 announcements, it is noteworthy to underline that both leverage and market risk have significantly higher marginal effects when compared to the results obtained for IGSG announcements; the same applies to the respective *z*-values. Such results suggest a higher influence of these variables 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 4.1.1, we select the nearest-neighbor matching method, whence the estimates of ATT, reported in Table 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.[20] 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.

[20] 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 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 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 2.2.4, when we estimated 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 2.2.5. 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 extend the analysis to the Heckman treatment effects approach.

4.3. Results of the Heckman treatment effects approach

Estimating a Heckit model requires that we first define the variables both in the selection equation (11) and in the regression equation (12). Given the high accuracy revealed by our previous estimations, we use variables selected for estimating credit default (Table 2) and credit announcements (Table 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 do not accept 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 (1). Anyhow, the value of $\hat{\rho}$, equal to 0.0332, is actually quite low, 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 13. The estimate of ρ indicates once more a negligible value ($\hat{\rho}$ = -0.002), implying that the risk of endogeneity bias in equation (1) remains remote. With a p-value of 0.765, H_0: $\rho = 0$ is now accepted, supporting the remoteness of such risk.

Table 13: Treatment effects model estimates for SGSG14 announcements

This table shows 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 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.

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 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 is investors’ confidence; therefore, the stronger is the impact on the issuer financial performance and on its risk of default.

Table 14: Estimated effects caused by IGSG and SGSG14 announcements on credit default
This table summarizes the results achieved using the methodologies discussed in Sections 5 and 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.

However, these results should not be seen as a red light for 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 suggest 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, our findings imply 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.

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 is 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, 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 corroborate and mainly provide an explanation for the finding in Löffler and Maurer (2011), that ratings provide valuable information for default prediction. 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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