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The impact of credit ratings on firms' capital structure decisions

A study on the European market

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Abstract

Title	The impact of credit ratings on firms' capital structure decisions – A study on the European market
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Keywords	Credit ratings, capital structure, financing policy, trade-off theory, pecking order theory
Purpose	The aim of this study is to empirically investigate the impact of credit ratings on European firms' capital structure decisions based on the premise of Darren Kisgen's Credit Ratings–Capital Structure (CR-CS) hypothesis: that firms face discrete costs (benefits) associated with differences in credit rating levels.
Methodology	The methodology employed in this study is of a deductive and quantitative nature, investigating the relationship between credit ratings and capital structure with the use of multiple regression models.
Theoretical perspectives	This study's theoretical framework consists of previous research on credit ratings and their impact on capital structure decisions, as well as the main theories on capital structure, namely the trade-off theory and the pecking order theory.
Empirical foundation	This project's empirical investigations are based on historical data from Standard & Poor's long-term issuer rating and firm financials on a sample of 169 firms. The data collected covers a 10-year period, amounting to a total of 1,464 firm-years (1,374 excluding missing values for commonly used variables).
Conclusions	The findings of this study support the hypothesis of credit ratings as a determinant in firms' choice of capital structure. We find that concerns of discrete costs associated with changes in credit ratings result in adjustments being made to capital structure: firms near a change in Broad Rating and investment-grade/speculative-grade status issue 0.97% and 1.60% less debt relative to equity, respectively, than firms not near a change. This behaviour does not appear to be explained by the trade-off and pecking order theories. This study also expands the empirical scope on this topic. Previous investigations have largely been limited to the US (and to some extent, international) market, whilst this study investigates the CR-CS hypothesis on a European sample. Moreover, the analytical structure of this study further refines and strengthens the analytical basis of the hypothesis.

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List of abbreviations

BLUE	Best linear unbiased estimators
CLRM	Classical linear regression model
CRA	Credit rating agency
CR-CS	Credit Rating–Capital Structure hypothesis
IG	Investment grade
IGSG	Investment Grade vs Speculative Grade
MM theorem	Modigliani and Miller theorem
OLS	Ordinary least squares
POM	Plus or Minus
SG	Speculative grade
S&P	Standard and Poor's

1 Introduction

1.1 Background to the study

The decision of a firm's management regarding the combination of long-term debt and equity capital used to finance its assets – i.e. its capital structure decision – is one of the firm's most important financial decisions, and one to which managers devote substantial attention (Ogden et al., 2003). There has therefore been considerable debate in the academic literature around which factors influence capital structure decision making.

The modern theory of capital structure decision making originates from the seminal work of Modigliani and Miller (1958), which under strict assumptions concludes that the value of a firm should be independent from its capital structure, i.e. a firm's value is not affected by its leverage. However, the Modigliani–Miller (MM) theorem includes the assumption of a perfect market and ignores a number of important factors in the capital structure discussion making process, and was therefore later adjusted as well as further developed into other theories due to the realization of market imperfections, such as bankruptcy costs, taxes, agency costs and information asymmetry (Myers, 1984; Myers and Majluf, 1984; Kraus and Litzenberger, 1973; Modigliani and Miller, 1963).

Following the works of Modigliani and Miller (1958, 1963), substantial research efforts have been made into determining the optimal capital structure for firms. Two main theories have emerged: the "trade-off" theory and the "pecking order" theory, introduced by Myers (1984) and Myers and Majluf (1984), respectively. While the trade-off theory relaxes the MM theorem assumptions of bankruptcy costs and taxation, the pecking order theory introduces information asymmetries as an underlying assumption. Several studies have found evidence to support both the trade-off and pecking order theories (e.g., Brounen et al., 2005; Fama and French, 2002; Shyam-Sunders and Myers, 1999), but due to the complex nature of the field of capital structure, these theories do not capture all relevant factors that may affect a firm's debt–equity choice, and there is yet no universally accepted theory explaining the capital structure decision of firms (Adeyemi and Oboh, 2011; Kronwald, 2009).

Credit ratings have come to serve an important role in today's financial markets, informing market participants about companies' creditworthiness (Gonis, 2010). Gonzalez et al. (2004) point out that achieving a desirable credit rating is frequently incorporated into company goals and represents an integral part of a firm's capital structure policy. For example, McWilliams (2004, p. B.10) reported in the *Wall Street Journal* that "hoping to forestall a credit-rating downgrade", Electronic Data Systems was issuing more than USD 1 billion in new shares, whereas Cimilluca (2009, p. B.3) reported that Xstrata was planning to sell USD 6 billion in shares to "shore up its investment grade credit rating amid a fierce downturn in the mining industry". In a US survey based on the response of 392 CFOs, Graham and Harvey (2001) found that maintaining a good credit rating was the second most important factor affecting a firm's financing policy.

While previous survey-based research has revealed credit ratings to constitute an important factor in capital structure decisions, little prior research empirically investigated the effect of credit rating changes on firms' leverage levels. Kisgen (2006) provided the first empirical evidence that credit ratings directly affect capital structure decision making.

1.2 Problem statement

Although there has been extensive prior research examining the determinants of capital structure decisions, there is limited research explaining credit ratings as one of these determinants. Kisgen (2006) found that credit ratings directly affected capital structure decisions on the US market in the period 1986 to 2001. In his study, he found that companies near a credit rating upgrade or downgrade issued less debt relative to net equity as a percentage of total assets than firms not near a credit rating change, a finding which is inconsistent with the traditional capital structure theories, as their predictions do not include the impact of credit ratings on capital structure decisions. A similar study performed by Michelsen and Klein (2011) on an international sample in the period of 1990 to 2008 found further evidence of credit ratings' impact on firms' financial gearing decisions. What the previous studies on the topic have in common is that they largely focus on US data due to the extensive use of corporate bonds as well as credit ratings in the US capital markets. An interesting extension of these previous studies would be to investigate a

European sample in order to determine if the results would fall into a similar pattern and whether European and US managers follow a similar approach in their choice of financial gearing.

To our knowledge, no previous studies investigating the relationship between credit ratings and capital structure have focused empirically solely on the European market, rendering this present study unique. In addition, none of these previous studies spanned the entire 2002–2011 period. While we recognize that including the years of the recent global crisis may add some statistical noise to our results, this nevertheless renders this study's scope both up-to-date and relevant.

1.3 Aim and objectives

Kisgen (2006) found that, due to concerns of discrete costs (benefits), firms near a credit ratings change issued less debt relative to equity than firms not near a credit rating change. The aim of this study is to empirically investigate the effect of credit ratings on European firms' capital structure decisions, extending the scope of previous works on the topic by focusing on the European market and taking into account a period of study not as yet investigated.

More specifically, the aim is to investigate the aforementioned relationship in a sample of 169 firms, present or historical constituents of the leading STOXX Europe 600 Index over the period of 2002 to 2011.

This study is based on the premise of Kisgen's Credit Rating–Capital Structure hypothesis (CR-CS) that firms face discrete costs (benefits) associated with differences in credit rating levels, and its aim is to empirically investigate whether or not capital structure decisions are affected by these costs (benefits).

1.4 Research question

In order to examine whether credit ratings have a measurable impact on firms' capital structure policy making in Europe, the following two specific research questions were formulated to guide the study:

(1) *Do potential Broad Rating category changes lead to pronounced effects in firms' subsequent capital structure decisions?*

(2) *Do potential investment and speculative grade rating changes lead to pronounced effects in firms' subsequent capital structure decisions?*

1.5 Scope and limitations

As mentioned above, little prior research has examined whether CR-CS holds true outside the US market. The Swedish market, or even the Nordic market, may be too small a sample as historically there has been a rather limited number of rated companies. Therefore in order to obtain significant results, this study focuses on a sample representative of the European region as a whole.

The time period for this study is set at 2002–2011 and the sample includes 169 non-financial firms currently trading on a stock exchange and with a presence on the STOXX Europe 600 Index in the period under study. The credit ratings data used in this study is Standard & Poor's long-term domestic issuer rating, which Kisgen (2006) argues represents the "corporate credit rating". Chapter 3 will discuss the selection procedures and criteria in greater detail.

The present study will focus on the so-called Plus or Minus (POM) and Investment Grade vs Speculative Grade (IGSG) tests constructed by Kisgen (2006) in the empirical investigation of his CR-CS hypothesis. The POM and IGSG tests will constitute the basis of our empirical investigation.

2 Theoretical framework

2.1 Credit ratings

Since John Moody pioneered the ratings business of securities in 1909 by publishing publicly available bond ratings focusing solely on railroad companies, credit ratings and rating agencies have evolved over time and come to serve an important role in today's financial markets (Gonis, 2010; White, 2010). The increased role of credit ratings is largely attributable to the expansion and globalization of the financial markets, with a larger number of debt securities issued by corporations and the development of new financial instruments such as asset-backed securities and credit derivatives. It also relates to the increased use of credit ratings in financial regulations and contracting, where credit ratings serve as a credit quality benchmark (Frost, 2007).

The three most prominent credit rating agencies (CRAs) in today's financial markets are: 1) Standard & Poor's, 2) Moody's, and 3) Fitch (White, 2010). Commonly, they assign credit ratings for a number of different issuers (e.g. companies, nations and local governments) of specific debt. These credit ratings are independent assessments designed to measure the fundamental credit strength of issuers of debt, i.e. their ability and willingness to meet ongoing financial obligations as they fall due (Gonzalez et al., 2004; Ogden et al., 2003). This thesis will focus solely on credit ratings assigned to companies.

Cantor and Packer (1994) point out that CRAs, in general, base their ratings on both quantitative and qualitative information regarding a firm's financial condition, and Kisgen (2006) adds that credit ratings may provide information on the quality of a firm beyond publicly available information. Moreover, Gonzalez et al. (2004) argue that these ratings, which stem from fundamental analysis, are opinions used to classify firms' creditworthiness on an ordinal scale. As such, ratings do not constitute a trading recommendation or indication of an investment's sustainability for a particular investor.

As there is no standard approach to credit ratings, each CRA defines its own ratings and employs its own set of criteria or methodology. Therefore, the precise meaning of credit ratings depends on the CRA that issues them (Al-Hindawi, 2006).

This present study employs Standard and Poor's long-term issuer credit rating, also known as a firm's "corporate credit rating" (Kisgen, 2006). In summary, Standard and Poor's (2009) states that its credit ratings:

- Express forward-looking opinions about the creditworthiness of issuers and obligation
- Are designed primarily to provide relative ranking among issuers and obligations of overall creditworthiness; the ratings are not measurements of absolute default probability. Creditworthiness encompasses likelihood of default, and includes (i) payment priority, (ii) recovery, and (iii) credit stability.

Source: Standard and Poor's, 2009

In other words, Standard and Poor's (S&P) credit ratings are designed to capture a company's overall creditworthiness and provide a relative ranking of default risk across firms. However, creditworthiness is a summary of a complex and multifaceted phenomenon that, in itself, is difficult to define. S&P's primary factor in estimating creditworthiness is the likelihood of default, i.e. that the issuing firm will fail to meet promised payments on a timely basis. Other factors in estimating credit quality include the firm's priority of payments and capacity of recovery, as well as the sensitivity of its default risk to rating changes (Standard & Poor's, 2009).

S&P (2009) distinguishes between *issuer* ratings (applied to corporate entities) and *issue* ratings (applied to specific financial obligations). The former is used on obligors in their entirety and assesses their overall capacity and willingness to meet ongoing financial obligations, while the latter addresses an obligor with respect to a specific financial obligation or financial programme. Credit ratings are further categorized by S&P on the basis of their rating horizon, and as a result are stated either as *long-term* or *short-term*. The time horizon distinction is used due to the pro-cyclicality concept where the long-term credit rating indicates the creditworthiness without taking into account the effects of business or credit cycles (Gonis, 2010). Volatility of rating due to temporary effects on an obligor's creditworthiness is hence reduced when using the long-term rating.

Table 1 *S&P's long-term credit ratings classification*

Explanation	Rating	Definition
Investment grade	AAA	Extremely strong capacity to meet its financial commitments
	AA(+/none/-)	Very strong capacity to meet its financial commitments
	A(+/none/-)	Strong capacity to meet its financial commitments
	BBB(+/none/-)	Adequate capacity to meet its financial commitments
Speculative grade	BB(+/none/-)	Inadequate capacity to meet its financial commitments. Major ongoing uncertainties
	B(+/none/-)	Adverse business, financial or economic conditions will likely impair the capacity or willingness to meet its financial commitments
	CCC(+/none/-)	Vulnerable and dependent upon favourable business, financial or economic conditions to meet its financial commitments
	CC, C	Highly vulnerable
	D	Failed to pay one or more of its financial obligations when came to due

Source: Standard and Poor's, 2009

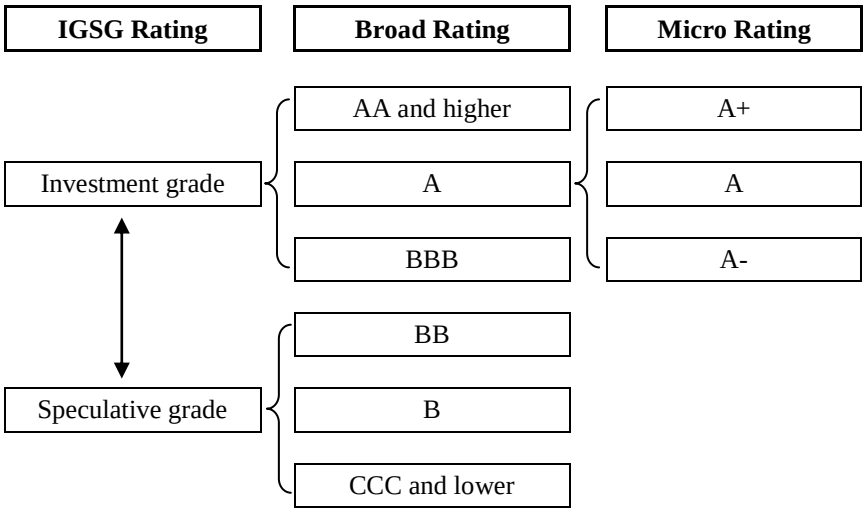
As illustrated in Table 1, S&P uses a system of letter grades from AAA (highest) to D (lowest). To refine the ratings scale so as to indicate the relative standing within the major categories (or "Broad Ratings" as Kisgen (2006) puts it, e.g., AA), S&P divides its ratings into subcategories by the addition of "+" and "-" (e.g., AA+ and AA-) (Al-Hindawi, 2006).

It is important to distinguish between two broad classifications of credit ratings: 1) investment, and 2) speculative grade. A company with an at least adequate capacity to meet its financial obligations is classified as investment grade, namely a rating of BBB- or higher. A company with a rating below BBB- carries elements of uncertainty that renders it more susceptible to default, and is therefore regarded a speculative investment. If a firm has already failed to meet its financial obligations, it is assigned a D and classified as in default.

Kisgen (2006) states that the proximity to credit rating changes can be measured in three different ways (as shown in Figure 1 below) in order to capture the concern of firms for the different types of credit rating classification changes. In addition to the investment grade and speculative grade classification, Kisgen (2006) defines a "Broad Rating" as a credit category including the plus, middle and minus specification of a certain rating, e g. B+, B and B-. Furthermore, in Kisgen's study the individual credit rating (i.e. any rating a firm can be given by S&P) is referred to as a

"Micro Rating". However, only potential changes in speculative grade status and Broad Rating category are relevant to the present study.

Figure 1 *Three kinds of rating changes*



2.2 Capital structure – Main theories

As touched on in the introduction, the seminal work of Modigliani and Miller (1958) presented one of the first theories explaining firms' capital structure choice, concluding under certain restrictive assumptions[1] that a firm's value should be independent of its capital structure. They argue that the correct action is to try to maximize the value of the firm, and that only changes that increase firm value are beneficial to shareholders. However, the realization of the tax advantages of debt financing led Modigliani and Miller (1963) to conclude that the capital structure mix is relevant to the total value of the firm, as the value of levered firms is higher than that of non-levered firms in the same risk class due to tax deductibility on interest.

[1] The main assumptions of Modigliani and Miller (1958) are as follows:

- Firms can issue only two types of securities: equity and risk-free debt (the Weighted Average Cost of Capital (WACC) is the same for both);
- Financial markets are perfect and frictionless;
- Thereare no transaction costs;
- There are no default risks, i.e. firms cannot go bankrupt;
- There is no taxation;
- Firms and investors both have the same set of information;
- Company management acts exclusively on the behalf of shareholders.

However, the assumptions of Modigliani and Miller (1958) do not hold in practice as the market contains imperfections (Kraus and Litzenberger, 1973). It is therefore necessary to loosen some of these assumptions in order to arrive at a theoretical framework that better reflects the reality of firms. Subsequently, two main theories explaining how firms determine their capital structure have emerged, namely the trade-off theory and pecking-order theory (Myers, 1984; Myers and Majluf, 1984), a brief overview of which is provided below.

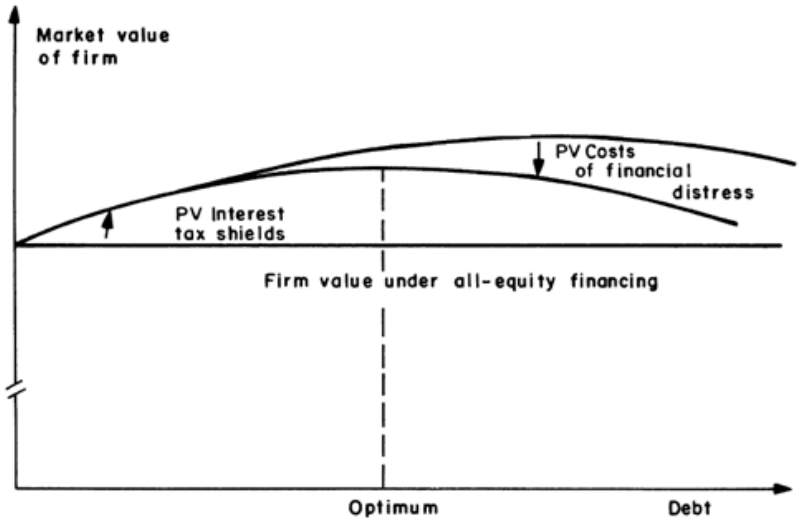
2.2.1 Trade-off theory

In the trade-off theory, capital structure decisions depend on the costs and benefits associated with debt financing, or to put it another way, a firm's optimal leverage is determined by a trade-off of the costs and benefits of holding debt (Myers, 1984). The theory holds that a firm, in order to achieve an optimal capital structure that maximizes the total market value, seeks debt levels that balance the value of interest tax shields against the various costs of bankruptcy or financial distress.

Fama and French (2002) argue that costs associated with leverage, apart from the actual capital cost in terms of interest payments, include costs of financial distress or bankruptcy and agency conflicts between stockholders and bondholders caused by risky debt. But in contrast to the cost of debt, leverage also brings benefits to the firm. Holding debt results in the deduction of interest payments from a firm's taxable income, which is referred to as its tax shield and is an important factor in capital structure decision. Another benefit of holding debt is the monitoring effect leverage has on cash flows, i.e. reduced waste of internal funds through interest payments and amortization (Fama and French, 2002).

In the theory, it is important to note that firms are financed partly with debt and partly with equity. The trade-off theory states that at the leverage optimum, the benefit of the tax advantages of additional debt just offsets the cost of possible financial distress (Kronwald, 2009). In line with this, Marsh (1982) argues that value-maximizing firms will systematically adjust their leverage to reach their target debt ratio, i.e. the optimal leverage level. Hence, when the debt–equity ratio is below the optimal level, the firm will issue more debt, and vice versa.

Figure 2 *The trade-off theory of capital structure*



Myers, 1984, p.30

Figure 2 depicts the trade-off theory of optimal capital structure and shows that a firm seeks debt levels that balance the marginal present value of interest tax shields and costs of financial distress or bankruptcy.

2.2.2 Pecking order theory

The pecking order theory takes a different approach to capital structure decisions, including the underlying assumption of asymmetric information, claiming that firms follow a certain pecking order when determining their capital structure (Myers and Majluf, 1988). As a result of asymmetric information, firms prefer internal funds to external capital, and debt opposed to equity (Myers, 1984). Kronwald (2009) suggests that this problem occurs because managers have an incentive to use private information to issue new shares when these are over-priced, which investors will take into account and which causes them to demand a higher risk premium. In turn, this increases the cost of equity and therefore makes debt more preferable.

In contrast with the trade-off theory, here the benefits related to tax shields and the costs of financial distress are of second order (Shyam-Sunder and Myers, 1999; Myers and Majluf, 1988). Furthermore, Shyam-Sunder and Myers (1999) stress that in the pecking order model, the optimal capital structure does not determine the level of debt; unlike the trade-off theory, there is no optimal debt ratio. Firms will issue more or less debt depending on access to internal funds when

financing an investment. Leverage will function as a short-term offset to finance a predicted deficit. Thus, when investments exceed internal capital, firms will increase the amount of debt, and vice versa (Frank and Goyal, 2003).

2.3 Relationship between credit ratings and capital structure

2.3.1 Credit Rating–Capital Structure hypothesis

As an extension of the existing capital structure theories, Kisgen (2006) proposed the Credit Rating–Capital Structure hypothesis (CR-CS), which holds the following:

- Credit ratings are a material consideration in managers' capital structure decisions due to the discrete costs (benefits) associated with different rating levels;
- Concern for the impact of credit rating changes directly affects capital structure decision making, with firms near a ratings change issuing less net debt relative to net equity than firms not near a ratings change.

Kisgen, 2006, p.1037

This hypothesis holds that different credit ratings are associated with discrete costs (benefits) to the firm. If the rating-dependent costs (benefits) are material, managers will balance these discrete costs (benefits) against the costs and benefits implied by the trade-off theory when making capital structure decisions. Further, CR-CS states that firms near a ratings change are more likely to undertake leverage-reducing activities than firms not near a ratings change.

Per Kisgen (2003), there may be several reasons behind the discrete costs (benefits) and the premise that credit ratings are likely to affect capital structure decisions:

(1) Kisgen points to *regulatory effects*: that a number of regulations on financial institutions and other intermediaries are directly tied to ratings. In line with this, Cantor and Packer (1994) suggest that financial regulators, including the public authorities that oversee capital markets, banks, insurance companies, thrifts, mutual funds and pension funds, have made increasing use of credit ratings in their decisions and adopted ratings-dependent rules. Gonzalez et al. (2004)

argue that the use of ratings and the influence of credit rating agencies' (CRAs) opinions has now grown to the extent that it has become ubiquitous in financial markets, acting increasingly as a credit quality benchmark. Rating-based rules are less common in Europe compared to the US, yet they functions as an important regulatory framework within Europe as well. In the Basel II project, for instance, credit ratings were used as a way of weighing risk exposure for a standardized approach to credit risk (Van Roy, 2005). In line with this, Michelsen (2011, p.6) puts forward that *"the capital requirements of Basel II and III increase the regulatory costs of lower rated securities for banks, which, in turn, also add to the required yield on the investment."* As a result of regulatory effects, Kisgen argues that although the firm itself may not have a higher default risk, it may be required to pay higher interest rates on its debt merely as a result of its credit rating. It is important to note that the discrete costs of the regulatory effects are most prominent in the change from investment to speculative grade, and not within a rating category.

(2) Kisgen points to *pooling effects*: that credit ratings may provide information to investors and that the information content of ratings on the credit quality of a firm could go beyond other publicly available information, as CRAs may have access to information that is not publicly available. As such, credit ratings signal the overall quality of the firm to investors, resulting in discrete differences in its cost of capital from different rating levels. The impact of these signals may disfavour high-performing firms within the same rating, as these are pooled together with lower performing firms. The rating will signal the same risk of default and yield spread irrespective of the fact that the quality of the firms within a specific group will differ. By this argument, any kind of change in credit rating should be significant for capital structure decisions.

(3) Kisgen also suggests that credit ratings may affect the firm's *third party relationships*, including its relationship with employees, suppliers and customers. Lower credit ratings may incur direct costs by limiting a firm's access to the financial markets (e.g. the commercial paper market), and also negatively affect the firm's business operations. Credit ratings affect the commercial paper market's ratings, which in turn determine which investors will invest in a firm. Major investors, such as the money market funds, exclusively invest in high-rated commercial papers. Furthermore, business operations are negatively affected due to restrictions on entering into long-term contracts and swap arrangements dependent on credit rating level.

(4) Kisgen contends that *utility-maximizing managers' concern for their reputation* may induce discrete costs related to credit rating changes. Due to the effect that credit ratings have on reputation, managers might target a level of debt that is not optimal for the firm but is a debt ratio that increases the chance of an upgrade. The association that higher credit ratings have with higher reputation and how it may affect managers' compensation, job security and other work opportunities, can make credit rating changes material in capital structure decisions.

(5) Kisgen also argues that *ratings triggers* may impose discrete costs due to the impact of credit rating changes on bond covenants directly tied to the firm's credit rating. That is, a change in credit rating can cause a change in the firm's coupon rate or a forced repurchase of bonds, which would limit the firm's liquidity. Bond covenants are mainly tided to larger changes in credit ratings, which implies that the impact of rating triggers is more significant around the speculative-to-investment-grade end of the scale.

Kisgen's (2003) arguments, as summarized above, underlying the predictions of the CR-CS model provide support for the relevance of credit ratings in capital structure decisions due to the various discrete costs incurred in case of a change in IGSG or Broad Rating status.

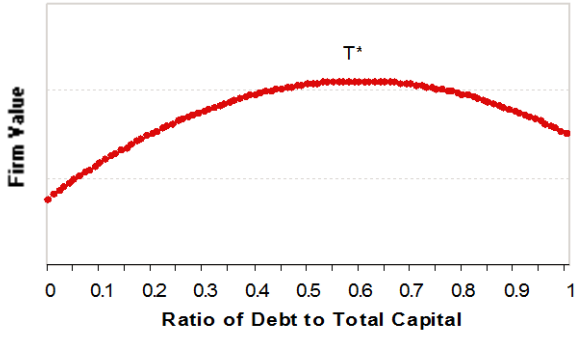
2.3.2 Credit ratings in the context of traditional capital structure theories

Kisgen (2006) states that the CR-CS hypothesis complements the traditional capital structure theories by explaining deviations in leverage from the debt level implied by the trade-off and pecking order theories with the discrete costs associated with a potential credit rating change. Recall that per Kisgen's CR-CS model, if these costs are material, managers will balance these discrete costs (benefits) against the costs and benefits implied by the traditional capital structure theories in order to decide capital structure. The trade-off theory implies that the benefits of holding debt (e.g. the tax shield) will cause firms of higher quality (rating), and thereby lower risk of bankruptcy, to issue more debt relative to firms of lower quality. In contrast, CR-CS predicts that firms irrespective of credit quality will issue less debt when close to a credit rating change. Comparing the CR-CS theory with the trade-off theory, in certain cases the credit rating effects in the CR-CS model will outweigh those in the trade-off theory, and vice versa, depending on how near the firm is to a change in credit rating.

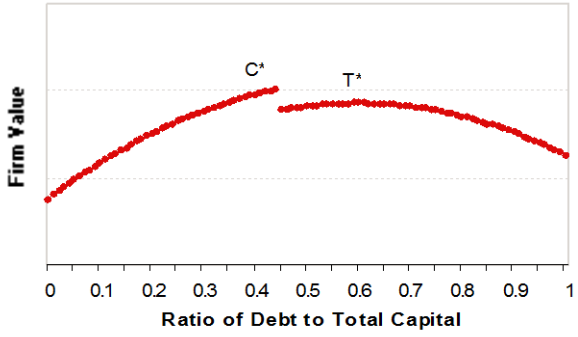
Figures 3A–E, illustrate the firm value as a function of leverage, and depict the balance of costs implied by the CR-CS and trade-off theories.

Figure 3 *Firm value with trade-off and credit rating effects*

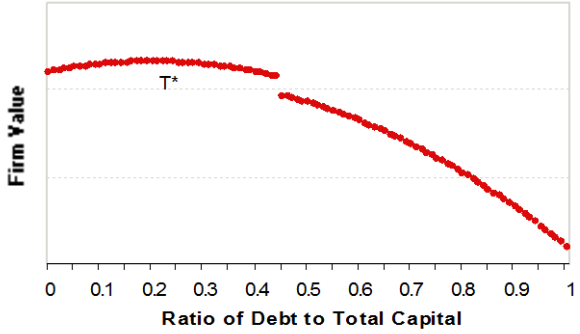
Panel A: No credit rating level costs (benefits)



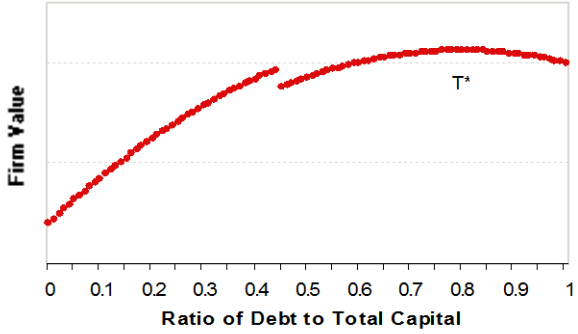
Panel B: One rating cost, firm near ratings change



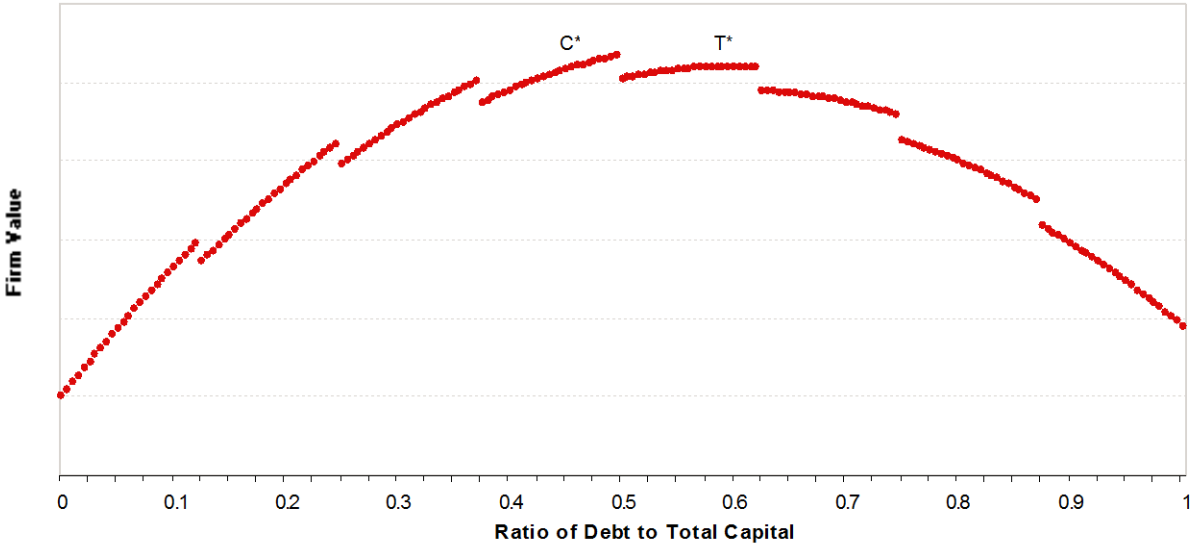
Panel C: One rating cost, firm not near change



Panel D: One rating cost, firm not near change



Panel E: Trade-off theory and discrete costs (benefits) associated with different rating levels



Kisgen, 2006, p.1042

In panel A, *T** indicates the optimal capital structure implied by the trade-off theory that maximizes the overall value of the firm in the case of no discrete costs (benefits) associated with credit rating changes.

Panels B–E graphically illustrates situations where discrete costs (benefits) of credit ratings exist. Figure 3B depicts a situation where CR-CS factors outweigh the trade-off theory factors. If a firm is close to a potential rating change, the firm will maximize the overall value by issuing less debt relative to equity than implied by the trade-off theory in order to either avoid a downgrade or to obtain an upgrade. *T** shows the optimal leverage level when only the trade-off theory factors are taken into account, while *C** denotes the new optimum level that maximizes the firm value by including the impact of discrete costs (benefits).

In contrast to Panel B, Panels C and D depict situations where the implications of the trade-off theory outweigh the CR-CS. If *T** relates to a credit rating where the risk of a potential downgrade (Panel C) or upgrade (Panel D) is low, the discrete costs will not be considered material in managers' capital structure decisions. The cost of moving too far from the optimal debt level implied by the trade-off theory (*T**) by issuing less debt in order to obtain an upgrade will therefore outweigh the cost of a lower rating.

Figure 3E depicts the discontinuous relationship between leverage and firm value caused by discrete costs for multiple credit rating levels, in the graph illustrated as several jumps. *T** indicates the optimal leverage based solely on the trade-off theory predictions, whilst *C** shows the optimum including the effect of credit ratings.

The pecking order theory implies that firms use internal capital rather than external capital and prefer debt to equity due to information asymmetry (Myers, 1984). An implication of the theory is that firms near a downgrade or an upgrade in certain cases issue equity over debt. Kisgen (2006) argues that as a result of the discrete costs deriving from credit ratings, firms will weigh the benefits of debt against the costs of a credit rating change. This contradicts the pecking order model’s predictions that debt will be preferred to equity unless only risky debt is available. The costs imposed by a credit rating change do in some cases outweigh the costs of equity and therefore make equity more preferable, resulting in capital structure behaviour not consistent with that implied by the pecking order theory.

2.3.3 Literature review and CR-CS model specifications

Kisgen (2006) carried out the first empirical examination of the effects of changes in credit ratings on subsequent capital structure decisions by investigating the US market over the period 1986–2001 with 12,851 firm-years. His study was later complemented by the works of Michelsen and Klein (2011), who investigated an international sample over the period of 1990–2008 with 13,363 firm-years. Both these studies employed the CR-CS hypothesis developed by Kisgen (2006), attempting to prove that managers' capital structure decisions were affected by credit ratings and that they made strategic decisions concerning the capital structure of their business based on the potential impact that these might have on the company's credit rating.

As pointed out in section 2.1, Kisgen distinguishes between three rating changes associated with discrete costs (benefits). In section 2.3.1, several reasons (e.g. regulatory effects, pooling effects and ratings trigger) were given as explanations behind these discrete costs (benefits), anticipated by a change from investment grade to non-investment grade, from one Broad Rating category to another (e.g. AA to BBB), or from one Micro Rating to another (e.g. AA to AA-). In his methodological set-up, Kisgen employed three tests, one for each kind of credit rating change. The two which are most relevant to the present study are the so-called Plus or Minus (POM) and Investment Grade vs Speculative Grade (IGSG) tests (Kisgen, 2006). These tests were used by both Kisgen (2006) and Michelsen and Klein (2011).

The POM and IGSG tests employ the same dependent variable to quantify capital structure behaviour as an adequate measure of debt relative to equity issuance. Based on the beginning-of-the-year credit rating situation for a firm, it is calculated on a 12-month subsequent period of time as the net amount of net debt and net equity raised for the year. To allow for a formal investigation of the relationship between changes in Broad Rating categories, changes in investment and speculative grade categories, and managers' leverage policies, Kisgen introduced dummy variables to distinguish between firms near an upgrade/downgrade and those that were not. Kisgen's tests can be summarized as follows:

POM test:

$$NetDIss_{it} = \alpha + \beta_1 CR_{POM} + \phi K_{it} + \varepsilon_{it} \tag{2.1}$$

$$NetDIss_{it} = \alpha + \beta_2 CR_{Plus} + \beta_3 CR_{Minus} + \phi K_{it} + \varepsilon_{it} \tag{2.2}$$

$$NetDIss_{it} = \alpha + \beta_4 CR_{POM} + \varepsilon_{it} \quad (2.3)$$

and

IGSG test:

$$NetDIss_{it} = \alpha + \delta_1 CR_{IGSG} + \phi K_{it} + \varepsilon_{it} \quad (2.4)$$

$$NetDIss_{it} = \alpha + \delta_2 CR_{IGSG} + \beta_5 CR_{POM} + \phi K_{it} + \varepsilon_{it} \quad (2.5)$$

where:

$NetDIss_{it}$	=	the net debt relative to net equity issuance, scaled to total assets
CR_{IGSG}	=	dummy for firms with a BBB, BBB-, BB+ or BB rating, then CR_{IGSG} = 1; 0 otherwise
CR_{POM}	=	dummy for firms with a rating followed by "+" or "-", then CR_{POM} = 1; 0 otherwise
CR_{Plus}	=	dummy for firms with a rating followed by "+"; then CR_{Plus} = 1; 0 otherwise
CR_{Minus}	=	dummy for firms with a rating followed by "-"; then CR_{Minus} = 1; 0 otherwise
K_{it}	=	set of lagged control variables, including leverage: total debt to total capitalization, profitability: EBITDA divided by assets, and size:the natural logarithm of Sales.

Furthermore, the empirical set-up of the POM and IGSG tests that both Kisgen (2006) and Michelsen and Klein (2011) tested was based on the following hypotheses:

POM Test:

$H_0 : \beta_i \geq 0 \qquad i = 1, 2, 3, 4$

$H_1 : \beta_i < 0$

and

IGSG Test:

$$H_0 : \delta_i \geq 0 \qquad i = 1, 2$$
$$H_1 : \delta_i < 0$$

The null hypothesis imply that managers are unconcerned about ratings in their capital structure decisions. In order to reject the null hypothesis, and for the CR-CS to hold true, the coefficient value of each of the dummy variables in the models are expected to be negative, since firms represented by these, as hypothesized, should be less likely to issue debt relative to equity compared to firms not represented.

Firms with a credit rating accompanied by a plus or minus are given the value of 1 in the dummy variable CR_{Plus}, CR_{Minus} or CR_{POM}. Kisgen (2006) interprets the plus or minus following a credit rating as a signal that the firm is near a Broad Rating change, and thereby concluded that firms designated with such a rating (e.g. BBB+ and A-) were less likely to issue debt relative to equity than firms in the middle of a Broad Rating category (e.g. A). Kisgen argues that this approach should accurately reflect whether a firm is near a credit rating change, but highlights one disadvantage: namely that in some cases this approach might be too broad, as a strong A- might not in all cases be near a downgrade and conversely, a weak A+ might not in all cases be near an upgrade (Kisgen, 2006). Similarly, for the IGSG test, Kisgen defines the CR_{IGSG} dummy variable for firms near an IGSG rating change, taking on the value of 1 for firms in the crossover rating areas BBB, BBB-, BB+ or BB.

The results of the POM regression analyses carried out by Kisgen (2006) and Michelsen and Klein (2011) presented in Table 2 below show strong support for the CR-CS model in all cases. Both Kisgen and Michelsen and Klein (2011) excluded firm-years with very large debt offerings (>10% of assets) in their regressions, arguing that the impact of credit ratings on capital structure behaviour was more prominent for small and medium-sized offerings.

Table 2 *Empirical results of the POM test carried out by previous studies*

	Kisgen (2006)			*Michelsen and Klein (2011)*		
	Model 2.1	**Model 2.2**	**Model 2.3**	**Model 2.1**	**Model 2.2**	**Model 2.3**
Intercept	-0.0787**	-0.0787**	-0.0006	1.4922**	1.4931**	-
	(0.0082)	(0.0082)	(0.0012)	(0.6129)	(0.6134)	-
CR_{POM}	-0.0058**	-	-0.0102***	-0.0196**		-
	(0.0016)	-	(0.0017)	(0.0087)		-
CR_{Plus}	-	-0.0064***	-	-	-0.0239	-
	-	(0.0020)	-	-	(0.0189)	-
CR_{Minus}	-	-0.0051***	-	-	-0.0175**	-
	-	(0.0019)	-	-	(0.0086)	-
D/(D+E)	-0.0153**	-0.0153**	-	-0.0170**	-0.0170**	-
	(0.0066)	(0.0066)	-	(0.0083)	(0.0083)	-
EBITDA/A	0.1288***	0.1293***	-	0.2668**	0.2677**	-
	(0.0265)	(0.0264)	-	(0.0965)	(0.0962)	-
ln(Sales)	0.0090***	0.0090***	-	-0.1055**	-0.1055**	-
	(0.0008)	(0.0008)	-	(0.0434)	(0.0434)	-
Adi. R^2	0.0541	0.0542	0.0030	0.0136	0.0137	-
N	10,842	10,842	10,842	11,308	11,305	-

*, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2 above show coefficients and standard errors from pooled time-series cross-sectional regressions of models (2.1)–(2.3). Both studies employ the White diagonal standard errors for all regressions. The coefficient value of CR_{POM} in regression (2.3) by Kisgen (2006) shows that firms near a ratings change annually issued 1% less net debt relative to net equity as a percentage of total assets over the subsequent period than firms not near a change in rating. Michelsen and Klein (2011), however, did not perform equation (2.3) as Kisgen did, but instead developed the approach of incorporating firms' credit rating outlook as an additional measurement of imminent rating change. Their paper showed that firms near a rating change annually issued 1.8% less net debt relative to net equity over the subsequent period than firms not near a change in rating.

Table 3 *Empirical results of the IGSG test carried out by previous studies*

	Kisgen (2006)		*Michelsen and Klein (2011)*	
	Model 2.4	**Model 2.5**	**Model 2.4**	**Model 2.5**
Intercept	-0.0814***	-0.0745	0.7555**	-
	(0.0083)	(0.0084)	(0.3783)	-
CR_{IGSG}	-0.0073***	-0.0091***	-0.0275***	-
	(0.0020)	(0.0021)	(0.0076)	-
CR_{POM}	-	-0.0071***	-	-
	-	(0.0017)	-	-
D/(D+E)	-0.0153**	-0.0151	-0.0171**	-
	(0.0066)	(0.0066)	(0.0080)	-
EBITDA/A	0.1262***	0.1251***	0.1957**	-
	(0.0267)	0.0268	(0.0821)	-
ln(Sales)	0.0092	0.0089***	-0.0489*	-
	(0.0007)	(0.0008)	(0.0251)	-
Adj. R^2	0.0545	0.0559	0.0134	-
N	10 842	10 842	11 308	-

*, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3 above presents coefficients and standard errors from pooled time-series cross-sectional regressions of models (2.4) and (2.5) by Kisgen (2006) and model (2.4) by Michelsen and Klein (2011).

For Kisgen, the coefficient value of CR_{IGSG} is negative for both models with a statistical significance at the 1% level (from -0.73% to -0.91%). Kisgen (2006) points out that the sum of the coefficients of model 2 suggests that firms with a BBB- or BB+ credit rating issue 1.62% less net debt relative to net equity (as a percentage of total assets) than other firms.

Michelsen and Klein (2011) only performed regression (2.4), which suggests, with a statistical significance at the 1% level, that firms rated in the crossover area (BBB, BBB-, BB+ and BB) issue 2.75% less debt than equity compared to other firms. Furthermore, the empirical results presented in Table 3 suggest that credit ratings are incrementally more significant at the investment-grade-to-speculative-grade than Broad Rating category crossover.

3 Methodology

3.1 Methodological approach

The empirical investigation of the CR-CS hypothesis on a European sample will largely be carried out based on the methodological set-up of Kisgen (2006). To examine whether the implications of CR-CS are identifiable on this study's sample, POM and IGSG testing will be carried out. Thus, this study employs a deductive approach, as its empirical investigations are performed on the basis of existing theories. Furthermore, this study adopts a quantitative approach as the objective is to analyze quantitative data and investigate whether there is a statistically significant relationship between credit rating and capital structure. In research based on measurements of a large sample with the intention of testing a hypothesis, a quantitative method is the appropriate approach (Lundahl and Skärvad, 1999). This study aims to investigate the CR-CS hypothesis on a sample of 169 firms, which is therefore best suited to a quantitative approach.

3.2 Sample and sampling method

The proposed sample is composed of rated constituents of the STOXX Europe 600 Index, bar financial companies. With 600 components, the STOXX Europe 600 Index is a leading benchmark representing listed large-, mid- and small-cap companies from 18 countries in the European region: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom (STOXX, 2012). However, as we will later show, some of these countries become eliminated from the sample as a result of the selection procedure applied.

The sample is composed of two kinds of secondary data obtained from the Datastream database:

1. Firms' financial information taken from their financial statements during the period 2002–2011.

2. Firms' credit ratings using the long-term domestic issuer credit rating by S&P (Datastream code BSPL). As noted earlier, this rating is the "corporate credit rating" that S&P states is designed to measure a company's "overall capacity to pay its financial obligations" (Standard & Poor's, 2009; Kisgen, 2006).

The selection criteria for the data sample are as follows:

1. The proposed sample includes present as well as historical constituents of the STOXX Europe 600 Index in the period Q1 2002 to Q1 2012.

2. Constituents deleted from the STOXX Europe 600 Index due to merger/takeover/delisting during the period under study are excluded (e.g., Al-Hindawi, 2006; Shyam-Sunder and Myers, 1999).

3. Financial institutions (ICB codes 8000–8999), i.e., banks, insurance and investment firms, are excluded from the study (e.g., Michelsen and Klein, 2011; Gonis, 2010; Al-Hindawi, 2006; Kisgen, 2006; Lasfer, 1995). Michelsen and Klein (2011) contend that the capital structure of a financial firm may differ significantly from that of a service or industrial firm. Similarly, Al-Hindawi (2006, p.99) states that *"financial firms' debt-like liabilities are not strictly comparable to the debt issued by non-financial firms"*, while Lasfer (1995) points out that financial firms should be excluded due to their specific financial gearing characteristics and their special tax treatment.

4. Any company not recognized by Datastream with a five-character mnemonic issuer/borrower code (BCOD) is excluded from the sample, as only historic S&P credit ratings can be obtained through a firm's BCOD in the Datastream database. Moreover, only the listed company's BCOD (of the holding company) is of interest, which means that any recognized subsidiaries are also excluded. As a result, a small number of constituents which in fact have been rated by S&P in their entirety during the period Q1 2002 to Q1 2012 are excluded in the final sample (simply because their credit ratings are not historically available).

5. The sample includes only companies whose credit rating and financial statements are available through the Datastream and Worldscope databases.

6. Firm-years with missing values for commonly used variables are excluded from the study (for a similar approach, compare Kisgen, 2006 and Michelsen and Klein, 2011).

7. Because the S&P rated universe in Europe is relatively small compared to its American counterpart, the sample size of this study is limited in comparison to the studies of both Kisgen (2006) and Michelsen and Klein (2011). Therefore, excluding any observations (where values are not missing) may not be the most fruitful approach. In contrast to the findings of Kisgen (2006), which were only robust with the exclusion of large debt offerings or both large debt and equity offerings, Michelsen and Klein (2011) showed in an international context that the inclusion of large debt and equity offerings may also prove robust. Due to the limited size of our sample, our empirical analysis is carried out across two different data panels: Panel A and Panel B. Panel A excludes large-sized debt offerings (>10% of total assets; for a similar approach, compare Kisgen, 2006), whereas the broader Panel B excludes the most sizeable outliers for each year. Gonis (2010) argues that models that include outliers may produce inefficient, or in extreme cases even biased, results. Therefore, after examining the dataset, Panel B excludes the two highest percentiles of both net debt offerings and net equity offerings (used for calculating the *NetDIss* variable). The idea behind excluding the most sizeable net debt and net equity offerings on a year-by-year basis is to mitigate the effect of events driven more by managements' strategic decisions (e.g. M&As, large diverstures/restructuring) than by rating considerations, whilst maximising the sample size. Thus Panel A adopts Kisgen's approach and extends it to the European sector (excluding approximately 10% of total observations with values reported for all variables later used in our regressions), whilst Panel B (excluding 4% of total observations) represents a new methodology developed by this present study not only to create a better fit for the (target) European market, but also a more robust set of results than would be obtained by only employing Kisgen's methodology.

Our selection procedure is summarized in Table 4 below:

Table 4 *Selection procedures*

First step	Second step	Third step	Fourth step	Final sample
Select all present and historical STOXX Europe 600 constituents in the period Q1 2002 to Q1 2012 → 1,020 companies	Exclude equities that are dead due to delistings, mergers and takeovers → 783 companies	Exclude financial companies with ICB classification 8000-8999 → 609 companies	Exclude companies not recognized by Datastream as a borrower/issuer on the corporate bond market → 291 companies	Exclude companies not rated by S&P in any year from 2002 to 2011. → 169 companies

As this study does not directly address or analyze the financial distress of companies, the potential effect of survivorship bias may not be substantial (Lasfer, 1995). However, in order to minimize survivorship bias, the present study also takes into account constituent changes in the STOXX Europe 600 Index during the period under study by including all historical constituents that are still listed on a stock exchange today (and have financial information available through the Datastream database). Consequently, the initial data of this study consisted of a sample of 1,020 firms, of which 237 were historical constituents that are no longer active on a public stock exchange (largely due to delistings, mergers or takeovers), leaving 783 active companies before excluding financials firms, firms without data available in the Datastream database, and unrated firms.

The elimination of more than two-thirds of the sample after the third step of the selection procedure can largely be explained by an immature European corporate bond market (in comparison to the US corporate bond market), and subsequently a lack of recognized issuers in Datastream and a lack of S&P-rated European companies.

The size of the final sample of firms is 169, providing 1,464 firm-years for analysis in the 2002 to 2011 period, as later shown in Table 6.

3.2.1 Descriptive statistics of final sample

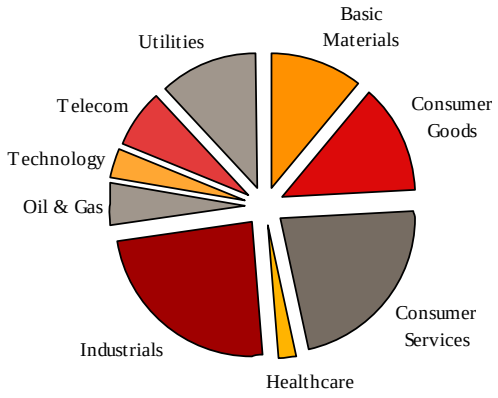
The sample for this study is presented in Appendix 1. It includes 169 firms across 9 sectors and 15 European countries. This study uses the Industry Classification Benchmark (ICB) for the

companies' industry classification. The distribution of the industries in the entire dataset is presented in Table 5 and graphically in Figure 4 below:

Table 5 *ICB industry classification of all firms in the sample*

Industry classification (IBC)	No. of firms	% of sample
Basic Materials	19	11.2%
Consumer Goods	22	13.0%
Consumer Services	38	22.5%
Healthcare	3	1.8%
Industrials	41	24.3%
Oil & Gas	8	4.7%
Technology	6	3.6%
Telecommunications	12	7.1%
Utilities	20	11.8%
Total	**169**	**100.0%**

Figure 4 *ICB industry classification of all firms in the sample*



The two most represented sectors are Industrials and Consumer Services, with a 23.8% and 22.1% share of the sample, respectively. While we recognize that firms' capital structure decisions may differ somewhat for the Utilities and Oil & Gas sectors relative to other firms in the sample. Kisgen (2006) and Michelsen and Klein (2011) point out that by including these, the POM and IGSG tests, which this study employs, will still be robust. Therefore, in order not to further restrict the size of the sample, we estimate the regressions by including these.

Table 6 below illustrates the sample's distribution over geographical regions. UK, France and Germany account jointly for nearly 58% for all firms. This shows how the S&P-rated universe in Europe is distributed. Moreover, a potential drawback in the European sample is the differences in jurisdictions between countries in terms of their respective financial markets. As a result, there may be differences in capital structure behaviour between countries. Similarly, we recognize that there may be slight differences in accounting methods in the years 2002–2004 before the mandatory implementation of the IFRS accounting standards for the European countries. This study therefore employs country dummy variables to absorb differences in regulatory effects.

Table 6 *Geographic regions of the sample*

Geografic region	No. of firms	% of sample
Belgium	5	3.0%
Denmark	1	0.6%
Finland	7	4.1%
France	39	23.1%
Germany	19	11.2%
Italy	12	7.1%
Ireland	1	0.6%
Luxembourg	2	1.2%
Netherlands	9	5.3%
Norway	6	3.6%
Portugal	1	0.6%
Spain	4	2.4%
Sweden	13	7.7%
Switzerland	10	5.9%
United Kingdom	40	23.7%
Total	**169**	**100.0%**

Table 7 below illustrates the distribution of the sample firms' credit ratings in the period 2002–2011, showing a wide spread from AAA to D ratings, although not all lower credit ratings, such as CCC, CCC- and C, are represented. The majority of the firm-years in the dataset are categorized by an investment grade rating, whereas only 207 firm-years, or 14% of total observations, are not. The firms' credit ratings gather predominantly around the lower end of the investment grade scale, and the credit ratings BBB+, A- and BBB are the three largest groups represented.

Table 7 also shows an evident increase in the number of credit-rated (non-financial) firms on the STOXX Europe 600 Index in the period under study, from 93 in 2002 to 166 in 2011. It is important to note that while the study includes 169 firms overall, some of those firms may have withdrawn their public credit ratings in the period under study, which is why only 166 firms are rated in 2011, whereas others may have acquired a public credit rating in later years but not had one back in 2002.

Additionally, it is possible to recognize a deteriorating credit quality in European companies and a downward shift in the distribution of ratings with a larger number of speculative relative to investment grade ratings assigned in 2011 than in 2002; this can be illustrated by the ratio of speculative grade to total observations (SG/Total), which shows a steady increase through the years, from 4.3% in 2002 to 19.3% in 2011.

Table 7 *The firms' credit ratings*

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	02-11
AAA	5	5	4	3	2	2	1	0	0	0	**22**
AA+	2	2	2	3	2	2	1	1	0	0	**15**
AA	3	4	3	3	4	3	4	3	4	3	**34**
AA-	7	8	6	7	7	7	8	9	7	5	**71**
A+	7	14	13	12	14	9	5	1	4	5	**84**
A	11	12	17	19	14	16	14	16	10	12	**141**
A-	19	24	19	19	26	22	27	32	34	27	**249**
BBB+	20	26	28	28	27	30	31	30	28	33	**281**
BBB	13	20	24	24	26	28	29	25	25	24	**238**
BBB-	2	6	5	10	9	12	13	17	23	25	**122**
BB+	0	1	6	8	10	8	8	7	9	10	**67**
BB	3	5	7	4	3	1	2	2	6	6	**39**
BB-	0	0	0	3	5	10	10	11	4	6	**49**
B+	1	2	3	4	6	4	1	2	7	3	**33**
B	0	0	0	1	0	0	0	1	2	2	**6**
B-	0	1	1	0	0	0	1	1	1	4	**9**
CCC+	0	0	0	0	0	0	0	0	1	1	**2**
CCC	0	0	0	0	0	0	0	0	0	0	**0**
CCC-	0	0	0	0	0	0	0	0	0	0	**0**
CC	0	1	0	0	0	0	0	0	0	0	**1**
C	0	0	0	0	0	0	0	0	0	0	**0**
D	0	0	0	0	0	0	0	0	1	0	**1**
Total	**93**	**131**	**138**	**148**	**155**	**154**	**155**	**158**	**166**	**166**	**1,464**
IG	89	121	121	128	131	131	133	134	135	134	**1,257**
SG	4	10	17	20	24	23	22	24	31	32	**207**
PLUS	30	45	52	55	59	53	46	41	49	52	**482**
MINUS	28	39	31	39	47	51	59	70	69	67	**500**
SG/Total	**4.30%**	**7.60%**	**12.30%**	**13.50%**	**15.50%**	**14.90%**	**14.20%**	**15.20%**	**18.70%**	**19.30%**	

3.3 Definition of variables

Definitions of the variables used in the regressions of this study are presented below. Some commonly used notations are first defined, together with a five-digit number that corresponds to the data items beginning with "WC" in the Worldscope database:

- A_{it-1}: closing value of total assets for firm *i* at year *t-1* (equal to beginning-of-the-year value at year *t*) as measured as [(02999) Total assets]
- D_{it}: book debt for firm *i* at year *t*, as measured as [(03051) Short-term debt and current portion of long-term debt + (03251) Long-term debt]
- ΔD_{it}: debt issuance for firm *i* at year *t*, as defined as y-o-y change in D_{it}
- E_{it}: book value of shareholder's equity for firm *I* at year *t*, as measured as [(03995) Shareholder's equity]

- ΔE_{it}: equity issuance for firm *i* at year *t*, as defined as y-o-y change of [(03995) Shareholder's equity – (03495) Retained earnings]
- $EBITDA_{\text{it-1}}$: [(18198) Earnings before interest, taxes and depreciation/amortization] for firm *i* at year *t-1*
- $Sales_{\text{it-1}}$: [(01001) Net Sales] for firm *i* at year *t-1*

Consistent with the works of Kisgen (2006) and Michelsen and Klein (2011), we use book values for the variables because these are the values CRAs rely on in their risk assessments (Standard & Poor's, 2008). Additionally, Kisgen (2006) argues that the book value more directly reflects managerial decision making.

3.3.1 Dependent variable – *NetDIss*

The dependent variable *NetDIss* in our regressions is defined as the net amount of net debt and net equity raised for the year, divided by the beginning of the year's total assets:

$$NetDIss_{it} = \frac{(\Delta D_{it} - \Delta E_{\text{it}})}{A_{it-1}}$$

This factor aims to measure a firm's actions regarding its capital structure given its credit rating situation. As this study employs the credit rating situations of firms at the beginning of each fiscal year, the dependent variable shows the firms' 12-month subsequent capital structure behaviour. To identify debt issuance and reduction, yearly changes in long-term debt plus short-term debt are calculated (Michelsen and Klein, 2009). Yearly changes in book equity minus retained earnings were used when estimating equity offerings and reductions, as suggested by Michelsen and Klein (2009). An alternative approach would be to use, instead of balance sheet data, cash flow data; however, this would have reduced the number of observation since cash flow data was not available for all firm-years. It is worth mentioning that Kisgen (2006) points to certain implications linked to the dependent variable, such as (1) the transaction costs associated with debt and equity issuance, (2) the time lag in the capital structure decision-making process from making the decision to its execution, (3) the absence of issued capital. These may add noise to the empirical tests.

3.3.2 Explanatory variables

The independent variables aim to explain the behaviour of the dependent variable. Generally, several variables are predicted to have explanatory power in determining the dependent variable, resulting in a multiple regression, i.e. a regression with more than one independent variable (Gujarati and Porter, 2010). The independent variables of the regressions of this study are a set of dummy variables and a set of control variables. These serve different purposes in the search for a relationship between a firm's capital structure decision and credit rating situation and will therefore be presented separately.

3.3.2.1 Dummy variables

In order to analyse the tests of this study, we define four dummy variables. A dummy variable is a qualitative variable that indicates the presence or absence of a particular quality (Gujarati and Porter, 2010). In the present study, the dummy variables used will indicate whether a firm is near a change in credit rating or not. This change could either be related to a change in investment grade/speculative grade or in Broad Rating category.

Due to the important distinction of investment grade and speculative grade ratings, we define firms near the IGSG crossover area, in line with Kisgen's (2006) wider definition of crossover credits, as firms rated BBB, BBB-, BB+ and BB. Therefore, the credit-rating dummy variable in this study, CR_{IGSG}, is set to the value of 1 for these firms. Including only the Micro Ratings closest to the IGSG distinction line (BBB- and BB+) would likely reduce the statistical significance of the results due to the present study's already limited sample. Our choice of CR_{IGSG} is supported by the previous studies of Kisgen (2006) and Michelsen and Klein (2011), which found economically and statistically larger significance when including the wider definition of crossover credits.

For firms near a Broad Rating category change, we define three different dummy variables: 1) CR_{POM} equal to 1 for firms followed by "+" or "-"; 2) CR_{Plus} that takes on the value of 1 for firms with a rating followed by "+"; and 3) CR_{Minus} that takes on the value of 1 for firms followed by "-".

The dummy variables in this study represent the credit rating situations of firms at the beginning of each period, and the dependent variable represents the subsequent 12-month periods. Again, we employ S&P's long-term domestic issuer credit rating in this study (Datastream code BSPL). Additionally, in order to allow for aggregate time effects, we use year dummy variables in our pooled time-series cross-sectional regressions. Moreover, this study employs country dummy variables to absorb differences in regulatory effects, as well as minor differences in the different countries' accounting standards.

3.3.2.2 Control variables

A set of control variables have been included to control for firm -specific factors and to identify the effect of credit ratings on capital structure distinct from the effect of financial distress. Financial distress concerns and CR-CS may have similar empirical implications and including the control variables will mitigate concerns that results may be driven by financial distress. Michelsen and Klein (2011) suggest that high-rated firms tend to issue more debt relative to equity, whilst the CR-CS model centres around concerns of credit-rating changes rather than the impact of certain credit rating levels on firms' capital structure.

This thesis follows Kisgen's (2006) approach in selecting control variables that determine capital structure; consequently the following three variables will be defined: book leverage (*BL*), profitability (*PROF*) and size (*SIZE*). This allows us to compare our results with both Kisgen (2006) and Michelsen and Klein (2011), who also applied the same control variables. The variables are defined as follows:

BL is defined as total book debt divided total assets (total debt + total equity). A higher ratio of leverage is expected to relate to a more conservative capital structure policy. Therefore we expect the coefficient of this variable to have a negative sign.

$$BL_{it-1} = \frac{D_{it-1}}{(D_{it-1} + E_{it-1})}$$

PROF is defined as a firm's earnings before interest, taxes and depreciation/amortization (EBITDA) and divided by the beginning of the year's total assets. As Rajan and Zingales (1995) conclude, the expected sign of this variable may depend largely on the region being examined. In

their study, they found that profitable US firms were more likely to issue debt than equity. However, they found the opposite relationship in the UK market, with the explanation for this being that the UK market differs significantly from the US market, as equity is the most dominant source of external finance in UK in the period 1987 to 1991. Moreover, they could not establish a relationship between leverage behaviour and firm profitability in Germany and France in their period of study.

Kisgen's (2006) results, as presented in section 2.3.3, suggest that more profitable firms are more reluctant to issue equity. Should this behaviour hold true in a European sample, we would expect the coefficient of the variable to have a positive sign.

$$PROF_{it-1} = \frac{EBITDA_{it-1}}{A_{it-1}}$$

SIZE is measured as the natural logarithm of sales. The natural log value of sales is used to allow for comparability between firms, as the absolute number of the firms' sales figure would not be comparable to the other control variables, which are ratio values. By taking the natural log of total sales, we also reduce the risk of having heteroscedasticity affecting the results. Rajan and Zingales (1995) argue that the size of a firm "may be a proxy for the (inverse) probability of default", and Kisgen (2006) also suggests that a firm's size is an "explicit measure of financial distress". As such, large firms have a lower probability of default. The coefficient of the *SIZE* variable is expected to have a positive sign, indicating that firms with lower probability of distress issue more debt relative to equity (Kisgen, 2006). Book value of sales at the end of the fiscal year will be converted into EUR millions for all observations, further enabling comparability

$$SIZE_{it-1} = \ln(Sales_{it-1})$$

3.4 Econometric techniques

To empirically examine the CR-CS hypothesis on our sample, several multiple regressions will be conducted, in line with the work of Kisgen (2006).

A multiple regression analysis concerns the analysis of the relationship between one variable, the dependent variable, and a set of other variables, the independent or explanatory variables. The objective is to explain the behaviour of the dependent variable in relation to the behaviour of the independent variables. The regression estimates a linear relationship, although an error term is included, allowing for the fact that the relationship is inexact (Gujarati and Porter, 2010).

The data collected in this study's sample is of both time-series and cross-sectional character, where the time-series data refers to the time perspective of the data (Gujarati and Porter, 2010), which in the case of this thesis is a 10-year sample period, and the cross-section data refers to the width of the data (Gujarati and Porter, 2010), which in this case is the 169 firms included. Therefore pooled data will be employed, combing both types of data and both the time-series and cross-sectional dimensions. A general model, presented below, explains the features of a multiple regression of a pooled sample. The *i* indicates the particular observation and *t* indicates the period (the year).

$$Y_{it} = \alpha + \beta_1 X_{1it} + \ldots + \beta_n X_{nit} + \varepsilon_{it}$$

where;

Y_{it} is the dependent variable

α is the intercept

X_{nit} are the independent variables

ε_{it} is the error term

Panel data is a special type of pooled data (Gujarati and Porter, 2010), and in order to avoid some of the disadvantages associated with pooled data analyses, the pooled data regressions employed in this study will be estimated using panel analysis (for a similar approach, see Al-Hidrawi, 2006).

The panel data analysis is based on sample data over the whole sample period of 10 years. The analysis combines times-series and cross-sectional observations, providing results regressed on between 1240 and 1344 observation.

The method of Ordinary Least Squares (OLS) is used to estimate the regression models and investigate the linear relationship between the dependent variable and the independent variables. OLS is the most frequently used method in regression analysis (Gujarati and Porter, 2010). The linear relationship between the variables in the regression models used in this study aim to fit the observed values of the dependent variable and correspond to the observed values of the explanatory variables (Johnson and Wichern, 2007),. The OLS method determines these values of the coefficients in such a way that the sum of squared residuals is minimized. The residual represents the error of the linear relationship estimated, or more specifically the differences between the actual and estimated values of the dependent variable. Given a few assumptions, later presented in section 3.5.4, this method has minimum variance in the class of linear estimators; which is to say that OLS estimators are Best Linear Unbiased Estimators (BLUE) (Gujarati and Porter, 2010). Only if these assumptions are met can the regressions be considered reliable.

Finally, the econometrics software program EViews 7 will be used for all regression analyses employed in this study.

3.5 Regressions and hypotheses

3.5.1 POM and IGSG tests

Section 3.3 provided a brief explanation and definition of the variables and notations used in the present study. This section will provide a brief explanation of the regressions of this study as well as the hypotheses tested.

This study follows the methodological set-up of Kisgen (2006) in order to achieve its objectives and to directly answer the research questions, namely whether potential changes in IGSG and Broad Rating categories lead to more pronounced effects in European managers' capital structure decisions. For this purpose, the study employs the cross-sectional time series regression models put forward in the literature review under section 2.3.3.

Thus, the regressions that will be tested are as follows:

$$\left.\begin{aligned} NetDIss_{it} &= \alpha + \beta_1 CR_{POM} + \phi K_{it} + \varepsilon_{it} && (4.1)\\ NetDIss_{it} &= \alpha + \beta_2 CR_{Plus} + \beta_3 CR_{Minus} + \phi K_{it} + \varepsilon_{it} && (4.2)\\ NetDIss_{it} &= \alpha + \beta_4 CR_{POM} + \varepsilon_{it} && (4.3)\end{aligned}\right\} \text{POM}$$

$$\left.\begin{aligned} NetDIss_{it} &= \alpha + \delta_1 CR_{IGSG} + \phi K_{it} + \varepsilon_{it} && (4.4)\\ NetDIss_{it} &= \alpha + \delta_2 CR_{IGSG} + \beta_5 CR_{POM} + \phi K_{it} + \varepsilon_{it} && (4.5)\end{aligned}\right\} \text{IGSG}$$

where:

$NetDIss_{it}$	=	the net debt relative to net equity issuance, scaled to total assets
CR_{IGSG}	=	dummy for firms with a BBB, BBB-, BB+ or BB rating, then CR_{IGSG} = 1; 0 otherwise
CR_{POM}	=	dummy for firms with a rating followed by "+" or "-", then CR_{POM} = 1; 0 otherwise
CR_{Plus}	=	dummy for firms with a rating followed by "+", then CR_{Plus} = 1; 0 otherwise
CR_{Minus}	=	dummy for firms with a rating followed by "-", then CR_{Minus} = 1; 0 otherwise
K_{it}	=	a set of control variables, including BL_{it-1}, $PROF_{it-1}$ and $SIZE_{it-1}$.

3.5.2 Specification of hypotheses

The present study will test the relationship between credit ratings and manager's subsequent debt–equity decisions on a 10% significance level for firms near a Broad Rating change as well as firms in the crossover area of an IGSG change.

The first proposed hypothesis is:

H_{POM}: Firms near a Broad Rating change issue less debt relative to equity than companies not close to a Broad Rating change.

$$H_0 : \beta_i \geq 0 \qquad i = 1, 2, 3, 4$$

$$H_1 : \beta_i < 0$$

In turn, the second hypothesis concerns a near IGSG rating change, and can be stated as follows:

H_{IGSG}: Firms near an IGSG rating change issue less debt relative to equity than firms not close to an IGSG change.

$$H_0 : \delta_i \geq 0 \qquad i = 1, 2$$
$$H_1 : \delta_i < 0$$

3.5.3 Assumptions of the classical linear regression model (CLRM)

As stated in section 3.4, this study's regression models must meet a few assumptions before being considered reliable. More specifically, to show that the OLS estimation technique fulfils its desirable properties (BLUE) and that hypothesis testing regarding the coefficient estimates is validly conducted, the assumptions of the classical linear regression model (CLRM) must be fulfilled (Brooks, 2008).

The assumptions underlying OLS are:

(1) The model is correctly specified

(2) No correlation exists between the error term and any independent variable: $Cov(\varepsilon_i | X_i) = 0$

(3) The error term, ε_i, has a 0 mean value: $E(\varepsilon_i | X_i) = 0$

(4) The variance of ε_{it}, is constant, that is; homoscedasticity: $Var(\varepsilon_i | X_i) = \sigma^2$

(5) No autocorrelation exists between the error term ε_i and ε_j: $Cov(\varepsilon_i, \varepsilon_j | X_i, X_j) \quad i \neq j$

(6) No exact collinearity exist between the independent variables

(7) For hypothesis testing, the error term ε_i follows the normal distribution with a mean zero and (homoscedastic) variance of σ^2: $\varepsilon_i \sim \mathrm{N}(0, \sigma^2)$

Gujarati and Porter (2010)

The first assumption states that the model must be correctly specified; this includes linearity in the parameters and neither omission of relevant variables nor inclusion of irrelevant variables (Gujarati and Porter, 2010).

The second assumption, zero correlation between error terms and independent variables, is necessary to obtain unbiased estimates of regression coefficients. This assumption will be controlled for with the correlation matrix in EViews (Gujarati and Porter, 2010).

The third assumption states that the error term has an expected value of 0, implying that the error in estimating the linear relationship is random and on average equal to 0 (Gujarati and Porter, 2010).

The fourth assumption, that of the homoscedastic error term (i.e., constant variance of the error term), is controlled for by using the White heteroscedasticity-corrected standard errors for all regressions. With a sample of the size analyzed in this thesis, this method is a preferable action in order to obtain homoscedasticity (Gujarati and Porter, 2010). In both the studies of Kisgen (2006) and Michelsen and Klein (2011), White's heteroscedasticity-consistent standard errors are used for all regression analyses. Only in the case of homoscedasticity are OLS estimators efficient; which is to say they have a minimum variance and thus generate optimal estimations. If not fulfilled, the standard error could be wrong, causing incorrect statistical inference (Brooks, 2008).

The fifth assumption states that no autocorrelation should exist between the error terms, which is to say that the observations are random and independent of each other. The implications of autocorrelation are similar to the ones of heteroscedasticity, but in contrast with being associated with cross-sectional data, autocorrelation is associated with time-series data. If the error term of one observation is related to or influenced by the error term of any other observation, OLS estimators are not efficient. The OLS estimators could thus underestimate true variances and standard errors, thereby inflating the t-values. A Durbin-Watson test, controlling for the relationship between the error term and its immediately previous value, can detect autocorrelation. In this study, we will analyze the Durbin-Watson statistic for all employed regressions in order determine whether our error terms suffer from autocorrelation. The Durbin-Watson statistic can assume values between 0 and 4. If it assumes the value of 0, this suggests that there is a perfect positive autocorrelation. If it assumes the value of 2, this suggests that no

autocorrelation exist, and if it assumes the value of 4, this suggests that there is a perfect negative autocorrelation (Gujarati and Porter, 2010).

The sixth assumption, that of no exact collinearity (i.e. no linear relationship between the independent variables in the regression), must also be controlled for. The consequences of multicollinearity are that standard errors of coefficients tend to be large in relation to their coefficient values and this will reduce the t-values. As a result, the individual or marginal contribution of the variables with low t-values cannot, problematically, be identified (Gujarati and Porter, 2010). This assumption will be controlled for by a correlation matrix of the variables. Correlation values greater than 0.8 indicate collinearity and the regression model should be reconsidered, and dropping out one or more of the collinear variables is often suggested (Gujarati and Porter, 2010; Westerlund, 2005).

The seventh assumption of normal distributed error term is required in order to conduct a hypothesis test about the regression parameters and to make a valid statistical inference (Brooks, 2008). However, though it is not strictly required for this assumption to be fulfilled when hypothesis testing is based on larger samples, it should still be controlled for.

3.5.4 Interpretation of regression results

The regression coefficients indicate the marginal effect of the independent variables (the dummy and control variables) on the dependent variable (the net debt issuance relative to net equity issuance as a percentage of total assets). The CR-CS predicts the dummy coefficients to have a negative sign, indicating that the dummy variable has a negative impact on the dependent variables, i.e., firms near a change in Broad Rating or IGSG issue less net debt relative to net equity as a percentage of total assets in the following year than firms not near a change in credit rating. The null hypotheses of this study designates only the dummy variables, thus the analysis of the control variables will be viewed as a secondary analysis in addition to the H_{POM} and H_{IGSG} analysis.

Our null hypothesis cannot be rejected for any positive values of the dummy coefficients, i.e., a one-sided statistical test is carried out in the hypothesis testing. The variables will be individually analysed in terms of their statistical significance using the p-value, which indicates the minimum

significance level at which the null hypothesis can be rejected for the individual test statistic (Gujarati and Porter, 2010). If the p-value for the dummy variable coefficients, after been divided by two (due to the one-sided hypothesis), falls below 0.10, the null hypothesis will be rejected.

The overall significance of the estimated regression line will further be measured with an F-test. The null hypothesis of the F-test is that there is no linear relationship between the dependent variable and any of the independent variables. The null hypothesis will be rejected if the p-value of the F-statistic falls below 0.10 (Westerlund, 2005).

Finally, the multiple coefficient of determination, R^2, denotes the percentage of the total variation in the dependent variables explained by the independent variables (Gujarati and Porter, 2010). The panel data of this study will contain "cross-sectional like" R^2-values, which can be compared to R^2 from cross-sectional regressions but not from time-series models. For example, if we compare company A with its own capital structure decisions for 10 years (time-series), we can explain a great deal of the variation in the explanatory variables used. However, if we compare company A's capital structure behaviour to, say, company B and C, etc., for 10 years (cross-sectional time-series) the explanatory variables will explain less. Now, clearly there are many factors that may affect the capital structure decisions of a company. This study puts forward credit ratings as a potential determinant, and while it may very accurately be able to measure the impact of credit ratings on capital structure decisions in European firms, it cannot predict the overall behaviour of firms' capital structure decisions. Therefore, a low R^2 value is to be expected in absolute terms, which is in line with previous CR-CS studies in terms of POM and IGSG testing. Results from previous studies on the CR-CS hypothesis reveal low R^2 in the POM and IGSG tests, and a similar outcome in this study can therefore be expected. However, previous studies stress that, despite poor R^2, their results show both economical and statistical significance in favour of the CR-CS hypothesis, so this study's analysis will thus not focus on this measurement to any large extent.

3.6 Reliability and validity

3.6.1 Reliability

Reliability is information on whether the test or procedure is producing data in a consistent and accurate way over similar samples on all occasions (Lu, 2005). As such, Bryman and Bell (2011) contend that anyone following outlined procedures should be able to come up with the same results or findings. Furthermore, they suggest that reliability is about making sure that the results are not influenced by temporary or random differences in the sample.

For gathering firm-level financial data and the long-term domestic credit rating by S&P, we used the Datastream and Worldscope financial databases by Thomson Financial. Datastream is considered a reliable database as it is used regularly by academic researchers in corporate finance as well as by professional practitioners in the financial industry. Using Datastream was deemed necessary for this study to access the information required. It is worth noting that the financial data used from Datastream is derived from the financial statements of each individual firm, which means that the data is reliable and has been approved and reviewed by auditors. We therefore believe there is a high level of reliability in the data collected.

The reliability of this research has been strengthened in several ways. First, the sampling period was increased to a 10-year period (2002–2011) with the aim of maximizing the data available and minimizing the temporality or irregularity of the data. Second, in order to minimize the risk of having any incorrect calculations, these were subjected to a number of independent verifications. Third, the sampling procedure was clearly articulated and therefore can easily be replicated and applied in future research.

3.6.2 Validity

Validity refers to the extent to which the method used in the study measures what it is supposed to measure (Bryman and Bell, 2003; Svenning, 2003). In other words, validity can be defined as a criterion of the absence of systematic errors in the measurements (Lundahl and Skärvald, 2009). The literature distinguishes between (i) internal and (ii) external validity (Lundahl and Skärvald, 2009).

(i) Internal validity is a criterion of whether there is a causal relationship between the variables being measured, meaning that the suggested independent variable is the variable causing the variations in the dependent variable (Bryman and Bell, 2003). This thesis employs the proven POM and IGSG tests developed by Kisgen (2006), which have been used in similar previous studies and are recognized as measuring what they are supposed to measure. In our final sample, financial firms were excluded to provide a more homogenous sample, as the capital structure of financials and non-financial firms may differ substantially. Higher validity has also been obtained controlling for firm-specific factors and financial distress arguments when including the control variables. By using long-term credit ratings, the effects of business or credit cycles were mitigated. Furthermore, Panel A then excluded large debt offerings (defined as >10% of total assets) in order to provide robust results. However, to further strengthen the internal validity of the study, we developed an additional sampling strategy – shown under Panel B in Chapter 5 – excluding only extreme values so as to provide accurate and relevant results for the European market.

(ii) External validity refers to the question of whether the results of a test are generalizable beyond the study (Svenning, 2003). In order to present a true and meaningful picture of the European S&P rated universe, we developed rigorous sample criteria to arrive at a dataset with high representativeness for the European market. A few European countries were not represented by listed non-financial S&P-rated firms, which is why not all 18 European countries of the STOXX Europe 600 Index are represented in the final sample. Although we believe our sample represents the European corporate bond market well, we acknowledge the difficulties in generalizing results. Michelsen and Klein (2011) found differences between international markets when examining CR-CS, a finding that may relate to several factors such as differences in regulations and laws and differences in the debt security market's proliferation, all of which must be taken into consideration before generalizing our results to other geographical regions. To minimize external effects such as these on our results, year and country dummy variables have been included to take into account differences in time as well as differences between the countries represented in the sample.

4 Results

4.1 Descriptive results

Table 8 below presents a summary of the sample's statistics in terms of the relationship between credit rating and leverage, measured as debt to total capitalisation, per rating category. Observations with missing values or with a leverage ratio greater than 1 or less than 0 were excluded. Although it may be difficult to compare, for example, 17 AAA ratings with 290 BBB+ ratings, Table 8 shows that firms with high credit ratings carry less debt in their capital structure compared to businesses with lower ratings. As not all credit ratings were represented, ratings of B or below have been merged into one group.

Table 8 *Summary of the sample's statistics – rating level and firm leverage*

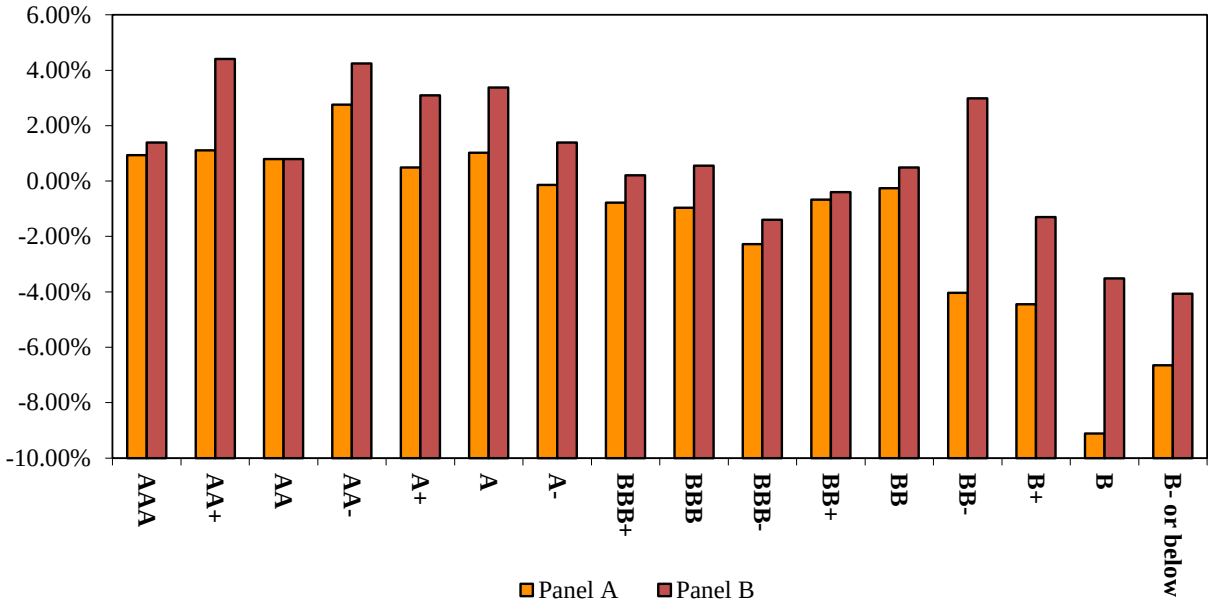
	AAA	**AA+**	**AA**	**AA-**	**A+**
Number of firm-years	17	13	32	64	79
Debt/(Debt+Equity)					
Mean	32.6%	15.4%	28.8%	35.8%	49.3%
Median	30.6%	15.5%	30.1%	32.9%	48.0%
Std Dev.	17.0%	7.8%	9.1%	16.9%	14.6%
	A	**A-**	**BBB+**	**BBB**	**BBB-**
Number of firm-years	142	254	290	243	138
Debt/(Debt+Equity)					
Mean	46.8%	44.9%	47.5%	48.6%	49.2%
Median	45.5%	43.7%	46.5%	48.5%	47.5%
Std Dev.	20.8%	17.8%	16.8%	17.1%	19.0%
	BB+	**BB**	**BB-**	**B+**	**B or below**
Number of firm-years	75	44	52	27	22
Debt/(Debt+Equity)					
Mean	51.6%	49.5%	54.5%	58.2%	67.3%
Median	49.6%	44.0%	54.3%	54.3%	60.7%
Std Dev.	15.8%	15.3%	18.0%	13.6%	13.2%

Notes: This figure displays the means, medians and standard deviations of leverage, measured as Debt/(Debt + Equity), by rating category of 1,492 firm-years in the period 2002 to 2011. The credit rating is calculated in the start of the fiscal year. In line with leverage statistics, firm years with D/(D + E) greater than 1 or less than 0 are excluded.

Figure 5 shows the mean value of the dependent variable *NetDIss* per rating category, clarifying the relationship between credit rating and issuance of debt relative to equity. For Panel A, the relationship is evident: firms with higher creditworthiness issue more debt and less equity than firms with lower creditworthiness. But in Panel B, this relationship is it not as clear. However, it

is apparent in both panels that net debt issuance relative to net equity issuance differs around the IGSG borderline, where the BBB- and BB+ rated firms takes on more equity relative to debt (or less debt relative to equity) compared to contiguous groups of firms.

Figure 5 *Average net debt minus equity issuance per category, 2002–2011*



Notes: This figure displays the mean value of the dependent variable, measured as the net amount of the net debt and net equity raised for the year scaled by beginning-of-the-year total assets. The credit rating is calculated in the start of the fiscal year. Panel A excludes debt offerings greater than 10% of total assets, whereas Panel B excludes the highest 2% of observations for both debt offerings and equity offerings in any given year.

4.2 Regression results

4.2.1 Diagnostic testing of the CLRM assumptions

All required assumptions of CLRM, introduced in section 3.5.3, have been controlled for all regressions. First, the assumption of 0 mean variance for the error term was fulfilled by all regressions, indicating that the errors in the estimations are random. Second, we assessed the Durbin-Watson statistic in order to detect potential autocorrelation, but the regressions showed Durbin-Watson statics in the range of 1.96 and 2.11, suggesting the absence of any autocorrelation. Third, we conducted correlation matrixes for all regression, none of which showed evidence of either correlation between the error term and the explanatory variables nor among the explanatory variables. OLS assumptions 2 and 6 can therefore be confirmed. Finally, we corrected for heteroscedasticity problems using the White standard errors and covariance for the panel data analysis.

The assumption of normal distributed error terms was not fulfilled in all regressions. However, the econometric literature suggests that this assumption can be ignored provided that all other CLMR assumptions are fulfilled and the sample consists of a sufficiently large number of observations (e.g., Brooks, 2008; Kennedy, 2008; Westerlund, 2005). By those standards, the sample of this thesis can be considered sufficient large.

4.2.2 POM and IGSG tests

Results of the POM and IGSG regressions for the period 2002 to 2011 are shown below in Tables 9 and 10, respectively, where Panel A excludes large debt offerings (>10% of assets) and Panel B excludes the highest 2% of observations for both debt offerings and equity offerings in any given year. The tabulated results, which have been obtained using panel analysis, show coefficients, the White standard errors (in parentheses), and the level of significance (in bold and in parentheses) of the panel analysis.

Table 9 *Regressions of the POM test*

	Panel A			*Panel B*		
	Model 4.1	**Model 4.2**	**Model 4.3**	**Model 4.1**	**Model 4.2**	**Model 4.3**
Intercept	0.0827	0.0856	0.0314	0.1149	0.1145	0.0364
	(0.0357)	(0.0365)	(0.0224)	(0.0373)	(0.0378)	(0.0202)
	(0.0208)	**(0.0192)**	**(0.1607)**	**(0.0021)**	**(0.0025)**	**(0.0726)**
CR_{POM}	-0.0071	-	-0.0076	-0.0094	-	-0.0097
	(0.0053)	-	(0.0054)	(0.0056)	-	(0.0056)
	(0.1835)	-	**(0.1587)**	**(0.0933)**	-	**(0.0835)**
CR_{Plus}	-	-0.0048	-	-	-0.0097	-
	-	(0.0062)	-	-	(0.0066)	-
	-	**(0.4399)**	-		**(0.1395)**	-
CR_{Minus}	-	-0.0094	-	-	-0.0091	-
	-	(0.0062)	-	-	(0.0066)	-
	-	**(0.1305)**	-		**(0.1681)**	-
BL	-0.0550	-0.0559	-	-0.0539	-0.0538	-
	(0.0177)	(0.0178)	-	(0.0185)	(0.0186)	-
	(0.0019)	**(0.0017)**	-	**(0.0036)**	**(0.0038)**	-
PROF	-0.0085	-0.0073	-	0.0196	0.0194	-
	(0.0248)	(0.0251)	-	(0.0328)	(0.0330)	-
	(0.7315)	**(0.7724)**	-	**(0.5499)**	**(0.5553)**	-
SIZE	-0.0013	-0.0015	-	-0.0040	-0.0040	-
	(0.0021)	(0.0022)	-	(0.0025)	(0.0025)	-
	(0.5368)	**(0.5044)**	-	**(0.1032)**	**(0.1086)**	-
Adj. R^2	0.0488	0.0484	0.0367	0.0804	0.0797	0.0714
F-statistic	3.4424	3.3336	3.0594	5.4313	5.2264	5.4130
Firm-years	1,240	1,240	1,244	1,318	1,318	1,322

Note: the results are for the pooled sample 2002–2011. Numbers in brackets are the standard errors which are corrected for heteroscedasticity using the White diagonal standard errors. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm-years with missing values of any used variable are excluded. Panel A excludes debt offerings greater than 10% of total assets, whereas Panel B excludes the highest 2% of observations for both debt offerings and equity offerings in any given year. Country and year dummy variables (not shown) have been included to absorb differences in regulatory effects and allow for time aggregated effects.

The first hypothesis to be tested is H_{POM}, $H_0 : \beta_i \geq 0$ versus $H_1 : \beta_i < 0$ for i = 1, 2, 3, 4, where the null hypothesis (H_0) implies that firms are unconcerned with Broad Rating category changes. In both panels in Table 9, the credit rating dummy variables show the predicted negative sign across the tested POM regressions. Their coefficients are statistically stronger and economically larger when excluding the most sizeable outliers of debt and equity offerings (Panel B) rather than in the exclusion of debt offerings greater than 10% of assets (Panel A). As the values of β_i for i = 1, 2, 3, 4 show the predicted negative sign in all regressions, we can reject the H_0 depending on whether the one-sided p-value of the credit rating dummy variables is below the

10% significance level. Notice that the tabulated numbers in brackets and in bold of Table 9 are the p-values for a two-tailed test, whereas the one-sided p-value is of interest when we conduct our hypotheses' tests. Table 10 depicts the results of our first hypothesis for the POM tests and shows the one-sided p-values of the credit rating dummy variables for each and every regression.

Table 10 *Results of first hypothesis test: H_{POM}*

	Panel A			*Panel B*		
	Model 4.1	**Model 4.2**	**Model 4.3**	**Model 4.1**	**Model 4.2**	**Model 4.3**
$\mathbf{H_0}$	Rejected	Accepted	Rejected	Rejected	Rejected	Rejected
$\mathbf{CR_{POM}}$	0.0918	-	0.0794	0.0467		0.0420
$\mathbf{CR_{Plus}}$	-	0.2200	-	-	0.0698	-
$\mathbf{CR_{Minus}}$	-	0.0653	-	-	0.0841	-

Note: numbers in the table are the one-sided p-values of the credit rating dummy variables. If respective p-values fall below the 10% significance level, the model's null hypothesis is rejected.

In Panel A, H_0 is rejected at the 10% level for model (4.1) and (4.3), but accepted for model (4.2) where CR_{Plus} show insignificance. Worth noting is that CR_{Minus} shows significance in (4.2), though H_0 is rejected only when $\beta_i \geq 0$ for both β_2 and β_3. In Panel B, on the other hand, all models' H_0 are rejected, with model (4.1) and (4.3) on the 5% level and model 4.2 on the 10% level.

Results from Panel A suggests that firms with a credit rating followed by a plus or minus subsequently issue 0.71% less net debt relative to net equity in the following financial year than the middle Broad Rating firms (model (4.1)). Panel B's results of the POM tests are similar for all three models. Results of model (4.3) show that firms near a change in Broad Rating issue 0.97% less debt relative to equity as a percentage of assets than firms that are not. (Model) 4.2 further shows that both CR_{Plus} and CR_{Minus} coefficients have a similar affect on the dependent variable (-0.97%, -0.91%).

Moving on to the results of the IGSG tests, Table 11 below displays the regression coefficients of model (4.4) and model (4.5), together with heteroscedasticity-corrected standard errors (in brackets) and p-values for a two-tailed test (in bold and brackets). The coefficients for the credit rating dummy variables are negative in both panels and, again, statistically stronger and

economically larger in Panel B. The hypothesis to be tested is H_{IGSG}, $H_0 : \delta_i \geq 0$ versus $H_1 : \delta_i < 0$ for i = 1, 2, where if the null hypothesis (H_0) is rejected, this implies that firms are concerned with rating changes over the IGSG transition line.

Table 11 *Regressions of the IGSG test*

	Panel A		*Panel B*	
	Model 4.4	**Model 4.5**	**Model 4.4**	**Model 4.5**
Intercept	0.0811	0.0866	0.1166	0.1239
	(0.0358)	(0.0360)	(0.0375)	(0.0374)
	(0.0237)	**(0.0160)**	**(0.0019)**	**(0.0009)**
CR_{IGSG}	-0.0068	-0.0071	-0.0160	-0.0164
	(0.0055)	(0.0053)	(0.0056)	(0.0056)
	(0.2162)	**(0.1977)**	**(0.0045)**	**(0.0035)**
CR_{POM}	-	-0.0074	-	-0.0101
	-	(0.0053)	-	(0.0056)
	-	**(0.1667)**	-	**(0.0705)**
BL	-0.0535	-0.0530	-0.0497	-0.0495
	(0.0179)	(0.0178)	(0.0185)	(0.0184)
	(0.0028)	**(0.0029)**	**(0.0071)**	**(0.0073)**
PROF	-0.0102	-0.0132	0.0129	0.0092
	(0.0257)	(0.0256)	(0.0328)	(0.0322)
	(0.6898)	**(0.6068)**	**(0.6941)**	**(0.7746)**
SIZE	-0.0016	-0.0017	-0.0048	-0.0049
	(0.0022)	(0.0022)	(0.0025)	(0.0025)
	(0.4504)	**(0.4263)**	**(0.0546)**	**(0.0466)**
Adj. R^2	0.0487	0.0494	0.0843	0.0858
F-statistic	3.4400	3.3841	5.6651	5.5799
Firm-years	1,240	1,240	1,318	1,318

Notes: the results are for the pooled sample 2002–2011. Numbers in brackets are the standard errors which are corrected for heteroscedasticity using the White diagonal standard errors. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm years with missing values of any used variable are excluded. Panel A also excludes debt offerings greater than 10% of total assets, whereas Panel B excludes the highest 2% of observations of both debt offerings and equity offerings in any given year. Country and year dummy variables (not shown) have been included to absorb differences in regulatory effects and allow for time aggregated effects.

The second hypothesis, H_{IGSG}, can be rejected in both Panel A and Panel B. In Panel A, the null hypothesis is however accepted for model (4.4) but rejected at 10% significance level for model (4.5). The one-sided t-test for $H_0 : \delta_i \geq 0$ versus $H_1 : \delta_i < 0$ for i = 1, 2, for models (4.4)–(4.5) is summarized in Table 12 below.

Table 12 *Results of second hypothesis test: H_{IGSG}*

	Panel A		*Panel B*	
	Model 4.4	**Model 4.5**	**Model 4.4**	**Model 4.5**
$\mathbf{H_0}$	Accepted	Rejected	Rejected	Rejected
$\mathbf{CR_{IGSG}}$	0.1081	0.0989	0.0023	0.0018
$\mathbf{CR_{POM}}$	-	0.0834	-	0.0353

Notes: numbers are the one-sided p-values of the credit rating dummy variables. If the respective p-value is below the 10% significance level, the model's null hypothesis is rejected. In Panel A, model (4.5) is rejected on the 10% significance level, whereas in Panel B, both models are rejected.

The results of models (4.4) and (4.5) in Panel B show that firms are concerned about investment grade and sub-investment grade changes, with significance at the 1% level in both cases. The IGSG dummy variable coefficient of model (4.4) suggests that firms on the borderline between investment grade and speculative grade assigned BBB, BBB-, BB+ and BB ratings issue 1.60% less debt relative to equity than other firms. Along these lines, the sum of the coefficients in model (4.5) suggest that firms with a BB+ and BBB- rating issue 2.65% less debt than equity relative to other firms. The credit rating dummy variable coefficients in (model) 4.5 of Panel B amounts to -1.45%.

4.2.3 Control variables, model fit and robustness

It is worth noting in the context of control variables that *BL* shows a negative value, as expected, and is statistically significant at the 1% level across all estimated regressions and panels. This strongly indicates that firms with a higher leverage ratio have a more conservative capital structure policy, being more likely to issue equity than debt. Furthermore, the *SIZE* control variable is statistically insignificant in all regressions of Panel A, and in the case of Panel B only in the IGSG tests (although marginally close to the 10% significance level in POM). As for the IGSG regressions of Panel B, *SIZE* is negative and statistically significant at the 5% and 1% levels for models (4.4) and (4.5), respectively. As for the *PROF* control variable, although statistically insignificant across all regressions, it shows the expected positive sign in both panels.

Moreover, the F-statistics are significant at the 0.0002% level or better in all five regressions (see Appendix 2), which suggests that there exists a strong link between the *NetDIss* and all or some of the explanatory variables. The model fit – measured by the adjusted R^2 – for all the estimated regressions ranges from 0.0367 to 0.0494 in Panel A and 0.0714 to 0.0858 in Panel B.

As a robustness check, we have also run the same regressions using a reduced sample of 141 firms over the period 2002 to 2011, excluding Utilities and Oil & Gas firms. The results (not reported) are close to those tabulated for both panels. Similarly, we also conducted tests adding a dummy variable for industry sectors (not reported) to absorb potential variations in credit rating effect across industries, which showed very similar results as those already reported but with a slightly better model fit. Furthermore, we tested with the exclusion of the 2002–2004 period (prior to the IFRS implementation), as the financial information in these observations may differ slightly from the financial information in the period 2005–2011. However, inclusion of the years 2002–2004 showed similar results, but with more significance as a result of the larger sample. Therefore, we include these years and use the country dummy variable to also absorb differences between countries. This shows the robustness of the present dataset.

5 Analysis

The research questions of this study address whether there are pronounced effects in firms' subsequent capital structure decisions as a result of potential changes in (1) Broad Ratings; and (2) IGSG status. The CR-CS hypothesis puts forward the premise of discrete costs (benefits) associated with different rating levels and argues that if a firm's credit rating is on the point of being either raised or lowered, it is more likely to adopt a conservative debt financing policy than firms with stable credit ratings. If these discrete costs (benefits) are material, managers' consequent capital structure behaviour is inconsistent with traditional capital structure theories. In order to be able to formally investigate these questions, we have formulated two null hypotheses (H_{POM} and H_{IGSG}), which state that managers are unconcerned about obtaining or losing a Broad Rating or IGSG status in their capital structure decisions.

To test these hypotheses, we conducted both POM and IGSG tests, with two different data panels. Panel B, our own added panel, demonstrates the relationship between credit ratings and capital structure decisions on the European S&P-rated universe with better statistical and economic significance than Panel A by only mitigating outliers and keeping a broader sample by including more firm-years and large debt offerings. With a better model fit – measured by the adjusted R^2 – Panel B shows more robustness and credit rating dummy variables with more explanatory power regarding firms' subsequent choice of capital structure than the results produced through the methodology employed in previous studies on the subject (Panel A). This study's own methodology has therefore produced results, as shown in Panel B, of greater reliability and import to the subject at hand.

It should also be noted that the descriptive statistics presented in Table 8 show that firms with high credit ratings carry less debt in their capital structure than firms with lower ratings. On a related note, Figure 5 suggests that firms at the higher end of the credit-rating spectrum use their financial strength to alter their capital structure by issuing more debt relative to equity, while firms with lower credit ratings, to a larger extent restrict their debt issuance, perhaps to avoid further impairment in credit quality. The most interesting result of the descriptive statistics is the evident change in net debt relative to net equity issuance around the IGSG borderline that suggest

that firms in the IGSG crossover area restrict their debt issuance to increase their chances of a ratings upgrade or avoid a ratings downgrade.

The estimated regressions show that the (one-sided) p-value of the credit rating dummy variables of Panel B reject the null hypothesis of H_{POM} and H_{IGSG} in all cases, suggesting that there is a significant relationship between credit ratings and firms' subsequent capital structure decisions. In other words, the findings of this study show that concerns about potential Broad Ratings and IGSG changes do indeed lead to pronounced effects in European firms' subsequent capital structure decisions.

The negative coefficient value of the credit rating dummies (CR_{POM}, CR_{Minus}, CR_{Plus} and CR_{IGSG}) indicate that firms deemed to be near changes in their ratings issue less debt than equity (as a percentage of assets). The findings of this present study, as shown in Panel B, are that in the European context, managers' Broad Rating considerations mean that firms near a potential change (i.e. with a plus or minus rating) issue 0.97% less net debt relative to equity (as a percentage of assets) than firms that are not, which is comparable to the very similar result (-1.02%) obtained by Kisgen (2006) on the US market in the period 1986 to 2001.

However, our results show that the borderline between investment grade and speculative grade has a more pronounced effect on European firms' capital structure rationale. Indeed, the lagged credit rating effect on crossover firms show both economically and statistically stronger results than those near Broad Rating change, with crossover firms (assigned a BBB, BBB-, BB+ and BB rating) issuing 1.60% less debt than equity (as a percentage of assets) than other firms. Similarly, the sum of the CR_{IGSG} and CR_{POM} coefficients of model (4.5) in Panel B implies that firms with a BBB- and BB+ rating are even more conservative in their leverage reduction behaviour, issuing 2.65% less debt than equity relative to other firms. Our findings, which are consistent with the results of Kisgen (2006) on the US market and Michelsen and Klein (2011) on the international market, show that concerns about changes in corporate credit ratings amongst European companies, as with US and international firms, are associated with conservative leverage policies.

The main theories of capital structure, the trade-off and pecking order theories, cannot explain the behaviour of firms near a change in credit rating issuing less debt relative to equity than firms not near a change. The rejected null hypotheses of this study imply that costs (benefits) of different

rating levels are indeed material (e.g. as a result of regulatory effects, pooling effects, rating triggers, etc.), and therefore capital structure choices may deviate from the implied behaviour of the trade-off theory, which is depicted in Figure 3B. Moreover, the statistically significant results of the POM test shows that the effect of credit ratings are distinct from the financial distress arguments of the trade-off theory, as its predictions compared to those of CR-CS for firms close to an upgrade are the opposite. The negative coefficient of CR_{Plus} implies that firms near an upgrade issue less debt relative to equity, whereas trade-off theory predicts that firms of higher relative rating issue more debt than equity due to the lower costs of financial distress and risk of bankruptcy. As the trade-off theory and CR-CS share the same implications for firms with a minus rating but the opposite for firms with a plus rating, this finding provides strong evidence for the CR-CS hypothesis to hold true and mitigates the risk of results driven by financial distress concerns. In terms of the pecking order theory, which suggests that firms issue capital in a certain order, preferring internal funds over external capital and debt over equity, our results show that firms do not follow this order, as they tend to choose equity in favour of debt due to the discrete costs (benefits) of credit rating changes. This behaviour cannot be explained by the pecking order theory and therefore stresses the relevance of CR-CS as an extension to existing theories, thereby contributing further to our understanding of capital structure determinants.

As touched on in the introductory chapter, credit ratings are often incorporated into company goals and the effects of this can be discerned in our results. The increased reliance on credit ratings in today's financial markets may be an overall reason behind credit ratings becoming a material consideration for corporations. In line with this are regulatory effects, pointed out as a prominent factor with significant impact on obligors (Frost, 2007; Gonzalez, 2004). Although we recognize that regulations may differ over time and between the countries represented in this study, international financial regulatory frameworks incorporating CRAs' credit quality assessments, such as the Basel Accords, will likely have been of major importance in managers concerns for credit rating changes. In contrast to the study of Kisgen (2006), who focused solely on US firms under the same jurisdiction, we introduced a country dummy variable to absorb differences in discrete costs (benefits) associated with regulatory effects between countries and differences in accounting standards for the years 2002–2004 that may exist before the mandatory implementation of IFRS standards in 2005. In addition, we used year dummy variables in line with Kisgen (2006) and Michelsen (2011) to allow for time aggregated effects. It is important to

note that the "cross-sectional like" R^2 values obtained by the models in this study may seem low in absolute terms, however these results are not surprising as CR-CS does not predict credit ratings to be a single decisive factor in firms' capital structure decisions but only one determinant among others. In comparison to the studies of Kisgen (2006) and Michelsen and Klein (2011) the model fit of our Panel B is significantly stronger than the model fit of their regressions, whereas the R^2 value of our Panel A is in line with their results. Therefore, Panel B's R^2 values (in the range of 0.0714 to 0.0858) are more than acceptable.

5.1 Limitations

The data collected for this study covers a 10-year period: from 2002 to 2011. Our findings are therefore restricted to the period under study and may have been driven by period-specific events, such as the recent global financial crisis. Furthermore, in the period 2002–2004, we recognize that the commonly used variables in the regressions may differ slightly with the post-IFRS implementation date variables. A risk with the present study is also that there the sample may not be totally homogenous; differences in jurisdiction between the countries may affect firms' capital structure decisions differently. While we have proxied for these time-related and country-specific factors and issues by the inclusion of country and period dummy variables, we recognize that these might not have absorbed all effects.

6 Concluding remarks

6.1 Conclusion

This paper examined whether credit ratings directly affect the capital structure decisions of European firms. Inspired by the limited but growing literature on credit ratings effect on capital structure, this study expands the empirical scope on the topic, where previous investigations have largely focus on US data, by investigating the CR-CS hypothesis on a European sample.

To formally test the relevance of credit ratings in managers' capital structure decisions, two tests were conducted in line with the seminal study of Kisgen (2006); the Plus or Minus and the Investment Grade vs Speculative Grade tests. Moreover, the analytical structure of this study further refined and strengthened the analytical basis of the CR-CS hypothesis as applied to a European context, with Panel B showing a more robust set of results than would be obtained by only employing Kisgen's methodology.

The findings of this study support the hypothesis of credit ratings as a determinant in firms' choice of capital structure. We find that concerns of discrete costs (benefits) associated with changes in credit ratings result in adjustments being made to capital structure: firms near a change in Broad Rating and IGSG status issue 0.97% and 1.60% less debt relative to equity, respectively, than firms not near a change. Our findings further suggest that credit ratings are incrementally more significant, both in statistical and economical terms, at the investment-grade-to-speculative-grade crossover than the Broad Rating category crossover. This documented behaviour is not consistent with the trade-off and pecking order theory.

6.2 Suggestions for further research

An interesting topic for further research would be to investigate the leverage behaviour of European firms following a Broad Rating or IGSG status change, and not the subsequent financing choices of managers' rating considerations. For example, an interesting question would be: what are the effects on firms' leverage behaviour after losing an investment grade rating?

It would also be interesting to complement this study by investigating firms' responses in terms of leverage behaviour with regard to the implementation of Basel III and Solvency II, which may further increase the regulatory costs for lower-rated firms and the discrete costs (benefits) associated with different rating levels.

Another extension of the present study would be to employ the same empirical set-up on the European market but using the corporate credit ratings of another CRA (e.g. Moody's) and see whether there are any differences between the impacts of rating considerations between the different CRAs.

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7.4 Databases

Thomson Datastream Advance 5.0, Thomson Financial Ltd.

Appendices

8.1 Appendix 1: Table of sample companies

Id	Company name	ICB Sector	Nation	Website
1	**A2A**	Utilities	Italy	www.a2a.eu
2	**ABB**	Industrials	Switzerland	www.abb.com
3	**Abertis Infraestructuras**	Industrials	Spain	www.abertis.com
4	**Accor**	Consumer Services	France	www.accor.com
5	**Acea**	Utilities	Italy	www.acea.it
6	**Adecco**	Industrials	Switzerland	www.adecco.com
7	**ADP**	Industrials	France	www.aeroportsdeparis.fr
8	**Air Liquide**	Basic Materials	France	www.airliquide.com
9	**Alcatel-Lucent**	Technology	France	www.alcatel-lucent.com
10	**Alstom**	Industrials	France	www.alstom.com
11	**Anglo American**	Basic Materials	United Kingdom	www.angloamerican.com
12	**Anheuser-Busch InBev**	Consumer Goods	Belgium	www.ab-inbev.com
13	**ArcelorMittal**	Basic Materials	Luxembourg	www.arcelormittal.com
14	**Ashtead Group**	Industrials	United Kingdom	www.ashtead-group.com
15	**ASM International**	Technology	Netherlands	www.asm.com
16	**Assa Abloy**	Industrials	Sweden	www.assaabloy.com
17	**AstraZeneca**	Healthcare	United Kingdom	www.astrazeneca.com
18	**Atlantia**	Industrials	Italy	www.atlantia.it
19	**Atlas Copco**	Industrials	Sweden	www.atlascopco.com
20	**Autoroutes du Sud de la France Sa**	Industrials	France	www.asf.fr
21	**Autoroutes Paris-Rhin-Rhône**	Industrials	France	www.aprr.com
22	**BAE Systems**	Industrials	United Kingdom	www.baesystems.com
23	**Barry Callebaut**	Consumer Goods	Switzerland	www.barry-callebaut.com
24	**BASF**	Basic Materials	Germany	www.basf.com
25	**Bayer**	Basic Materials	Germany	www.bayer.com
26	**Belgacom**	Telecommunications	Belgium	www.belgacom.com
27	**Bouygues**	Industrials	France	www.bouygues.com
28	**BP**	Oil & Gas	United Kingdom	www.bp.com
29	**BSkyB**	Consumer Services	United Kingdom	www.sky.com/corporate
30	**Buzzi Unicem**	Industrials	Italy	www.buzziunicem.it
31	**Cap Gemini**	Technology	France	www.capgemini.com
32	**Carnival**	Consumer Services	United Kingdom	www.carnivalplc.com
33	**Carrefour**	Consumer Services	France	www.carrefour.com
34	**Casino Guichard-P**	Consumer Services	France	www.groupe-casino.fr
35	**Centrica**	Utilities	United Kingdom	www.centrica.com
36	**Clariant**	Basic Materials	Switzerland	www.clariant.com
37	**Compagnie Générale de Géophysique**	Oil & Gas	France	www.cggveritas.com
38	**Compass Group**	Consumer Services	United Kingdom	www.compass-group.com
39	**Continental**	Consumer Goods	Germany	www.conti-online.com
40	**CRH**	Industrials	Ireland	www.crh.com
41	**Daily Mail**	Consumer Services	United Kingdom	www.dmgt.com

42	**Daimler**	Consumer Goods	Germany	www.daimler.com
43	**Danone**	Consumer Goods	France	www.danone.com
44	**Delhaize Group**	Consumer Services	Belgium	www.delhaizegroup.com
45	**Deutsche Lufthansa**	Consumer Services	Germany	konzern.lufthansa.com
46	**Deutsche Post**	Industrials	Germany	www.dp-dhl.com
47	**Deutsche Telekom**	Telecommunications	Germany	www.telekom.com
48	**E On**	Utilities	Germany	www.eon.com
49	**EDF**	Utilities	France	www.edf.com
50	**Edison**	Utilities	Italy	www.edison.it
51	**EDP Energias de Portugal**	Utilities	Portugal	www.edp.pt
52	**Electrolux**	Consumer Goods	Sweden	group.electrolux.com
53	**Elisa**	Telecommunications	Finland	www.elisa.com
54	**Enagas**	Utilities	Spain	www.enagas.es
55	**Enel**	Utilities	Italy	www.enel.com
56	**Eni**	Oil & Gas	Italy	www.eni.com
57	**Enterprise Inns**	Consumer Services	United Kingdom	www.enterpriseinns.com
58	**Ericsson**	Technology	Sweden	www.ericsson.com
59	**Eutelsat Communications**	Consumer Services	France	www.eutelsat.com
60	**Evraz**	Basic Materials	United Kingdom	www.evraz.com
61	**Finmeccanica**	Industrials	Italy	www.finmeccanica.com
62	**First Group**	Consumer Services	United Kingdom	www.firstgroup.com
63	**Fortum**	Utilities	Finland	www.fortum.com
64	**France Telecom**	Telecommunications	France	www.orange.com
65	**G4S**	Industrials	United Kingdom	www.g4s.com
66	**GDF Suez**	Utilities	France	www.gdfsuez.com
67	**GKN**	Consumer Goods	United Kingdom	www.gkn.com
68	**Heidelbergcement**	Industrials	Germany	www.heidelbergcement.com
69	**Henkel**	Consumer Goods	Germany	www.henkel.com
70	**Hera**	Utilities	Italy	eng.gruppohera.it
71	**Holcim**	Industrials	Switzerland	www.holcim.com
72	**Holmen**	Basic Materials	Sweden	www.holmen.com
73	**Homeserve**	Industrials	United Kingdom	www.homeserveplc.com
74	**Iberdrola**	Utilities	Spain	www.iberdrola.es
75	**Intercontinental Hotels Group**	Consumer Services	United Kingdom	www.ihgplc.com
76	**International Power**	Utilities	United Kingdom	www.iprplc-gdfsuez.com
77	**ITV**	Consumer Services	United Kingdom	www.itvplc.com
78	**J Sainsbury**	Consumer Services	United Kingdom	www.j-sainsbury.co.uk
79	**K + S**	Basic Materials	Germany	www.k-plus-s.com
80	**Kabel Deutschland**	Consumer Services	Germany	www.kabeldeutschland.de
81	**Kingfisher**	Consumer Services	United Kingdom	www.kingfisher.com
82	**Koninklijke Ahold**	Basic Materials	Netherlands	www.akzonobel.com
83	**Koninklijke Ahold**	Consumer Services	Netherlands	www.ahold.com
84	**Koninklijke DSM**	Basic Materials	Netherlands	www.dsm.com
85	**Koninklijke KPN**	Telecommunications	Netherlands	www.kpn.com
86	**Koninklijke Philips Electronics**	Consumer Goods	Netherlands	www.philips.com
87	**Lafarge**	Industrials	France	www.lafarge.com
88	**Legrand**	Industrials	France	www.legrand.com
89	**Lottomatica**	Consumer Services	Italy	www.lottomaticagroup.com
90	**LVMH**	Consumer Goods	France	www.lvmh.com
91	**Man**	Industrials	Germany	www.man.de
92	**Marks & Spencer Group**	Consumer Services	United Kingdom	www.marksandspencer.com

93	**Metro**	Consumer Services	Germany	www.metrogroup.de
94	**Metso**	Industrials	Finland	www.metso.com
95	**Metsä Board**	Basic Materials	Finland	www.metsaboard.com
96	**Michelin**	Consumer Goods	France	www.michelin.com
97	**National Grid**	Utilities	United Kingdom	www.nationalgrid.com
98	**Nestle**	Consumer Goods	Switzerland	www.nestle.com
99	**Nexans**	Industrials	France	www.nexans.fr
100	**Next**	Consumer Services	United Kingdom	www.nextplc.co.uk
101	**Nokia**	Technology	Finland	www.nokia.com
102	**Norsk Hydro**	Basic Materials	Norway	www.hydro.com
103	**Norske Skogindustrier**	Basic Materials	Norway	www.norskeskog.com
104	**Novartis**	Healthcare	Switzerland	www.novartis.com
105	**Pearson**	Consumer Services	United Kingdom	www.pearson.com
106	**Pernod-Ricard**	Consumer Goods	France	www.pernod-ricard.com
107	**Petroleum Geo Services**	Oil & Gas	Norway	www.pgs.com
108	**Peugeot**	Consumer Goods	France	www.psa-peugeot-citroen.com
109	**Postnl**	Industrials	Netherlands	www.postnl.com
110	**PPR**	Consumer Services	France	www.ppr.com
111	**Publicis Groupe**	Consumer Services	France	www.publicisgroupe.com
112	**Remy Cointreau**	Consumer Goods	France	www.remy-cointreau.com
113	**Renault**	Consumer Goods	France	www.renault.com
114	**Rentokil Initial**	Industrials	United Kingdom	www.rentokil-initial.com
115	**Rexam**	Industrials	United Kingdom	www.rexam.com
116	**Rexel**	Industrials	France	www.rexel.com
117	**Rheinmetall**	Consumer Goods	Germany	www.rheinmetall.de
118	**Royal Dutch Shell**	Oil & Gas	Netherlands	www.shell.com
119	**RWE**	Utilities	Germany	www.rwe.com
120	**SABmiller**	Consumer Goods	United Kingdom	www.sabmiller.com
121	**Saint Gobain**	Industrials	France	www.saint-gobain.com
122	**Sandvik**	Industrials	Sweden	www.sandvik.com
123	**Sanofi**	Healthcare	France	www.sanofi.com
124	**SCA**	Consumer Goods	Sweden	www.sca.com
125	**Scania**	Industrials	Sweden	www.scania.com
126	**Seat Pagine Gialle**	Consumer Services	Italy	www.seat.it
127	**Securitas**	Industrials	Sweden	www.securitas.com
128	**SES**	Consumer Services	Luxembourg	www.ses.com
129	**Severn Trent**	Utilities	United Kingdom	www.severntrent.com
130	**SGL Carbon**	Industrials	Germany	www.sglgroup.com
131	**Sika**	Industrials	Switzerland	www.sika.com
132	**SKF**	Industrials	Sweden	www.skf.com
133	**Smiths Group**	Industrials	United Kingdom	www.smiths.com
134	**Sodexo**	Consumer Services	France	www.sodexo.com
135	**Solvay**	Basic Materials	Belgium	www.solvay.com
136	**SSAB**	Basic Materials	Sweden	www.ssab.com
137	**SSE**	Utilities	United Kingdom	www.sse.com
138	**Stagecoach Group**	Consumer Services	United Kingdom	www.stagecoach.com
139	**Statoil**	Oil & Gas	Norway	www.statoil.com
140	**STMicroelectronics**	Technology	Switzerland	www.st.com
141	**Stora Enso**	Basic Materials	Finland	www.storaenso.com
142	**Swedish Match**	Consumer Goods	Sweden	www.swedishmatch.com
143	**Swisscom**	Telecommunications	Switzerland	www.swisscom.ch

144	**Tate & Lyle**	Consumer Goods	United Kingdom	www.tateandlyle.com
145	**TDC**	Telecommunications	Denmark	www.tdc.com
146	**Technicolor**	Consumer Services	France	www.technicolor.com
147	**Technip**	Oil & Gas	France	www.technip.com
148	**Telecom Italia**	Telecommunications	Italy	www.telecomitalia.com
149	**Telefonica**	Telecommunications	Spain	www.telefonica.es
150	**Telenet Group**	Consumer Services	Belgium	www.telenet.be
151	**Telenor**	Telecommunications	Norway	www.telenor.com
152	**TeliaSonera**	Telecommunications	Sweden	www.teliasonera.com
153	**Tesco**	Consumer Services	United Kingdom	www.tescoplc.com
154	**Thales**	Industrials	France	www.thalesgroup.com
155	**Thyssenkrupp**	Industrials	Germany	www.thyssenkrupp.com
156	**Total**	Oil & Gas	France	www.total.com
157	**TUI**	Consumer Services	Germany	www.tui-group.com
158	**UBM**	Consumer Services	United Kingdom	www.ubm.com
159	**Unilever**	Consumer Goods	United Kingdom	www.unilever.com
160	**United Utilities Group**	Utilities	United Kingdom	www.unitedutilities.com
161	**UPM-Kymmene**	Basic Materials	Finland	www.upm.com
162	**Veolia Environnement**	Utilities	France	www.veolia.com
163	**William Hill**	Consumer Services	United Kingdom	www.williamhillplc.com
164	**Vinci**	Industrials	France	www.vinci.com
165	**Vivendi**	Consumer Services	France	www.vivendi.com
166	**Vodafone Group**	Telecommunications	United Kingdom	www.vodafone.com
167	**Wolters Kluwer**	Consumer Services	Netherlands	www.wolterskluwer.com
168	**WPP**	Consumer Services	United Kingdom	www.wpp.com
169	**Yara International**	Basic Materials	Norway	www.yara.com

8.2 Appendix 2: EViews outputs of regression results

$$NetDIss_{it} = \alpha + \beta_1 CR_{POM} + \phi K_{it} + \varepsilon_{it} \quad (4.1)$$

Panel A
Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:13
Sample: 2002 2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1240
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.082707	0.035746	2.313738	0.0208
CR_{POM}	-0.007083	0.005322	-1.330919	0.1835
BL	-0.055025	0.017685	-3.111354	0.0019
PROF	-0.008516	0.024809	-0.343275	0.7315
SIZE	-0.00132	0.002136	-0.617851	0.5368
GE="BD"	-0.054009	0.022085	-2.445484	0.0146
GE="BG"	-0.022353	0.031279	-0.714638	0.475
GE="DK"	-0.067956	0.03626	-1.874123	0.0612
GE="ES"	-0.003378	0.022756	-0.148451	0.882
GE="FN"	-0.060809	0.023436	-2.594636	0.0096
GE="FR"	-0.047277	0.022324	-2.117785	0.0344
GE="IT"	-0.033767	0.023094	-1.462177	0.144
GE="LX"	-0.023318	0.032775	-0.711467	0.4769
GE="NL"	-0.033439	0.027868	-1.199896	0.2304
GE="NW"	-0.066872	0.026867	-2.488989	0.0129
GE="SD"	-0.0218	0.023449	-0.929654	0.3527
GE="SW"	-0.033006	0.022857	-1.443991	0.149
GE="UK"	-0.04288	0.022454	-1.909667	0.0564

Effects Specification

Period fixed (dummy variables)

R-squared	0.068716	Mean dependent	-0.0067
Adjusted R-	0.048754	S.D. dependent var	0.089353
S.E. of regression	0.087147	Akaike info	-2.0209
Sum squared resid	9.212287	Schwarz criterion	-1.90936
Log likelihood	1279.96	Hannan-Quinn	-1.97895
F-statistic	3.442409	Durbin-Watson stat	1.971576
Prob(F-statistic)	0		

Panel B
Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:15
Sample: 1/01/2002 1/01/2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1318
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.114908	0.037275	3.082743	0.0021
CR_{POM}	-0.0094	0.005597	-1.679643	0.0933
BL	-0.053927	0.018482	-2.917781	0.0036
PROF	0.019616	0.032801	0.598037	0.5499
SIZE	-0.003994	0.00245	-1.630465	0.1032
GE="BD"	-0.040705	0.020602	-1.975786	0.0484
GE="BG"	0.000748	0.033588	0.022261	0.9822
GE="DK"	-0.036487	0.04842	-0.753536	0.4513
GE="ES"	0.000965	0.021234	0.045425	0.9638
GE="FN"	-0.048812	0.021584	-2.261464	0.0239
GE="FR"	-0.039511	0.020215	-1.954514	0.0509
GE="IT"	-0.031225	0.021287	-1.466905	0.1426
GE="LX"	-0.012736	0.033895	-0.375735	0.7072
GE="NL"	-0.016651	0.024979	-0.666578	0.5052
GE="NW"	-0.038858	0.032128	-1.209452	0.2267
GE="SD"	-0.016076	0.021694	-0.74105	0.4588
GE="SW"	-0.029175	0.0213	-1.369732	0.171
GE="UK"	-0.026503	0.020567	-1.28864	0.1978

Effects Specification

Period fixed (dummy variables)

R-squared	0.098598	Mean dependent	0.009208
Adjusted R-	0.080444	S.D. dependent var	0.099417
S.E. of regression	0.095334	Akaike info	-1.84258
Sum squared resid	11.73344	Schwarz criterion	-1.73639
Log likelihood	1241.26	Hannan-Quinn	-1.80276
F-statistic	5.431296	Durbin-Watson stat	2.086522
Prob(F-statistic)	0		

The results are for the pooled sample 2002–2011 for model (4.1). Numbers in brackets are the standard errors which are corrected for heteroscedasticity using White diagonal standard error. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm years with missing values of any used variable are excluded. Panel A also excludes debt offerings greater than 10% of total, whereas Panel B excludes the highest 2% of observations of both debt offerings and equity offerings in any given year. Country and year dummy variables have been included to absorb differences in regulatory effects and allow for time aggregated effects.

$$NetDIss_{it} = \alpha + \beta_2 CR_{Plus} + \beta_3 CR_{Minus} + \phi K_{it} + \varepsilon_{it} \quad (4.2)$$

Panel A

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:13
Sample: 2002 2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1240
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.085616	0.036499	2.345717	0.0192
CR_{PLUS}	-0.004828	0.006249	-0.77267	0.4399
CR_{MINUS}	-0.0094	0.006211	-1.513331	0.1305
BL	-0.055886	0.017742	-3.149992	0.0017
PROF	-0.007277	0.025149	-0.289346	0.7724
SIZE	-0.00146	0.002186	-0.667761	0.5044
GE="BD"	-0.054866	0.022067	-2.486361	0.013
GE="BG"	-0.023983	0.031559	-0.759941	0.4474
GE="DK"	-0.068156	0.036016	-1.892397	0.0587
GE="ES"	-0.003997	0.022736	-0.175819	0.8605
GE="FN"	-0.062122	0.02349	-2.644631	0.0083
GE="FR"	-0.048219	0.022271	-2.16509	0.0306
GE="IT"	-0.034837	0.02309	-1.508755	0.1316
GE="LX"	-0.025368	0.032771	-0.774116	0.439
GE="NL"	-0.034742	0.028282	-1.228407	0.2195
GE="NW"	-0.067782	0.026825	-2.526798	0.0116
GE="SD"	-0.022885	0.023482	-0.974606	0.33
GE="SW"	-0.034002	0.022849	-1.488119	0.137
GE="UK"	-0.043983	0.022477	-1.956808	0.0506

Effects Specification

Period fixed (dummy variables)

R-squared	0.06913	Mean dependent	-0.0067
Adjusted R-	0.048392	S.D. dependent var	0.089353
S.E. of regression	0.087164	Akaike info	-2.01973
Sum squared resid	9.208196	Schwarz criterion	-1.90406
Log likelihood	1280.235	Hannan-Quinn	-1.97623
F-statistic	3.333598	Durbin-Watson stat	1.967837
Prob(F-statistic)	0		

Panel B

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:15
Sample: 1/01/2002 1/01/2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1318
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.114525	0.037817	3.028426	0.0025
CR_{PLUS}	-0.00969	0.006553	-1.478738	0.1395
CR_{MINUS}	-0.009097	0.006596	-1.379144	0.1681
BL	-0.053814	0.018567	-2.89834	0.0038
PROF	0.019446	0.032959	0.590009	0.5553
SIZE	-0.003974	0.002475	-1.605847	0.1086
GE="BD"	-0.040609	0.020681	-1.963571	0.0498
GE="BG"	0.000965	0.033632	0.028702	0.9771
GE="DK"	-0.03643	0.048461	-0.751749	0.4523
GE="ES"	0.001018	0.021277	0.047848	0.9618
GE="FN"	-0.04865	0.021724	-2.239409	0.0253
GE="FR"	-0.039404	0.020249	-1.945943	0.0519
GE="IT"	-0.031095	0.021367	-1.455314	0.1458
GE="LX"	-0.012461	0.034077	-0.365657	0.7147
GE="NL"	-0.016476	0.025356	-0.649781	0.5159
GE="NW"	-0.038751	0.032343	-1.198124	0.2311
GE="SD"	-0.015954	0.021809	-0.731507	0.4646
GE="SW"	-0.029053	0.021406	-1.357284	0.1749
GE="UK"	-0.026372	0.020677	-1.275452	0.2024

Effects Specification

Period fixed (dummy variables)

R-squared	0.098604	Mean dependent	0.009208
Adjusted R-	0.079737	S.D. dependent var	0.099417
S.E. of regression	0.095371	Akaike info	-1.84107
Sum squared resid	11.73337	Schwarz criterion	-1.73094
Log likelihood	1241.264	Hannan-Quinn	-1.79978
F-statistic	5.226414	Durbin-Watson stat	2.08702
Prob(F-statistic)	0		

The results are for the pooled sample 2002–2011 for model (4.1). Numbers in brackets are the standard errors which are corrected for heteroscedasticity using White diagonal standard errors. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm years with missing values of any used variable are excluded. Panel A also excludes debt offerings greater than 10% of total, whereas Panel B excludes the highest 2% of observations of both debt offerings and equity offerings in any given year. Country and year dummy variables have been included to absorb differences in regulatory effects and allow for time aggregated effects.

$$NetDIss_{it} = \alpha + \beta_4 CR_{POM} + \varepsilon_{it} \quad (4.3)$$

Panel A

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:13
Sample: 2002 2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1244
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.031392	0.022365	1.403597	0.1607
CR_{POM}	-0.007569	0.005367	-1.410409	0.1587
GE="BD"	-0.048303	0.022482	-2.148556	0.0319
GE="BG"	-0.014263	0.03191	-0.446971	0.655
GE="DK"	-0.067224	0.038112	-1.76383	0.078
GE="ES"	-0.00303	0.023179	-0.130731	0.896
GE="FN"	-0.047138	0.02359	-1.998238	0.0459
GE="FR"	-0.039859	0.022673	-1.757961	0.079
GE="IT"	-0.029386	0.023545	-1.248064	0.2122
GE="LX"	-0.016811	0.032765	-0.513067	0.608
GE="NL"	-0.022705	0.027823	-0.816067	0.4146
GE="NW"	-0.051635	0.026411	-1.955048	0.0508
GE="SD"	-0.008046	0.023645	-0.340264	0.7337
GE="SW"	-0.020617	0.023064	-0.893894	0.3716
GE="UK"	-0.034378	0.022607	-1.520682	0.1286

Effects Specification

Period fixed (dummy variables)

R-squared	0.054531	Mean dependent	-0.00663
Adjusted R-	0.036707	S.D. dependent var	0.089454
S.E. of regression	0.087796	Akaike info	-2.00849
Sum squared resid	9.404015	Schwarz criterion	-1.90959
Log likelihood	1273.28	Hannan-Quinn	-1.9713
F-statistic	3.059364	Durbin-Watson stat	1.95896
Prob(F-statistic)	0.000002		

Panel B

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:16
Sample: 1/01/2002 1/01/2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1322
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.03636	0.020234	1.796983	0.0726
CR_{POM}	-0.009702	0.005601	-1.73203	0.0835
GE="BD"	-0.037502	0.020845	-1.799117	0.0722
GE="BG"	0.012359	0.034286	0.360459	0.7186
GE="DK"	-0.031052	0.050429	-0.615753	0.5382
GE="ES"	0.003906	0.021742	0.179652	0.8575
GE="FN"	-0.033712	0.021646	-1.557474	0.1196
GE="FR"	-0.032598	0.020555	-1.585877	0.113
GE="IT"	-0.025373	0.021728	-1.167741	0.2431
GE="LX"	0.001514	0.034037	0.044477	0.9645
GE="NL"	-0.004633	0.02485	-0.186422	0.8521
GE="NW"	-0.020827	0.03224	-0.646004	0.5184
GE="SD"	0.00013	0.021693	0.005975	0.9952
GE="SW"	-0.016063	0.021421	-0.749878	0.4535
GE="UK"	-0.016807	0.02067	-0.813088	0.4163

Effects Specification

Period fixed (dummy variables)

R-squared	0.087521	Mean dependent	0.009231
Adjusted R-	0.071352	S.D. dependent var	0.099466
S.E. of regression	0.095852	Akaike info	-1.83404
Sum squared resid	11.92548	Schwarz criterion	-1.73987
Log likelihood	1236.299	Hannan-Quinn	-1.79874
F-statistic	5.412955	Durbin-Watson stat	2.099399
Prob(F-statistic)	0		

The results are for the pooled sample 2002–2011 for model (4.3). Numbers in brackets are the standard errors which are corrected for heteroscedasticity using the White diagonal standard errors. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm years with missing values of any used variable are excluded. Panel A also excludes debt offerings greater than 10% of total, whereas Panel B excludes the highest 2% of observations of both debt offerings and equity offerings in any given year. Country and year dummy variables have been included to absorb differences in regulatory effects and allow for time aggregated effects.

$$NetDIss_{it} = \alpha + \delta CR_{IGSG} + \phi K_{it} + \varepsilon_{it} \quad (4.4)$$

Panel A

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:13
Sample: 2002 2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1240
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.081102	0.035806	2.265022	0.0237
CR_{IGSG}	-0.006824	0.005515	-1.237281	0.2162
BL	-0.053509	0.017877	-2.993137	0.0028
PROF	-0.010249	0.025673	-0.39922	0.6898
SIZE	-0.001638	0.002169	-0.755021	0.4504
GE="BD"	-0.04985	0.022008	-2.265085	0.0237
GE="BG"	-0.019988	0.031152	-0.641617	0.5212
GE="DK"	-0.063835	0.036139	-1.766392	0.0776
GE="ES"	-0.004267	0.022311	-0.191239	0.8484
GE="FN"	-0.054687	0.023376	-2.339419	0.0195
GE="FR"	-0.043161	0.022278	-1.937395	0.0529
GE="IT"	-0.029654	0.022779	-1.301826	0.1932
GE="LX"	-0.014772	0.032398	-0.455953	0.6485
GE="NL"	-0.031015	0.028255	-1.0977	0.2726
GE="NW"	-0.06272	0.026917	-2.330089	0.02
GE="SD"	-0.019806	0.02327	-0.851146	0.3949
GE="SW"	-0.029053	0.022706	-1.27951	0.201
GE="UK"	-0.038781	0.022381	-1.732771	0.0834

Effects Specification

Period fixed (dummy variables)

R-squared	0.06867	Mean dependent	-0.0067
Adjusted R-	0.048708	S.D. dependent var	0.089353
S.E. of regression	0.087149	Akaike info	-2.02085
Sum squared resid	9.212737	Schwarz criterion	-1.90931
Log likelihood	1279.93	Hannan-Quinn	-1.9789
F-statistic	3.439966	Durbin-Watson stat	1.97368
Prob(F-statistic)	0		

Panel B

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:18
Sample: 1/01/2002 1/01/2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1318
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.116567	0.037454	3.112253	0.0019
CR_{IGSG}	-0.016039	0.00564	-2.843721	0.0045
BL	-0.04974	0.018459	-2.694539	0.0071
PROF	0.012907	0.032808	0.393395	0.6941
SIZE	-0.004767	0.002478	-1.923536	0.0546
GE="BD"	-0.031533	0.020434	-1.543198	0.123
GE="BG"	0.004894	0.033158	0.147594	0.8827
GE="DK"	-0.025237	0.048215	-0.523437	0.6008
GE="ES"	-0.000277	0.020484	-0.013531	0.9892
GE="FN"	-0.036186	0.021486	-1.684145	0.0924
GE="FR"	-0.030103	0.019896	-1.513026	0.1305
GE="IT"	-0.022834	0.020802	-1.097657	0.2726
GE="LX"	0.004197	0.033272	0.126134	0.8996
GE="NL"	-0.009573	0.024923	-0.384082	0.701
GE="NW"	-0.030096	0.031779	-0.947025	0.3438
GE="SD"	-0.010427	0.021248	-0.490738	0.6237
GE="SW"	-0.020529	0.021018	-0.976714	0.3289
GE="UK"	-0.017087	0.020249	-0.843833	0.3989

Effects Specification

Period fixed (dummy variables)

R-squared	0.102409	Mean dependent	0.009208
Adjusted R-	0.084332	S.D. dependent var	0.099417
S.E. of regression	0.095133	Akaike info	-1.84682
Sum squared resid	11.68384	Schwarz criterion	-1.74062
Log likelihood	1244.051	Hannan-Quinn	-1.807
F-statistic	5.66514	Durbin-Watson stat	2.10625
Prob(F-statistic)	0		

The results are for the pooled sample 2002–2011 for model (4.4). Numbers in brackets are the standard errors which are corrected for heteroscedasticity using the White diagonal standard errors. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm years with missing values of any used variable are excluded. Panel A also excludes debt offerings greater than 10% of total, whereas Panel B excludes the highest 2% of observations of both debt offerings and equity offerings in any given year. Country and year dummy variables have been included to absorb differences in regulatory effects and allow for time aggregated effects.

$$NetDIss_{it} = \alpha + \delta CR_{IGSG} + \beta_0 CR_{POM} + \phi K_{it} + \varepsilon_{it} \quad (4.5)$$

Panel A

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:14
Sample: 2002 2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1240
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.08663	0.035905	2.412748	0.016
CR_{IGSG}	-0.007122	0.005526	-1.288902	0.1977
CR_{POM}	-0.007383	0.005335	-1.38377	0.1667
BL	-0.05304	0.0178	-2.979754	0.0029
PROF	-0.013204	0.025648	-0.514804	0.6068
SIZE	-0.001714	0.002154	-0.795802	0.4263
GE="BD"	-0.049336	0.022508	-2.191939	0.0286
GE="BG"	-0.01998	0.031417	-0.635953	0.5249
GE="DK"	-0.061592	0.036541	-1.68555	0.0921
GE="ES"	-0.002419	0.0228	-0.106088	0.9155
GE="FN"	-0.055545	0.023838	-2.330152	0.02
GE="FR"	-0.042602	0.022797	-1.8687	0.0619
GE="IT"	-0.030121	0.023295	-1.293022	0.1962
GE="LX"	-0.016563	0.033241	-0.498278	0.6184
GE="NL"	-0.029225	0.028587	-1.022304	0.3068
GE="NW"	-0.062472	0.027303	-2.288128	0.0223
GE="SD"	-0.017597	0.023782	-0.739941	0.4595
GE="SW"	-0.028767	0.023205	-1.239673	0.2153
GE="UK"	-0.038383	0.022895	-1.676441	0.0939

Effects Specification

Period fixed (dummy variables)

R-squared	0.070102	Mean dependent	-0.0067
Adjusted R-	0.049387	S.D. dependent var	0.089353
S.E. of regression	0.087118	Akaike info	-2.02078
Sum squared resid	9.198571	Schwarz criterion	-1.9051
Log likelihood	1280.884	Hannan-Quinn	-1.97728
F-statistic	3.384054	Durbin-Watson stat	1.976745
Prob(F-statistic)	0		

Panel B

Dependent Variable: NETDISS
Method: Panel Least Squares
Date: 05/21/12 Time: 12:18
Sample: 1/01/2002 1/01/2011
Periods included: 10
Cross-sections included: 169
Total panel (unbalanced) observations: 1318
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficien	Std. Error	t-Statistic	Prob.
C	0.123927	0.037367	3.316498	0.0009
CR_{IGSG}	-0.016439	0.005624	-2.92311	0.0035
CR_{POM}	-0.010077	0.005567	-1.810185	0.0705
BL	-0.049542	0.018437	-2.68707	0.0073
PROF	0.009214	0.03217	0.286415	0.7746
SIZE	-0.004896	0.002458	-1.9916	0.0466
GE="BD"	-0.030377	0.02111	-1.438944	0.1504
GE="BG"	0.0056	0.033621	0.166559	0.8677
GE="DK"	-0.021355	0.04864	-0.439048	0.6607
GE="ES"	0.003031	0.02124	0.142715	0.8865
GE="FN"	-0.036591	0.022114	-1.654692	0.0982
GE="FR"	-0.028602	0.020611	-1.387723	0.1655
GE="IT"	-0.022658	0.021504	-1.053639	0.2922
GE="LX"	0.003017	0.034453	0.087557	0.9302
GE="NL"	-0.006507	0.025533	-0.254851	0.7989
GE="NW"	-0.028865	0.032133	-0.898309	0.3692
GE="SD"	-0.006743	0.022032	-0.306052	0.7596
GE="SW"	-0.019458	0.021709	-0.896306	0.3703
GE="UK"	-0.01609	0.020957	-0.767754	0.4428

Effects Specification

Period fixed (dummy variables)

R-squared	0.104576	Mean dependent	0.009208
Adjusted R-	0.085834	S.D. dependent var	0.099417
S.E. of regression	0.095055	Akaike info	-1.84772
Sum squared resid	11.65564	Schwarz criterion	-1.73759
Log likelihood	1245.644	Hannan-Quinn	-1.80642
F-statistic	5.579909	Durbin-Watson stat	2.108603
Prob(F-statistic)	0		

The results are for the pooled sample 2002–2011 for model (4.5). Numbers in brackets are the standard errors which are corrected for heteroscedasticity using the White diagonal standard errors. Numbers in brackets and in bold below the standard errors are the probability of significance. Firm years with missing values of any used variable are excluded. Panel A also excludes debt offerings greater than 10% of total, whereas Panel B excludes the highest 2% of observations of both debt offerings and equity offerings in any given year. Country and year dummy variables have been included to absorb differences in regulatory effects and allow for time aggregated effects.