KHURRAM SHAHZAD

Credit Rating Agencies, Financial Regulations and the Capital Markets

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Kredietbeoordelaars, financiële regelgeving en de kapitaalmarkten

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Acknowledgements

Finally, it is time to write the last section of my PhD dissertation although it appears first in the printing order. A few years ago it was hard to imagine that I would be able to reach this far in pursuit of my Ph.D. The first time I thought of doing a Ph.D. was when I was working in a chartered accountant firm as an auditor. During that time a number of new regulations were introduced that were expected to have significant impact on the capital markets. In my role as an auditor, I noticed that the management of firms took advantage of weak spots in the regulations and were often able to escape requirements This inspired me to explore whether regulations that are introduced time after time actually achieve their intended goals. For this purpose, I first moved to academia and later proceeded to the Netherlands for my Ph.D in Accounting.

Getting in to Erasmus Research Institute of Management ERIM as a Ph.D. candidate gave me a great satisfaction, however, I soon realized that doing a Ph.D. is much more stressful and demanding compared to the professional life. Someone has very rightly said that Ph.D. seems to be a fun in the beginning, but later one begins to eat, sleep, and work, around it. Getting a PhD is a long process with constant and random ups and downs. Getting through the roller-coaster was, of course, not possible without the help and support of several individuals. In this regard, I would first like to thank my promoter, Professor Gerard Mertens, for his support and encouragement from beginning to end. His critical comments and creative ideas were instrumental in bringing my dissertation to its current form. Working with him, I not only found him to be a great researcher but also a true human. I also owe him a special thank for his efforts in bringing my family to the Netherlands. Next to Gerard, I must also extend thanks to the members of my Ph.D. committee, Prof.dr. M.B. Livingston, Prof.dr. E.M. Roelofsen, Dr. L. Norden, who thoroughly read my thesis and provided feedback that greatly improved my dissertation. I am especially thankful to Prof.dr. M.B. Livingston who took time out of his busy schedule to attend formal defense of my PhD dissertation in person.

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Khurram Shahzad
Amsterdam, the Netherlands
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Contents

Chapter 1

Introduction

1.1 Background

The significance of the capital market to the economic development of a country is well documented in both academic and professional literature. Even the success of the Industrial Revolution, which had profound effects on the social, economic, and cultural conditions of the world, is attributed to these markets.[1] Since their inception, the financial markets have developed tremendously. They have experienced enormous growth, and have reached previously unimagined levels of sophistication. Despite this, however, the capital markets are still far from perfect. Capital markets have seen many instances of failure, from the financial hiccups of 1850s that culminated in the Great Depression, to the series of financial crises witnessed in last couple of decades. The concept of free markets does not allow any governmental intervention; nonetheless, the importance of financial markets to the world's economy and the significance of the loss of public wealth at their failure warrants preventive measures. One of the approaches meant to deter market failures is to expand the information level of market participants and introduce regulations that ensure the smooth functioning of financial markets. Accordingly, different information intermediaries (such as credit rating agencies (CRAs)) are allowed to work in the capital markets to facilitate market participants whereas policymakers regularly develop new or update existing regulations to ensure the smooth functioning of the markets. The purpose point of this thesis is to study the role of CRAs (Moody's and Standard and Poor's (S&P)) in reducing the information asymmetry in capital markets and the effects of two regulatory steps - the introduction of International Financial Reporting Standards (IFRS) and Market Abuse Directive (MAD) - that are aimed to improve the quality of information and enhance the integrity of capital markets respectively.

1.2 Outline

Capital markets work as a bridge between the borrowers and the lenders in order to cater to formers' financing needs. A major barrier in arranging any sort of financing, whether through

[1] For instance, the famous English businessman Walter Bagehot argues in his book *Lombard Street* (1873) that the presence of efficient financial markets paved the way for the Industrial Revolution.

issuance of equity or debt securities, arises because of the information asymmetry that exists between the borrowing companies and the lenders. This information asymmetry makes the contracts for financial markets inefficient (Stiglitz and Weiss, 1981; Myers and Majluf, 1984; and Diamond, 1991) and leads investors to demand higher interest rates (e.g., Goyenko at al., 2011). A number of financial intermediaries, including the CRAs, function in the financial markets to facilitate debt contracting between the borrowers and the lenders. The role of CRAs in the financial markets is to provide an assessment as to whether the bond issuers would be able to meet their contractual and financial obligations when they become due. The significance of the assessments provided by CRAs is well documented in the literature (e.g., Allen et al., 1990; Poon and Chan, 2008). However, at the same time, several factors such as the lack of competition among credit ratings agencies, their compensation structure, and the lack of transparency of the rating methodology applied, raise questions about the accuracy and utility of the information provided by CRAs. Chapter 2 of this thesis examines whether or not the factors reported above affect the investors' trust on credit ratings. We argue that if investors doubt the accuracy of credit ratings and carry out analysis of their own to estimate the credit risk of various debt securities, as has been evidenced in several studies, then the investors' required bond yield should reflect the extent to which credit ratings are considered inaccurate by the investors. In other words, we posit that the bonds for which the ratings assigned by CRAs are higher than the ratings considered to be fair by the investors should have higher yield compared to the yield of the bonds for which the actual ratings match the expected ratings and vice versa. The results of our analysis reveals that the investors do indeed take into account the difference between the credit ratings assigned by credit CRAs and those that appear to be fair. In particular, the investors require higher yield on bonds that received higher than expected (fair) ratings compared to the base case bonds for which the credit ratings assigned by CRAs are equal to their expected ratings. Next, Chapter 2 analyzes and explains the higher yield required by investors on split rate bonds. The literature (e.g., Morgan, 2002; Livingston et al., 2007) shows that information asymmetry related to certain bond issues leads CRAs to issue split ratings which in turn leads such bonds to sell at a higher interest rate (e.g., Liu and Moore, 1987; Livingston et al., 2010). We revisit the split rated bonds yield and find that part of the extra yield charged on split rated bonds in fact relates to the investors' perception of higher than expected ratings assigned to the split rated bonds. The studies related to the split rated bonds further report Moody's to be a more conservative rater than S&P. We examine and compare the relative conservativeness of Moody's and S&P and find that Moody's is not only more conservative as compared to S&P, but also the ratings assigned by Moody's are generally lower than those predicted based on publically available information. Finally, this chapter provides evidence that Moody's updates the ratings of bonds that receive higher than expected ratings much earlier as compared to other bonds when former sell at higher than expected yield. We find no such evidence for S&P.

In Chapter 2 we examine the value relevance of credit ratings for the fixed income securities investors. An important building stone of Chapter 2, which is supported by both the literature and the CRAs, is that the availability of financial information is imperative for the CRAs to be able to analyze the financial risk of a firm. In fact, financial information is not only important for the CRAs but also is vital for all stakeholders of the firm including the equity and debt investors. Understanding its importance, regulators around the world constantly strive to introduce and incorporate measures that would improve the quality of financial information. The adoption of International Financial Reporting Standards (IFRS) by European Union (EU) in 2005 is one of the latest examples of such efforts. Since the European Commission's decision to move to IFRS is one of the biggest regulatory changes, it inspired many researchers to investigate if the adoption of IFRS achieved the desired objectives. Most of these studies on IFRS, such as Barth et al. (2008), Van der Meulen et al. (2007), and Van Tendeloo and Vanstraelen (2005), focused on equity markets, whereas evidence from the debt market, a much more important and bigger source of finance, remains relatively scarce. In Chapter 3 of this thesis we fill this gap in the literature. For this purpose, we compare the credit ratings assigned by Moody's and S&P to the bonds issued by European financial firms. Since credit ratings are largely determined based on the financial information, we posit that a properly chosen set of proxies based on credit ratings should serve as an appropriate criteria to examine the quality of financial information. A review of literature suggests that the level of credit ratings assigned by CRAs and the frequency and level of rating disagreements between CRAs could form a possible set proxies.

Chapter 3 provides strong evidence that application of IFRS improves the quality of accounting information. In particular, we find that the bonds issued by firms reporting under IFRS receive higher credit ratings, on average, compared to those that are issued by the firms that report under other sets of accounting standards. Next, consistent with previous research, we find that a high proportion of bonds jointly rated by Moody's and S&P are split rated. However, our results provide strong evidence that the probability of rating disagreements between Moody's and S&P lowers by about 17% after firms start to report under IFRS. Our results also show that not only the frequency but also the level of absolute disagreement between CRAs decline for IFRS sample firms in instances when a split rating occurs. As an additional source of evidence we observe the pattern of lopsided rating disagreements, another proxy of the information asymmetry, between Moody's and S&P. The analysis of lopsided ratings corroborates our main findings as our results show a decrease in this phenomenon once firms start to report under IFRS. We attribute these results to higher quality and more transparent accounting information being produced under IFRS.

The adoption of IFRS that is intended to improve the quality of information available to the security markets shows the level of importance the regulators place on these markets. In fact, the regulators consider securities markets that function smoothly and have investors' confidence as one of the most important prerequisites of the economic growth of a country (as stated by European Commission Directive 2003/6/EC). Accordingly, regulators always remain watchful of the operations of the security markets and, if necessary, bring in new regulations to correct or eliminate practices that may be detrimental to the integrity of these markets. In such an effort, regulators in Europe enacted a regulation called Market Abuse Directive (MAD) 2003/6/EC in year 2003. The main objective of this regulation is to deter market abuse activities that put certain investors in an advantageous position and to improve the proper flow as well as the quality of information to the security markets. MAD has already been in operation for more than 7 years; however, there is only limited evidence available regarding its success. In Chapter 4 we investigate the effects of MAD on the financial information environment. In particular we focus on its provisions that a) aim to reduce the market manipulation, b) require prompt provision of inside information to the public, and c) restrict selective disclosures.

To examine the success of provisions (a) and (b) as stated above, we focus on the stock return volatility around earnings announcements and the absolute cumulative abnormal returns during the period leading up to the earnings announcements. The market manipulation activities distort or lead the prices of a security to an artificial level. Based on Aggarwal and Wu (2006) and Jiang et al. (2005), we argue that the absence of or decline in market manipulation activities should lower the deviation of stock prices from their fundamental values and lessen their volatility. The provision of MAD that require prompt disclosure of inside information should also lead to a decrease in the volatility of stock prices at earnings announcements. According to Beaver (1968), the investors' reactions and the resulting movement in stock prices at the earnings announcements depend upon the gap between the information the investors already possess and the information content of earnings announcements. A larger information gap results in a higher stock price movement or volatility. If, in compliance of provisions of MAD, the inside information is released to the market on a more timely basis, then the amount of new information contained in the earnings announcement would be lower. This should leads to a lowered stock return volatility at the earnings announcements. Further, as a result of the prompt disclosure of the inside information the stock prices should remain closer to their fundamental values in all time periods, not only just before earnings announcements. To examine whether this is the case, we calculate absolute cumulative abnormal returns for each of the 60 days before earnings announcements day and until the day following the earnings report day.

To examine the effect of MAD on the quality of information and whether the implementation of MAD has resulted in lowering the provision of selective disclosures, we focus on the accuracy and dispersion of analysts' forecasts and level of analysts' following. The accuracy of analyst forecasts has been a well-accepted measure of the quantity and quality of information that is available to the financial market (e.g. Lang and Lundholm, 1996; Barron et al., 1998;). Several factors affect the accuracy of the analysts' forecast. One important factor is the analysts' dependence on the management of the firm for inside information. According to the management relation hypotheses (Kothari, 2001), analysts withhold negative views about firms to gain better access to management. Since MAD disallows selective disclosures and requires prompt release of inside information, its implementation is expected to the reduce analysts' dependence on firm managers for price sensitive, non-public information. As a result, the accuracy of analysts' forecasts is expected to improve. The practice of selectively disclosing private information also affects the dispersion of the analysts forecast. This is because providing private information to selected analysts results in a wider information gap between analysts. In other words, because they possess different information to analyze, analysts would have a higher divergence in their forecasts. This notion is also supported by the analysts' forecast dispersion model presented by Barron et al. (1998) and empirical studies such as Botosan et al. (2004). The implementation of MAD is also expected to affect the number of analysts following a particular firm. This is because analysts prefer to follow those firms that give them access to private information (Bushee et al., 2003; Hutton, 2003) which helps them to make more accurate forecasts. A restriction on the provision of private information may force the analysts to move away from those firms from which they used to receive private information and concentrate on a smaller number of firms so as to market themselves based on their ability to make more accurate forecasts.

The results of Chapter 4 provide evidence that the implementation of MAD has a positive impact on the financial information environment. Specifically, our results reveal a decrease in the level of stock return volatility around the earnings announcement date after implementation of MAD. Additionally, we also find that in the post-MAD period stock prices remain closer to their post announcement prices compared to the pre-MAD period. Our results also provide evidence of an increase in the level of accuracy in analysts' forecasts while the level of dispersion of the analysts' forecasts appears to have decreased in the post-MAD implementation years. Finally, there is strong evidence of decline in the average number analysts following a firm which we attribute to a decline in the level of private information available to analysts.

Chapter 2

The investors' reaction on the difference between actual and expected credit ratings

2.1 Introduction

The issuance of a debt security is a complex process facilitated by several information intermediaries including the credit ratings agencies (CRAs). The role of CRAs in the debt issuance process is to provide an assessment as to whether the security issuer would be able to meet its contractual and financial obligations when they become due. The significance of rating opinions is well documented in literature as both the initial ratings and their subsequent revisions are evidenced to influence the bond yields (Allen et al., 1990; Mitchell, 1991; Reiter and Ziebart, 1991) as well as stock prices (Poon and Chan, 2008; Jorion et al., 2005). In addition to borrowers and lenders, financial market regulators also use credit rating information to determine financial market regulations.[1]

Despite the evidence of utility and the market's substantial reliance on the information provided by CRAs, several issues surrounding them bring into question CRAs' independence and, consequently, the quality and accuracy of information they provide. The purpose of this study is to examine if bond investors take these possible inaccuracies in the credit ratings into account when making investment decisions based on these ratings.

Some of the most important of factors that raise doubt about the accuracy of the credit ratings relate to the fact that CRAs operate under an oligopoly structure which limits the competition among the rating agencies to improve the quality of their services (Becker and Milbourn, 2011), and the fact that CRAs rely on the clients they rate for most of their revenues which may lead CRAs to issue higher ratings (Smith and Walter, 2002; Benmelech and Dlugosz, 2009). Furthermore, CRAs are also criticized on the grounds that they update their ratings with a significant time lag (Norden and Weber, 2004; Hite and Warga, 1997) and issue unsolicited

[1] For instance, the U.S Security and Exchange commission (SEC) relies on credit ratings to monitor risk level of the investments held by regulated entities. Similarly, under Based II the minimum capital requirements of the financial institutions is determined based on their credit ratings.

ratings that generally do not truly reflect the default risk of an issuer (Poon, 2003).[1] The recent financial crisis has also opened a new avenue of criticism for CRAs. Some observers believe that CRAs are responsible for the occurrence of the current financial crisis while others accuse them of breaching the trust of investors who rely on CRAs for their financial decisions.[2] The seemingly poor performance of CRAs led to a big debate among regulators to take corrective actions. Resultantly, several new regulations are proposed that would require CRAs to disclose their rating methodology, prohibits compliance officers from working on rating methodologies or sales, and would make CRAs liable to investors for their knowing or careless failures.

We use two sets of studies as a foundation for our study. The first set consists of those studies, as discussed in the previous paragraph, that raise concerns about the accuracy of credit ratings issued by CRAs. The second set consists of the studies that document that investors distinguish among CRAs based on the credibility of the information CRAs provide and that investors carry out analyses of their own in order to make a judgment of the creditworthiness of a bond issuer (Ellis, 1998; Baker and Mansi, 2002; Livingston et al., 2010). Apart from these two sets of studies, we also lend support from the literature that shows that the investors' reaction to information at their disposal depends on the accuracy of both the source and the content of information. For instance, Hutton and Stocken (2009) document that the cross-sectional variation in the investors' response to the management predictions depends on the perceived accuracy of those predictions. Park and Stice (2000) find that the recent history of forecast accuracy influence the price reaction. The findings in Siha et al., (1997) suggest that investors' reaction to the analysts' forecasts is associated with the accuracy of their forecast revisions. Several other papers such as Shivakumar (2000), Abarbnell et al., (1995) also provide evidence that market response to the new information depends on the precision of information. Based on these findings, we posit that, if the investor indeed consider credit ratings assigned by CRAs to be inaccurate then, to the extent to which credit ratings issued by CRAs are considered unjustified should be reflected in the investors' required bond yield spread. In other words, we argue that bonds for which the ratings assigned by CRAs (for stylistic convenience, we label these ratings as "actual ratings") are higher than the ratings that are considered to be fair by the investor based on their own analysis (for stylistic convenience, we label these ratings as "expected ratings" or "predicted ratings") should have higher yield as compared to the yield of bonds for which the actual ratings match the expected ratings and vice versa.

To test our hypothesis we follow a two-step approach. In the first step we determine the expected ratings for each bond based on the available financial information. We do so by

[1] See, for example, The Economist (1997, p. 70) on the Asian crisis: "The raters, firms such as Moody's' Investors Service, Standard and Poor's', Duff and Phelps and IBCA, are supposed to be the financial markets' early warning system. Instead, the agencies have spent the past few months belatedly reacting to events."

[2] The US Government Oversight and Reform Committee gave the remarks that "The credit rating agencies occupy a special place in our financial markets. Millions of investors rely on them for independent, objective assessments. The rating agencies broke this bond of trust, and federal regulators ignored the warning signs and did nothing to protect the public." More importantly, the Financial Crisis Inquiry Commission in their January 2011 report commented that "The three credit rating agencies were key enablers of the financial meltdown."

following existing studies such as Blume et al. (1998), Jorion and Zhang (2007), and Pagratis and Stringa (2009) that build statistical models to predict (expected) credit ratings.[3] We then compare these expected ratings with the actual ratings assigned by CRAs. In the second step we run a regression with bond yield spread as the dependent variable. The control variables of this regression include the variables that are known to influence bond yields. Apart from these variables, we also include dummy variables that indicate whether the ratings assigned by CRAs are higher or lower than the expected ratings. A positive coefficient, for instance, on the dummy variable that indicates that a bond has higher than expected ratings, would indicate that investors accounted for the difference between actual and expected ratings by making an upward adjustment in the required yield. We also examine whether the difference between the actual and expected ratings damages the information content of credit ratings. We also revisit the premium charged on the split rate bonds and examine if the premium charged on these bonds relates entirely to the opacity of the information or if part of the premium charged relates to the investors' perception of inflated ratings issued to these bonds. Finally, we examine whether or not CRAs respond to the investors' reaction against the higher or lower than expected ratings and update the ratings of such bonds earlier than other bonds.

Using data on all newly publically issued US domestic, fixed rate, nonfinancial, non-perpetual and non-putable bonds issued between years 1983-2008, we report that the investors do indeed make an adjustment in the required yield when the actual ratings (assigned by CRAs) differ from the expected ratings. That is, on average, the investors require 22 (23) basis points higher (lower) yield when a bond receives higher (lower) than expected ratings compared to the yield they require for bonds of similar risk profile but for which the actual ratings are equal to expected ratings. Further we find that the required yield varies with the magnitude of difference between the actual and expected ratings. In particular, a two letter rating difference increases (decreases) the bond yield by up to 63 (41) basis points. These findings are apparently stronger for the investment grade bonds relative to the non-investment grade bonds. Apart from its impact on the yield spread, the difference in the actual and expected ratings also influences the capacity of the credit ratings to explain bond yield spread. Specifically, the power of credit ratings to explain residual bond yield spread declines by 7.4% when actual ratings are not equal to the expected ratings. With respect to the split rated bonds, as consistent with previous studies, we find that investors require a premium for such bonds. However, our analysis shows that part of the opacity premium fades away when we control for the possibility that the actual ratings assigned to the split rated bonds might be higher than the expected ratings. Finally, we find evidence that Moody's updates the ratings of bonds with higher than expected ratings much earlier than bonds that sell at a higher than expected yield. We find no such evidence for Standard and Poor's (S&P).

[3] Although there is no direct evidence available about the exact statistical models that investors use in their risk assessment calculations, Baker and Mansi (2002) document that about 80% of investors rank the financial information as the most important factor that helps them make an assessment about the credit risk of a debt security.

A number of studies examine whether CRAs assign inflated ratings or lower ratings. Pagano and Volpin (2010), Mählmann (2009) and Becker and Milbourn (2011) constitute the group of studies that find empirical evidence that CRAs tend to assign inflated ratings to the bond issues whereas studies such as Blume et al. (1998) and Poon and Chan (2003, 2005) report that the average ratings assigned to US corporate bonds has declined overtime and that the CRAs issue lower ratings when these ratings are not paid for. Our study extends this stream of literature by documenting the investors' response to the credit ratings that are higher or lower than the expected ratings. Our findings are also relevant to both CRAs and firm managers as these findings provide strong evidence of the investors' preference for ratings that are reconcilable with publically available information. For firm managers, our findings provides additional evidence of the benefits of higher level of disclosures. For CRAs, our findings indicate a demand for higher level of transparency in the rating process. These findings also highlights the need to disclose some of the non-public information that is provided to the CRAs during the meetings between firm managers and the CRAs' risk assessment team. Our findings are also relevant for regulators who are debating and contemplating bringing new regulations to the operating protocols of the CRAs.

The rest of the paper is organized as follows: The next section, Section 2, describes the data selection procedure. Section 3 elaborates the methodology used in this study. The results are discussed in Section 4. Section 5 presents our conclusions.

2.2 Literature review

Two streams of literature are relevant to this paper. The first stream of literature reviews the importance of credit ratings and identifies factors that affect their accuracy. The second stream of literature consists of studies that discuss the ways in which the accuracy of information influences investors' decisions.

CRAs began their services in the early twentieth century in the U.S and now represent a multi-billion dollar industry that spreads across the big economies of the world. CRAs provide individual and institutional investors an independent opinion of the creditworthiness of a firm or the debt securities issued by a firm. A large number of debt and equity markets studies provide evidence that CRAs bring new and decision relevant information to the capital markets. For instance, Hettenhouse and Sartoris (1976), Mitchell (1991) and Campbell and Taksler (2003) show that credit ratings help investors determine the yield of debt securities, and accordingly, a change in credit ratings leads to an adjustment in the prices of the debt securities. The equity market based studies, for instance Poon and Chan (2008) and Jorion et al. (2005); also come up with the analogous findings for firm stock prices. Credit rating information is also considered to improve the marketability and liquidity of debt securities, enhance firms' ability to borrow funds from external sources (Strahan, 1999), and advance the infrastructure of capital markets (Susan and Rechtschaffen, 1998).

Despite these tested benefits of credit ratings, the literature also indentifies several factors that raise questions about the accuracy and efficacy of credit ratings. A main concern regarding CRAs is that whether or not they update the credit ratings on timely basis. The answer to this question, based on both the anecdotal and academic studies, is that in many instances they do not. The major examples that support this belief are those of Enron and Lehman Brothers. Enron bonds continued to be rated as investment grade by both Moody's and S&P less than a week before Enron filed for bankruptcy. Lehman Brothers had an "A" grade rating from the major CRAs just before its collapse in mid-September 2008. With respect to the scientific evidence, Covitz and Harrison (2003) find that investors anticipate the change in rating profile and adjust the yield well before an actual rating upgrade is announced by CRAs. Additionally, Weinsstein (1977) show that credit ratings reflecting changes in the risk profile of a debt security lag by up to 18 months. Pinches and Singleton (1978) also show that the market adjusts stock prices several months prior to when a rating revision is actually announced by the CRAs. Zonana and Hertzberg (1981) show that a big portion of the outstanding bonds are even not reviewed for a possible change in their default risk by CRAs on a yearly basis. Many survey based studies that seek opinions of investors on the timeliness of credit rating information document evidence that corroborates the findings of archival data based studies. For instance, more than 1/3rd of the respondents surveyed in Ellis (1998), Baker and Mansi (2002), and Association of Financial Professionals (2002) believe that CRAs react with a significant delay in updating their credit ratings in response to a shift in the credit quality of a debt security or its issuer. The lag in updating credit ratings is sometimes attributed to the CRAs policy of taking a 3-5 year perspective so as to avoid rating updates that are prone to a reversal (Howe, 1997).[4] However, others attribute the lag to the relatively small number of staff working at CRAs monitoring a large number of issuers. Additionally, the fact that CRAs are paid primarily for initial ratings and not the subsequent rating updates serves as a good explanation for why ratings are not reviewed more frequently.[5] Regardless of the underlying reasons, the lag in rating updates is expected to harm the utility of credit rating information.

The current fee structure of CRAs is another source of criticism. Initially, the revenue of CRAs consisted of the subscription fee received from investors and the sale of publications. After an increase in the demand of ratings due to an increase in regulations in the late 1970s, the CRAs switched to an "issuer pays" fee model where bond issuing firms pay CRAs to rate their debt securities. Although the "issuer pays" model has several merits, it creates incentives for the CRAs to issue inflated ratings in order to retain and attract clients (Pagano and Volpin, 2010). This incentive for CRAs to issue lax ratings together with firms' to chose any of the CRAs

[4] Similarly (Cantor, 2001) also discusses that the credit rating agencies appear to follow an approach where the ratings are only updated when the reversal of updated ratings in not likely in the near future.

[5] For example, Mortensen, in a New York Times article (2005), says: ". . . rating agencies typically receive the largest fees when they analyze an initial bond issue. After that, a nominal fee is levied, providing something of a disincentive to do in-depth, time consuming work."

enable firms to shop for the highest ratings. Mählmann (2009) report that about $1/4^{th}$ of bonds issuers included in their study purchased additional ratings (in addition to the ratings from Moody's and S&P) from Fitch which on average provides higher ratings compared to S&P and Moody's. Benmelech and Dlugosz (2009) on the basis of 30,499 structured finance tranches find that the tranches rated by only one CRA are more likely to be downgraded compared to those tranches that are rated by two or more CRAs. Benmelech and Dlugosz (2009) argue that these findings show that firms purchase ratings from those CRAs that are more likely to give higher initial ratings. On the basis of a review of previous studies, Walter (2002) believes that a convincing amount of evidence exists that indicates the presence of the rating shopping especially when the expected rating lies close to the investment and non-investment boarder. Importantly, the accusation of rating "shopping" not only comes from a particular section of investors or researchers, but also, on certain occasions, even CRAs themselves accuse each other of helping issuers "shop" for higher ratings.[6] A study 1996 study by Federal Reserve Bank of New York also hinted at rating "shopping" especially for firms that initially received a non-investment grade rating from one of the CRAs.

It is also an interesting fact that, although CRAs earn most of their revenue from the firms they rate, CRAs assign ratings to bonds even if their issuers have not asked and paid for the ratings. Such ratings are called unsolicited ratings. The unsolicited ratings, on average, are found to be lower than solicited ratings (Poon, 2003) and thus are not always welcomed by the security issuers. The practice of issuing unsolicited ratings has raised many controversies and questions about the CRAs motives behind issuance of these ratings. From the CRAs' point of view, the unsolicited ratings are a service to "meet the needs of the market for broader ratings coverage" (Standard & Poor's, 2007). However, from the issuers point of view the unsolicited ratings are on average lower than the solicited ratings and are assigned by CRAs to persuade issuers to purchase solicited ratings. Parties unrelated to both CRAs and security issuers also appear to have a less positive view about the unsolicited ratings. For instance, as reported in Schultz (1991) and Harington (1997), a section of the financial market labels unsolicited ratings as "extortion" or "financial blackmailing" by the CRAs. Empirical studies also support the issuers view, at least to the extent that unsolicited ratings are lower than solicited ratings. For instance, based on the pooled data of 595 firms in 15 countries rated by S&P during 1998-2000, Poon (2003) find that firms that received "solicited" ratings were assigned higher ratings compared to the firms that received "unsolicited" ratings. Poon (2003) further report that firms with solicited ratings had a better probability of getting investment grade ratings as compared to firms with unsolicited ratings. In a later study, Poon and Firth (2005) reported similar findings for 1,060 banks rated by Fitch. Gan (2004) report that the unsolicited ratings issued by Moody's and S&P are on average 1/2 a notch lower than the solicited ratings and hence result in an 18 basis point increase in the borrowing cost. Fulghieri et al. (2010), in addition to the finding that unsolicited ratings are lower than solicited ratings, present even more telling evidence that CRAs use these

[6] For example, Moody accused Jefferson County of rating "shopping" when it assigned A2 rating and Jefferson County received a three notch higher rating of AA for S&P.

ratings as a credible threat to issuers and thus as a tool to extract a higher rating fee. Apart from the alleged "blackmailing" tool, CRAs are also believed to use unsolicited ratings to deter new entrants into the market (Setty and Dodd, 2003).

CRAs operate in an oligopoly market structure. The biggest barrier to entry is the fact that only a limited number of CRAs have been approved as Nationally Recognized Statistical Rating Organization NRSROs. The credit rating industry has historically been dominated by two big rating agencies, Moody's and S&P, which, at one point, accounted for above 90% of the market share (Skreta and Veldkamp, 2009). Partnoy (1999) argues that the SEC's policy to give NRSRO status to a limited number of CRAs has eliminated the incentive among CRAs to maintain the quality of their ratings. Even more surprising is that the entry of a third rating agency, Fitch, and the resulting increased competition in the credit rating market did not improve the quality of credit ratings. Becker and Milbourn (2011) report that the entry of Fitch resulted in lower quality, more inflated, and less informative ratings from the existing CRAs. The inability of CRAs to maintain the quality of their ratings can also be attributed to fact that the CRAs are not able to attract or retain sophisticated analysts since the salaries offered CRAs are not competitive compared to other financial services companies (Partony, 1999).

The second stream of literature shows that investors depend on various sources of information for their investment decisions. Many studies in this regard show that investors' trust and their resulting decision depends on their judgment about the accuracy and reliability of the source and its information. Financial information, especially earnings announcements, serves as an important gauge of the performance of a company and helps market participants adjust firm stock prices (Holthausen and Verrecchia, 1988; Atiase, 1985; Heflin et al., 2003). The extant studies, however, show that the market reaction to these announcements depends on the accuracy of the financial information. For instance, Zhang (2006) find that new information has a stronger impact share prices when such information is issued by firms with lower information asymmetry compared to the information issued by firms with higher information asymmetry. Similarly, although the literature shows that firms manage earnings prior to seasoned equity offering however, as shown by Shivakumar (2000), investors are able to identify possible management of earnings and adjust the share prices accordingly. Foster (1979) find that firms that managed their earnings experience a drop in their stock prices in the subsequent period. Dechow et al. (1996) document a similar downward adjustment in stock prices when regulators show suspicion over financial statement accuracy. The research shows that investors adjust for the possible inaccuracy in the information not only emanating directly from the firms but also from other, more sophisticated sources such as financial analysts. For instance, Abarbnell et al, (1995) in a theoretical framework built on the relationship between the analysts' forecasts and investors' beliefs, show that investors' responses to analysts' forecast revisions positively links with the expected accuracy of analysts' forecasts. Empirically, Stickel (1992) find that stock prices respond more strongly and predictably to more accurate forecast revisions. Park and Stice (2000), based on the analysis of all forecast revisions announced in the years 1990 through 1994, show that investors differentiate analysts' based on analysts' forecast accuracies and react to analysts' forecast revisions based on the perceived accuracy of analysts' forecasts. Similarly, Gleason and Lee (2003) show that the price reaction to forecast revisions is more swift and complete when the analysis is more accurate.

Based on the findings that the market response to new information depends on the precision of the new information, and the fact that more than 1/3rd of investors do not believe that credit ratings reflect true debt security credit risk, a natural question arises of whether or not investors adjust for the possible bias in the credit ratings. If so, then such an adjustment should be reflected in the investors' required yield.

2.3 Methodology

For purpose of this study, we follow a two-step approach. In the first step we construct a credit ratings prediction model using ordered probit regression based bonds issued between 1983 and 1994 and rated by both Moody's and S&P. We do not include (notch level) split rated bonds in our rating prediction model. The choice of period 1983-1994 is arbitrary, but, as shown by the robustness test analysis, choosing a different time period does not materially change our results. On the basis of this model, we predict credit ratings for the remaining set of bonds included in our sample of the bonds issued between 1995 to 2008. The dependent variable for this ordered probit regression is the actual rating assigned to a bond at its issue. Both Moody's and S&P assign ratings that are represented by various letters. Following existing literature, we convert these letter ratings into ordinal numbers. For example, we convert letter rating AAA to numerical rating 1, letter rating AA to 2, A to 3, BBB to 4, BB to 5, B to 6 and letter rating CCC to numerical rating 7. The specific variables that we use in this ordered probit model are the pre-tax interest coverage ratio *(Int_Cov)*, operating income to sales ratio *(OperInc_Rev)*, long term debt to assets ratio *(Ltd_Assets)*, total debt to assets ratio *(Td_Assets)*, and firm size *(Size)*. Apart from these ratios, we also include a firm beta *(Beta)* and standard errors from market model *(SE)* to control for the equity risk of a firm. The inclusion of these variables in our rating prediction model is based on previous studies such as Blume et al., (1998), Jorion and Zhang (2007) etc. Based on the these studies we expect higher pre-tax interest coverage ratio, operating income to sales ratio, and firm size to have a positive effect on the ratings assigned to the bonds. Higher long term debt to assets ratio and total debt to assets ratio are expected to be associated with lower ratings. Similarly, firms with higher beta and standard errors from market model are likely to receive lower ratings for their bonds issues. The ordered probit model used in our rating prediction analysis is defined as:

$$\begin{aligned} S\&P\_Rating = {} & \beta_0 + \beta_1 Int\_Cov_{i,t} + \beta_2 OperInc\_Rev_{i,t} \\ & + \beta_3 Ltd\_Assets\ ratio_{i,t} + \beta_4 Td\_\ Assets\ ratio_{i,t} \\ & + \beta_5 Size_{i,t} + \beta_6 Beta_{i,t} + \beta_7 SE_{i,t} + \varepsilon \end{aligned} \tag{1}$$

Panel A and B in Table 2.1 provides a detailed definition and description of variables. In the second step we use multivariate regression to examine the yield on bonds issued from 1995 to 2008. The dependent variable for this analysis is the yield spread *(T_Spread)* which is calculated as the difference between the offer yield to maturity of a bond less yield on comparable treasury at offer date. The independent variables are based on existing studies and include the dummy variables representing the default risk of a bond, the bond maturity *(Mat)*, the total bond proceeds *(Proc)*, and the bonds senior/subordinate status *(Sub)*. We also include dummy variables to identify callable bonds *(Call)*, bonds issued under Rule 415 *(R415)* or under Rule 144a *(R144a)*, split rated bonds *(Splitrated)*, and bonds issued by utility firms *(Utility)*. Following Livingston and Zhou (2010), we control for the influence of general market conditions on the yield spread of bonds by including a variable *(Riskprem)* that is defined as the difference between the Moody's AAA Corporate Bond Index Yields and yield for the 10-year treasury securities.[7] To examine whether the investors are sensitive to the difference between the ratings that are expected (based on the public information) and the rating actually assigned, we compare the ratings predicted in the first step with the actual ratings assigned to these bonds by the CRAs and construct two dummy variables *Higher* and *Lower*. The variable *Higher (Lower)* is set equal to 1 when the actual ratings are higher (lower) than the expected rating and 0 when actual ratings are equal to expected ratings. If the investors are sensitive to the difference between actual and expected ratings, they are also likely to be sensitive to the magnitude of the difference between the actual and expected ratings. To examine this we include four dummy variables *Dh1*, *Dh2*, *Dl1* and *Dl2* in the regression equation. The dummy *Dh1* equals 1 when the actual rating assigned to a bond is higher than the expected rating by one letter rating and 0 otherwis. The dummy variable *Dh2* equals 1 when the actual rating is higher by two or more letter ratings compared to the expected rating and 0 otherwise. Similarly, dummy variables *Dl1*and *Dl2* identify bonds with ratings that are one and two or more letters respectively lower than the ratings predicted by our model. The bonds with ratings that are equal to the ratings expected by our model are the reference categories. Therefore, the coefficient on *Dh2*, for instance, reveals the difference in yield on two bonds that have same actual ratings but with one that has an actual rating two or more letter ratings higher than expected and the other that has actual ratings equal to the expected ratings. The treasury spread regression model is defined as follows:

$$
\begin{aligned}
T\_Spread = \beta_0 &+ \beta_1 Mat_{i,t} + \beta_2 Proc_{i,t} + \beta_3 Sub_{i,t} + \beta_4 Call_{i,t} \\
&+ \beta_5 Utility_{i,t} + \beta_6 R415_{i,t} + \beta_7 R144a_{i,t} + \beta_8 Riskprem_{i,t} \\
&+ \beta_9 Default\ risk\ dummies_{i,t} + \beta_{10} Splitrated_{i,t} \\
&+ \beta_{11} Test\ variables_{i,t} + \varepsilon
\end{aligned} \tag{2}
$$

[7] We do not control for any firm specific variables such as firm size, return on equity, liquidity, etc. since the impact of these variables is already reflected in the bond ratings. (Bannier et al., 2010).

2.4 Data

We collect the required data from three different databases including Thomson Financial SDC database, COMPUSTAT, and EVENTUS. We start with Thomson Financial SDC database and retrieve issue specific information for all newly issued US domestic, fixed rate, nonfinancial, non-perpetual, and non-putable bonds issued between 1983 to 2008. We focus only on the newly issued bonds for two reasons. First, as argued by Livingston et al. (2010), the ratings assigned to new issues are more likely to be based on the most updated information of the issuer. This is especially true given the fact that CRAs lag in updating their rating opinions according to the new information available for the issuer (for instance, Ederington and Goh, 1998). Initial ratings are also likely to be more accurate than subsequent ratings as CRAs are likely to spend more time and effort on credit assessment at the time of bond issuance rather than after issuance. Accordingly, we believe that the yield of a bond is likely to have a higher association with the assigned ratings at the time of issue than it will in later periods. The issue specific information includes the total proceeds of the issue, the time to final maturity, the spread to the bench mark, and the ratings assigned by Moody's and S&P. Finally we use EVENTUS to estimate betas and standard errors from the market model.

Our final sample consists of 7,634 bonds issued by 885 distinct firms. Majority of them i.e., 6,652 bonds (issued by 548 distinct firms), are investment grade bonds while the remaining 982 bonds (issued by 337 distinct firms) are non-investment grade. Table 2.2 elaborates the sample construction steps.[8]

2.4.1 Descriptive statistics

Table 2.3 provides descriptive statistics of our sample. To facilitate comparison we divide the entire sample into three sub-samples and discuss their mean statistics. The first sub-sample consists of the observations in which the actual ratings are higher than expected ratings (AR>ER). The second sub-sample consists of observations in which actual ratings are equal to the expected ratings (AR=ER). Our final sub-sample consists of the bonds where the actual ratings are lower than the expected ratings (AR<ER).

Starting with the variables included in the rating prediction model, the three sub-samples appear to be quite similar in terms of long term debt to assets (*Ltd_Assets*: AR>ER; 0.25 AR=ER; 0.27, AR<ER; 0.26) and total debt to assets ratios (*Td_Assets*: 0.32, 0.34, 0.33). Also, these sub-samples do not differ from each other with respect to market beta (*Beta*: 1.01, 0.98, 0.98) and standard error of residuals (*SE*: 0.02, 0.02, 0.02). However, AR>ER sample has slightly better pre-tax interest coverage (*Int_Cov*: 9.18, 8.72, 8.59) and operating income to sales

[8] Following (John, 2010), we exclude a small number of bonds, precisely 11, with negative treasury spread from our analysis. The negative treasury spread might be caused by an error in the database since a close to zero but still positive treasury spread is expected even on very highly rated bonds.

ratios (*OperInc_Rev*: 0.21, 0.06, 0.14) compared to the other samples. The AR>ER sample firms are also bigger in terms of their average market value than the sample firm in the other two sub-samples (*Size*: 16033.6, 12385.1, 15338.2). The important thing to note here is that despite being similar to the other two sub-samples, the AR>ER sample firm have significantly better ratings compared to the AR<ER and AR=ER sample firms. On average the AR>ER sub-sample is 2.31 (or AA+ in terms of S&P rating symbols) against the average rating of 3.25 (AA) for AR<ER and 3.40 (AA) for AR=ER sample. In terms of yield spread, AR>ER sample firms have a lower yield spread (*T_Spread*: 0.95, 1.27, 2.22) as compared to firms in other sub-samples. With respect to the control variables used in our treasury spread regression, the bonds falling in AR>ER category have a longer term of maturity (*Mat*: 14.18, 13.58, 12.02) but are smaller in terms of total proceeds of the bonds (*Pro*: 198.13, 252.83, 364.84). With regard to the other control variables, the AR>ER sample contains a higher percentage of senior (*Sub*: 0.01, 0.01, 0.13, with respect to AR<ER only), non-callable (*Call*: 0.44, 0.46, 0.67), R415 registered (*R415*: 0.88, 0.88, 0.79, with respect to AR<ER only), and Rule144a (*R144a*: 0.06, 0.02, 0.02) bonds but a lower percentage of bonds issued by utility (*Utility*: 0.03, 0.08, 0.07) firms. Finally, all three sub-samples have quite similar *Riskprem*, 1.28, 1.29, 1.28 respectively, which indicates that these sub-samples are equally spread over the entire period of our sample.

2.5 Univariate results

The descriptive statistics in Table 2.3 show that the actual ratings differ from the expected ratings for approximately 50% of the bonds included in our sample. About 26.75% of the total bonds receive ratings that are lower than their expected ratings while 22.5% bonds received ratings that are higher than their expected ratings. Among these bonds, 18.92% bonds have actual ratings that are higher than their expected ratings by one rating category (letter level), while for 3.63% bonds the actual ratings are higher than the expected ratings by two or more rating categories. For 21.89% bonds the actual ratings are lower than the expected rating by one category, while for 4.86% bonds this difference is equal to or higher than two rating levels.

In this section we examine whether the difference between the actual and expected ratings assigned to a bond matters to investors and is reflected in their required yield spread. For this purpose, we divide the entire sample of our bonds into different categories on the basis of whether their actual ratings are higher than (AR>ER), equal to (AR=ER), or lower than (AR<ER) the expected ratings. For convenience, we call these categories higher-rated, base case, and lower-rated categories respectively. Next, we compare the mean yield for high-rated and low-rated categories with the mean yield for the base case. The results of this analysis are reported in Table 2.4. The average yield for high-rated bonds is significantly higher than the average yield for base case bonds. For instance, as reported in column C to E, the average yield for AAA bonds in higher-rated category is 0.233 points higher than the average yield for the base

category AAA rated bonds. This trend remains visible in all rating levels (i.e., from AAA till CCC). We further divide the higher-rated category into two sub-categories, one-level-higher-rated and two-or-more-level-higher-rated, on the basis of whether the actual ratings are higher than expected ratings by “one” or “two or more” levels. The results of these two sub-categories, as reported in column F to H and I to K respectively, show that the yield for one-level-higher-rated categories is significantly higher than the yield for base case in 4 out of 6 rating levels. Similarly, the average yield for two-or-more-level-higher-rated category is higher than the yield of base case in 4 out of 5 rating levels. With respect to the lower-rated category, the results are less convincing. For example, the average yield is lower than the yield for base case in of 3 out of 6 rating levels, but the difference is significant in the expected direction for only one rating level. However, the difference is significant in the opposite direction for two rating levels. The analysis for sub-categories based on whether the actual ratings are lower by “one” or “two or more” rating levels, in contrast to our expectations, also reveals the pattern that the required yield for these sub-categories is, in general, higher than the yield on our bases category.

2.6 Multivariate results

2.6.1 Determination of expected ratings

As described in the methodology section, we follow a two-step to approach to gather evidence that whether the difference between the actual and expected ratings has a bearing on the investors’ required bond yield.

The results of the first step where we predict ratings for newly issued bonds based on the publically available information are reported in Table 2.5. The coefficients on all of the variables, except for *Beta*, have predicted signs. The coefficients on variables *Int_Cov*, *OperInc_Rev* and *Size* are negative and significant. This is consistent with the previous findings that bonds issued by the bigger firms, or by the firms with high interest coverage or stronger operating performance receive higher ratings. Also, consistent with the earlier findings, the coefficients on the variables depicting the gearing levels of the issuers *(Ltd_Assets, Td_Assets)* are positive (although the coefficient on *Td_Assets* is not significantly different from zero) meaning that the gearing levels increase issuers’ default risk, and hence, the CRAs, holding everything else constant, prefer to assign lower ratings to bonds issued by high leveraged firms. With respect to the variables used to proxy the equity risk of the issuers, the coefficient on *Beta* is negative and significant which is opposite to the conjecture that bonds issued by risky issuers are expected to receive lower ratings. However, after the standard errors are adjusted for the firm clusters, the coefficient on *Beta* no longer remains significantly different from zero. The second proxy for the issuer risk *(SE)* is positive and significant in the expected direction.

Next, we predict ratings for our sample based on the model developed in Table 2.5. Table 2.6 tabulates the actual and expected ratings for the sample that is later used to examine whether the difference between the actual and expected rating has a bearing on the average bond yield spread. The prediction power of our model, based on the percentage of bond ratings correctly predicted, is 40.71%. This is relatively low compared to the prediction power of the models built by earlier studies.[9] However, in the context of this study, our aim is not to come up with a new model with a higher predictability power. If our model does not represent the ratings as might be expected by the investors then the variables that we construct based on these predicted ratings would not have any significant impact in our treasury spread regression.

2.6.2 Difference between actual and expected ratings and required yield

Having determined the expected ratings for the sample bonds, in this section we analyze whether the differences between expected and actual ratings have any impact on the average yield spread of the newly issued bonds. For this purpose, we modify the regression equation (2) by including indicator variables *Higher* and *Lower*. The variable *Higher* is equal to 1 when actual ratings are higher than the expected ratings and 0 otherwise, while variable *Lower* is set equal to 1 when the actual ratings are lower than the expected ratings and 0 otherwise. By this construction, all instances of bonds issues with the same actual and expected ratings become our base case. Model 1 in Table 2.7 reports the results of this analysis. In terms of our test variables, the coefficient on *Higher* is positive (0.222) and statistically significant, whereas the coefficient on *Lower* is negative (-0.235) and significant. The estimated effects of both variables are also economically significant. For instance, the coefficient of 0.222 on *Higher* suggests that investors on average require approximately a 22 basis point higher yield spread on the bonds with higher than expected ratings compared to the bonds for which the actual and expected ratings are the same. Likewise, the coefficient of -0.235 on *Lower* means that investors require 23 basis points lower yield spread when the actual ratings assigned to the bonds are lower than the expected ratings. With respect to the control variables, most of the issue and issuer specific variables are significant and have expected coefficient signs. These results show that the yield spread of a bond is positively associated with the length of its maturity *(Mat)*, whether the bond is callable *(Call)* or split rated *(Splitrated)*, and the market default risk premium prevalent at the issue date. The results also reveal that bonds issued under rule R415 *(R415)* and R144a *(R144a)* or by utility firms *(Utility)* have a lower yield spread compared to the other bonds. The positive coefficient sign on *Proc* is consistent with the notion that bonds with large proceeds are likely to have a negative impact on the leverage of a company and thus lead to higher yield spread. The coefficient on *Sub* is different than expected but is not significantly different from zero. The bond specific risk premium dummies (i.e., the dummies created based on the ratings assigned to the bonds) reveal a very instinctive pattern. The investors' required yield monotonically

[9] The percentage of out of sample bond ratings correctly predicted by our model is 40.71%. The prediction power of models used in previous studies remains about 55% (for example, Blume et al. (1998). One possible explanation for the lower predictability power of our model is that previous studies mainly limit their sample to investment grade bonds only while the sample used in this study contains both investment and non-investment grade bonds.

increases with the increase in the default risk of bonds. Importantly, there is a sudden rise (from -4.157 for BBB bonds to -2.884 for BB bonds) in the demanded yield spread for the bonds that are rated at below investment grade.

Next, we examine whether these findings are applicable for both investment and non-investment grade bonds. For this purpose, we break the full sample into two sub-samples, investment grade bonds sample and non-investment grade bonds sample, and perform our analysis for each of these two samples separately. The results for the investment grade sample, reported in Model 2, are very similar to those of the full sample. That is, the indicator variables *Higher* (0.162) and *Lower* (-0.232) have expected coefficient signs and are highly significant. In the non-investment sample, Model 3, the indicator variable *Higher* is also positive (0.565) and significant, whereas the indicator variable *Lower* has an expected negative sign but is not significant. In sum, these results provide evidence that, in general, the difference between actual and expected ratings matters to the investors for both investment and non-investment grade bonds, though the evidence is much stronger for the investment grade bonds compared to that of obtained for the non-investment grade bond.

Up to this point, we have only considered the effect of higher or lower than expected ratings but have not considered the magnitude of the difference between the actual and expected ratings on investors' required yield. The notion here is that if the expected ratings influence the investors' demanded yield, then the required yield should increase/decrease as the difference between the actual and expected ratings widens. Thus, accordingly, we include dummy variables *Dh2*, *Dh1*, *Dl1*, and *Dl2* to reflect the level of difference between the actual and expected ratings on both the higher and lower side.[10] The results of this analysis are reported in Model 4 in Table 2.7. The coefficient on *Dh1* and *Dh2* are 0.148 and 0.635 respectively. These coefficient values reveal that investors require about 15 basis points higher yield for the bonds that receive one letter level better than expected ratings compared to the base case bonds. The required yield raises by 64 basis points in the case of the bonds that receive two letter levels better than the expected ratings relative to the yield on base case bonds. These results indicate that investors demand a higher yield on bonds for which the actual ratings are higher than the expected ratings, and that the magnitude of demanded yield increases with the increase in the difference between the actual and expected ratings. The negative coefficients on *Dl1* (-0.185) and *Dl2* (-0.414), in line with expectations, reveal that investors adjust and require a lower yield for bonds with lower than expected ratings compared to the base case bonds.

2.6.3 Difference between actual and expected ratings and the information content of ratings

[10] Since there are only a few bonds for which the actual and expected ratings differ by more than two letter level ratings, we combine all such bonds together with the bonds for which the difference between actual and expected ratings is equal to two letter levels.

In this section we examine whether the association between the yield spread and credit ratings varies depending on whether or not the actual bond ratings correspond to the expected ratings. For this purpose we follow a two step approach as used in Becker and Milbourn (2011) and examine the contribution of credit ratings in R^2 for the yield spread regressions. Specifically, in the first step we run regress *T_Spread* on variables, except *S&P_Rating*, that are known to influence bond yields. In the second step, for each of the two sub-samples that we create on the basis that whether or not the actual ratings are equal to the expected ratings (called AR <> ER and AR = ER respectively), we regress the residuals from the first stage regression on *S&P_Rating*. The results of this analysis are reported in Model 1-3 in Table 2.8. For the AR = ER sample the R^2 is 32.87% which is higher than the R^2 , 25.41%, for AR <> ER model. For both AR = ER and AR <> ER samples the coefficient on *S&P_Rating* is significantly different from zero and is comparatively higher for AR = ER sample. Collectively, this analysis provides evidence that information content of credit ratings is rises when credit ratings are equal to the expected ratings and declines when the actual ratings do not correspond to the expected ratings.

2.6.4 Difference between actual and expected ratings and the information asymmetry premium

Split rated bonds are bonds for which CRAs do not agree on a default risk and hence assign divergent ratings. A number of studies identify information asymmetry as the main factor behind the occurrence of split ratings. Morgan (2002), for instance, report that bonds issued by firms operating in highly opaque industries (e.g., the financial industry) are more likely to receive split ratings compared to bonds issued by firms operating in other industries. Similarly, Livingston et al. (2007) based on a sample of non-financial firms, document that the instances of split ratings are more pronounced among firms that have a higher level of information asymmetry. Finally, the research on split rated bonds also shows that investors require an opacity premium on split rated bonds (e.g., Liu and Pu, 1987; Livingston and Zhou, 2010)..

Since split rated bonds receive two distinct ratings, a natural question arises of which of the two ratings determines the yield for such bonds. A number of previous studies try to provide answer for this question and come up with varied findings. Billingsley et al. (1985), Liu and Pu (1987) and Perry et al. (1988) find that the lower of the two split ratings determine the yield of bonds. In contrast, Hsueh and Kidwell (1988) and Ziebart and Reiter (1992) indicate that bond yield is associated more with the higher rather than the lower of the two ratings. Evidence also shows that the bond yield corresponds to the average of two ratings (e.g., Livingston et al., 2007). Recently, (e.g., Livingston et al., 2010) show that the yield on split rated bonds is associated with the ratings from Moody's which is generally considered to be a more conservative rater.

In the previous section we find that bonds with higher than expected ratings have higher yield compared to similar risk bonds for which the actual ratings are equal to the expected ratings. In this section we revisit the question of why investors require a higher premium on split rated bonds. Based on our findings in the previous section, we examine whether the extra yield charged on the split rated bonds consists only of the opacity premium only, as reported in various studies, or if it also includes an adjustment for the difference between the actual and expected ratings. To do so, we examine and compare the yield required for the split rating bonds over three different models. The first model is the traditional yield regression model that examines whether, after controlling for the relevant factors, the investors require a higher yield on split rated bonds. The second model includes variables *Higher* and *Lower* to indicate whether the rating assigned to a bond is higher or lower than the expected rating. The third model extends the second model by including an interaction term, *Splitrated*Higher*, between *Splitrated* dummy and indicator variable *Higher*. This interaction term essentially separates any extra yield required by investors for higher than expected ratings from the opacity premium charged on split rated bonds. The results of this analysis are presented in Table 2.9. In Model 1, which is our base model, the coefficient on *Splitrated* is positive (0.164) and significant at a 1% level implying that, on average, investors require 16 basis points higher yield on split rate bonds. The results of the Model 2 reveal that the investors' required yield on split rated bonds decreases slightly to 14 basis points after controlling for the difference between the actual and expected ratings. In Model 3, the coefficient on interaction term *Splitrated*Higher* is positive (0.229) and significant (p=0.06), while the coefficient on the *Splitrated* dummy falls to 0.109 and its significance lowers from 1% level to 5% level. These results provide some indication that the premium charged by investors on split rated bonds is not solely based on the opacity of information but partly on the investors' perception of prevision of higher than expected ratings assigned to these bonds.

2.6.5 The relative conservativeness of Moody's and S&P

There exists quite a consensus among researchers that Moody's is a relatively conservative rater when compared to S&P. That is, in the case of jointly rated split rated bonds, Moody's is found to assign slightly lower ratings than does S&P. In this section we examine whether Moody's is a conservative rater relative to S&P only or if Moody's conservativism may be generalized. In Table 2.10, we compare the ratings assigned by Moody's and S&P with each other and with the ratings predicted based on publically available information. Results show that 30% (40%) of the split rated bonds rated by Moody's (S&P) received ratings that are equal to the expected ratings. About 51% of the split rated bonds received lower than excepted ratings from Moody's whereas about 40% of the bonds received lower than expected ratings from S&P. Along the same lines, only 15% percent bonds apparently received higher than expected ratings from Moody's while 20% of the sample bonds received higher than expected ratings from S&P. These results suggest that the ratings issued by Moody's are not only lower than the ratings assigned by S&P but also lower than those that are predicted based on public information.

2.6.6 Difference between actual and expected ratings and rating revisions

Our analyses in the preceding sections show that bond investors take into account the difference between actual and expected ratings and adjust the required yield accordingly. An important point to examine here is whether CRAs respond to the investors' reaction and revisit the default risk of the bonds for which the actual ratings do not correspond to the expected ratings. At least one previous study i.e., Livingston et al. (2008) indirectly support the idea that the difference between the actual and expected ratings might be a factor for an earlier rating revision. In their study Livingston et al. (2008) compare the probability of rating migration between split and non-split rated bonds and document that the split rated bonds are more likely to receive a revised rating in the future compared to non-split rated bonds. The authors further find that the CRA that assigns higher (lower) initial ratings to a split rated bond is more likely to make a downward (upward) revision of the rating in a subsequent period.

To examine if the difference between actual and expected ratings also leads to an earlier rating revision, we divide the entire set of bonds, with all the necessary information available, in two groups based on whether the actual rating assigned to a bond is equal to the expected rating (AR=ER) or not (AR<>ER). We then compare the average number of days before which a rating revision occurs for each of these groups of bonds. The results of the univariate analysis are reported in Table 2.11. Results show that Moody's revises much earlier the ratings of AR<>ER group than they do for AR=ER group. Specifically, for AR<>ER group, the first rating revision on average takes place 854 days after the initial ratings as compared to 1,032 days for AR=ER. However, when a distinction is made between the bonds with higher than expected ratings and those with lower than expected ratings, Moody's appears to bring in early rating revisions only for bonds that have lower than expected ratings. There is no significant difference between the average time before Moody's revises a bond rating with higher than expected ratings and AR=ER group bonds. Specifically, the results show that Moody's, on average, updates the credit rating of bonds with lower than expected ratings 814 days after the initial ratings whereas it updates bond ratings with higher than expected ratings on average, after 1,108 days. The subsample analysis further reveals that the magnitude of difference between the actual and expected rating also has a bearing on the timing of rating revisions. For instance, the bonds with one level lower than expected ratings receive their first rating revision 851 days after their initial rating while bonds with two levels lower than expected ratings receive their first rating revision after 738 days. The sub-sample analysis does not reveal a consistent and significant evidence for bonds with higher than expected ratings. In terms of analysis based on S&P data, contrary to the expectations, S&P appears to maintain the ratings of AR<>ER bonds for a slightly longer period of time compared to AR=ER bonds (779 vs. 726 days). The sub-sample analysis reveals that this trend is more visible and significant for bonds that receive higher than expected ratings (1,151 vs. 726). The bonds that receive lower than expected ratings appear to receive a rating revision sooner than the base case bonds (684 vs. 726 in case of Lower by 1+ notch category) but these results are not statistically significant.

Next, we apply a multivariate analysis to analyze the impact of difference in actual and expected ratings on rating revision. The dependent variable of our regression analysis is the difference in number of days between the initial and first subsequent rating change for each bond issue. The test variable consists of variables *Higher* and *Lower* that indicate, for each bond, whether the bond received a higher or lower than expected ratings. A dummy variable, *Yield_High*, designates whether a bond's initial yield is higher or lower than the predicted yield.[11] We also include the interaction between *Yield_High* and the test variables *Higher* and *Lower*. Our motivation to include yield indicator variable *(Yield_High)* is based on the notion that the CRAs would not, for instance, find it necessary to revise the ratings on the bonds with higher than expected ratings if these bonds trade at a yield which corresponds to their actual ratings. The set of control variables are based on Livingston et al. (2008) . These control variables include the dummy variables that correspond to each bond's credit rating, dummy variables indicating the state of economy, (i.e., peak, normal and trough at the time of issue of a bond). Following Livingston et al. (2008) we define the year of a bond issue as a "peak year" if the real economic growth of that year remained higher than 4%, and a "trough year" if the real growth during the year remained below 3%. The remainder of the years which become the base case are defined as "normal". Previous studies show that the split rated bonds are more likely to receive a rating revision sooner compared to other bonds. Accordingly, we include variable *Splitrated* to identify these bonds. Finally we also include a list of year dummy variables.

The results of our multivariate analysis based on Moody's rating are reported in Model 1 of Table 2.12. The coefficient on variable *Higher* is positive (335.052) and significant while that coefficient on *Lower* is negative (-164.868) but not significant. The coefficient on variables *High_yield* is 220.803 which is significant at the 10% level. With respect to interaction terms *Higher*High_Yield* is negative (-540.629) and significant (p=0.022) whereas the *Lower*High_Yield* is negative (-153.578) but not significant (p=0.266). These results indicate that, on average, Moody's maintains the initial ratings of the bonds that receive higher than expected ratings for a much longer time than other bonds. However, the rating revision occurs considerably earlier for such bonds if they trade at higher than estimated yield. In terms of control variables, most have expected signs. Namely, the coefficients on *Splitrated*, *Trough*, and credit risk dummy variables are negative. This reveals that the credit ratings of the split rated bonds and of those issued during years with lower economic growth are updated earlier than bonds issued in years of normal or high economic growth (note that the coefficient on *Peak* is positive and significant). Furthermore, the coefficients on the rating dummies show that low risk bonds are expected to have more stable ratings compared to high risk bonds.

We repeat the analysis with the dependent variable based on the number of days after which S&P introduces the rating update after the initial rating. The results of this analysis are presented as Model 2 in Table 2.12. Once again, the coefficient on *Higher* is positive and significant

[11] To predict the yield for each bond we ran a bond yield regression for the entire sample of bonds. We then predict the yield for each bond based on this model. Next we compare the actual and estimated yield to determine whether a bond is traded at higher or lower than the predicted yield.

suggesting that S&P also maintain the ratings of the bonds that receive higher than expected ratings for a longer period of time compared to other bonds. However, none of the other test variables are significant suggesting that our findings based on the analysis of ratings from Moody's do not hold for S&P.

2.7 Robustness

We perform additional tests to assess the robustness of our findings. First, we use robust standard errors adjusted for two-way clustering by firm and year. The result of this analysis is reported in Model 1 in Table 2.13. According to these results, all the test variables have the expected coefficient signs and are highly significant. The resulting p-values are, in general, very similar to the ones reported for our main analysis.

Next, we replicate our main analysis based on random samples taken from the full sample. That is, we draw a random sample of approximately $1/4^{th}$ of the bonds included in our sample to build a rating prediction model. Based on this model, we predict expected ratings for the remaining bonds. Next, on the basis of these expected ratings, we construct several test variables such as *Higher*, *Lower* etc., following the procedure explained in methodology section. We then re-run regression equations (1) and (2) for 1,121 times. The average results of these replications are reported in Model 2 and Model 3 of Table 2.13. Similar to our main findings, the coefficient on all test variables have anticipated signs and, with one exception of *Dh2*, are highly significant. For instance, in line with the main results, the estimated average coefficient on *Higher* and *Dh1* are positive and significant at better than 0.05 levels while *Dh2* narrowly misses the 0.10 significance level with the average two-sided p-value of 0.155. Likewise, the estimated average coefficient on *Lower*, *Dl2*, and *Dl1* are negative and significant. The detailed replication results, presented in Table 2.14, further reveal that in the overwhelming majority of replications (well above 80%, except of *Dh2*) the coefficients on test variables are significant at better than 0.05 levels. Finally, in only 1 out of 1,121 replications a test variable has an unanticipated coefficient sign.

As an additional robustness check, we test whether our findings are applicable at all credit rating levels or if a particular rating category is driving our results. For this purpose, we include *Higher*, *Lower*, *Dh2*, *Dh1*, *Dl1*, and *Dl2* dummies for each rating categories in the yield spread regression. The results shown in Table 2.15 reveal that our previous findings almost consistently apply to all the rating categories. In particular, these results show that out of 22 dummies variables 15 have the significant expected signs.[12] Only 3 dummy variables with unexpected signs are significant at conventional level. These results indicate that investors nearly

[12] The reason that we have 22 rating dummies instead of 28 rating dummies is as follows: The expected ratings cannot be higher than AAA so for AAA ratings category the creation of dummies variables *Dl2* and *Dl1* is not possible. Similarly, for AA rating category *Dl2* will have zero observations. The same reasoning applies to the two lowest rating categories C and B.

consistently require higher (lower) yield when the actual ratings are higher (lower) than expected ratings.

2.8 Conclusion

Several factors raise questions about the objectivity and quality of the information provided by CRAs. These factors relate to a number of issues including the market and fee structure of the credit rating industry, the allegations to allow rating shopping, the lag in rating updates, and the issuance of punitive unsolicited ratings. All together, these factors raise questions about the utility of credit ratings and whether these ratings truly reflect the credit risk of an issuer.

In this paper we examine whether these factors effect investors' reliance on credit ratings issued by CRAs. Based on a large set of bonds jointly rated by Moody's and S&P, our analysis reveals following results. First, we find that the investors do indeed take into account the difference between the credit ratings assigned by credit CRAs and those considered fair. In particular, the investors require a higher (lower) yield on bonds that received higher (lower) than expected ratings compared to the base case bonds for which the credit ratings assigned by CRAs are equal to their expected ratings. These findings hold for both investment and non-investment grade bonds but the results are stronger for the investment grade bonds. Second, we find that the information content of credit ratings declines when these ratings are different than the expected ratings. Third, consistent with the prior literature, we find that that investors do require a higher yield for split rated bonds. However, we find evidence that this extra yield does not entirely relate to the information opacity. Rather, part of this yield is explained by the difference between the actual and expected ratings. Finally our results show that the difference between the actual and expected ratings forces Moody's to bring in a rating change earlier if such bonds sell at a yield that is higher than the expected yield. We do not find such evidence in the case of S&P.

Our study is also relevant to the stream of literature that examines whether the CRAs make a fair risk assessment of the debt securities. Our study contributes to this literature by documenting investors' response when the outcome of the CRAs' risk assessment of a bond issue differs from the outcome that is expected based on public information. Our findings are also relevant for firm managers as well as CRAs as they suggest that investors prefer those ratings that are reconcilable with the publically available information. For firm managers, our findings provide additional evidence of the benefits of a higher disclosure level. In other words, a higher disclosure level would help investors understand the basis of the ratings assigned to a firm's debt securities and would lead to lower interest costs. From the point of view of CRAs, the findings of this paper show that, although the credit ratings are one of the most important determinant of the yield of a bond, investors do not appear to trust these ratings unquestionably. A possible suggestion could be that CRAs should become more transparent about their rating criteria and, if practical, provide a brief description of the basis of the ratings assigned to a security. This would help CRAs keep investors believing in the CRA ratings especially in cases where the ratings assigned are not easily reconcilable with the publically available information.

Table 2.1: Definition of variables

Variables (short names)	Variable description
Panel A. Variable definition used in rating prediction regression.	
Int_Cov	*Int_Cov* represents pretax interest coverage ratio and is defined as the ratio of "operating income after depreciation" (178, OIADP) + "interest expenses" (15, XINT) to "Interest expenses" (15, XINT)15.
OperInc_Rev	*OperInc_Rev* stands for "operating income to sales" ratio and is calculated by dividing "operating income before depreciation" (13, OIBDP) by "sales-net" (12, SALES).
Ltd_Assets	*Ltd_Assets* is the long term debt to asset ratio and represents the ratio of "long term debt-total" (9, DLTT) to "assets-total" (6, AT).
Td_Assets	*Td_Assets* represents total debt to capitalization ratio. *Td_Assets* is calculated as follows. ("long term debt-total" (9, DLTT) + "debt in current liabilities" (34, DLC) + "short term borrowing-average" (104, BAST)) / "assets-total" (6, AT).
Beta	*Beta* is the beta of the issuer calculated using market model. The betas are downloaded from EVENTUS
SE	*SE* is the standard error from market model. The *SE*s are downloaded from EVENTUS
Panel B. Variables used in treasury spread regression.	
T_Spread	*T_Spread* is defined as the difference between the "offer yield to maturity" (Y)16 of a bond less "yield on comparable treasury at offer date" (COMPTY). Alternatively, the *T_Spread* is equivalent to the number of basis points over the comparable maturity treasury (BPS)
Mat	*Mat* is the item YTOFM in the SDC database and represents the number of years from issue date of bond till date of final maturity.
Proc	*Proc* is the gross proceeds of a bond in U.S dollars and is identified by "PROCDS" in SDC.
Sub	*Sub* is a dummy variable that refers to the senior (0) or subordinate (1) status of a bond. This identifier is based on "SENSUB" variable in SDC.
Call	*Call* identifies whether a bond is callable or not. *Call* is based on variable "CALLD" in SDC. All bonds that have a call protection till expiry are referred to as non-callable bonds while the others as callable.
Utility	*Utility*, a dummy variable, equals to 1 for bonds issued by a utility firm and 0 otherwise.
R415	*R415* identifies whether an issue is registered under "Rule 415 shelf registration". This variable is based on tag "SHF" in SDC.
R144a	*R144a* is equal to 1 for bonds issued under "Rule 144a" and 0 otherwise. "Rule144a" is the relevant identifier in SDC.
Riskprem	*Riskprem* is the difference between the yield on Moody's AAA bond index and the 10-year Treasury yield.
Splitrated	*Splitrated* is a dummy variable that identifies bonds for which Moody's and S&P differ in their ratings by at least one letter rating.
AAA-CCC	"AAA-CCC" is a series of dummy variables that refer to the rating assigned to a bond.
Panel C. Variables used in bond rating change regression.	
Yield_High	*Yield_High* is a dummy variable which is equal to 1 if the initial required yield on a bond is higher than its

[15] In panel A, the numeric figure and mnemonics inside parentheses represent a variable's old and new COMPUSTAT code.
[16] In Panel B, the mnemonics inside parentheses represent a variables identifier code in SDC database.

Table 2.1 (continued)

	predicted yield. We predict yield for each bond by running a bond yield regression for the entire sample of bonds. We then estimate the yield for each bond based on this model and term is a predicted yield.
Yield_low	*Yield_Low* is a dummy variable which is equal to 1 if the initial required yield on a bond is lower than its predicted yield. We predict yield for each bond by running a bond yield regression for the entire sample of bonds. We then estimate the yield for each bond based on this model and term is a predicted yield.
Higher*Yield_High	Higher*Yield_High is an interaction term between variable *Higher* as defined in Panel B of this table and the variable *Yield_High*.
Lower* Yield_Low	Lower*Yield_Low is an interaction term between variable *Lower* as defined in Panel B of this table and the variable *Yield_Low*.
Peak	*Peak* indicates the state of economy at the time of issue of a bond. Following Livingston et al. (2008) we define the year of a bond issue as a *Peak* if the real economic growth of that year remained higher than 4%.
Trough	*Trough* indicates the state of economy at the time of issue of a bond. Following Livingston et. al (2008) we define the year of a bond issue as a *Trough* if the real economic growth of that year remained below 3%.

Table 2.2: Sample construction

This table describes the sample construction and number of observations dropped at each step. The sample consists of all newly publically issued US domestic, fixed rate, nonfinancial, non-perpetual and non-putable bonds issued between years 1983-2008.

Initial sample (total domestic bonds issued by public US firms between (1983-2008))		132,109
Less:		
Non-fixed interest rate bonds	(26,478)	
Privately placed bonds	(12,128)	
Bonds with Perpetual maturity	(2,168)	
Bonds with credit enhancement	(12)	
Bonds issued by firms from financial sector, SIC(6011-6799)	(73,569)	(114,355)
Total sample of bonds retrieved from SDC		17,754
Less:		
Bonds with missing credit ratings	(2,952)	
Bonds with missing information required for rating prediction model.	(7,168)	
Sample of bonds used in credit rating model (885 unique firms)		7,634

Table 2.3: Descriptive statistics

This table presents descriptive statistics for the variable used in this study. Panel A reports descriptive statistics for the dependent and control variables used in rating prediction model. This model is based on all newly publically issued US domestic, fixed rate, nonfinancial, non-perpetual and non-putable bonds issued between years 1983-1994. Panel B contains descriptive statistics for the dependent and control variables used in the bond yield regression model. The sample for this model consists of all newly publically issued US domestic, fixed rate, nonfinancial, non-perpetual and non-putable bonds issued between years 1995-2008. To facilitate comparison, we divide the entire sample into three sub-samples. The first sub-sample, denoted as AR>ER, consists of the observations for which the ratings assigned by CRAs (for stylistic convenience, we label these ratings as 'actual ratings') are higher than those predicted based on publically available financial information (for stylistic convenience, we label these ratings as 'expected ratings'). The second sub-sample consists of observations where actual ratings are equal to the expected ratings (AR=ER). The final sub-sample consists of the bonds where the actual ratings are lower than the expected ratings (AR<ER). The variable definitions are provided in Panel A and Panel B of Table 2.1.

Variables	N	Mean	P25	P50	P75	Std. Dev
Panel A. Rating prediction model						
Ratings-Actual	2098	3.162	3.000	3.000	4.000	1.105
Ratings-Expected	2098	3.125	3.000	3.000	3.000	0.848
Int_Cov	2098	6.090	3.413	4.419	6.440	6.827
OperInc_Rev	2098	0.196	0.117	0.164	0.265	0.118
Ltd_Assets	2098	0.264	0.170	0.251	0.347	0.138
Td_Assets	2098	0.349	0.256	0.338	0.420	0.153
Size (billion)	2098	6.531	0.948	3.059	6.519	10.341
Beta	2098	1.171	0.820	1.213	1.477	0.481
SE	2098	0.016	0.013	0.015	0.019	0.006
Panel B. Treasury spread model. Actual ratings lower than the expected ratings (AR<ER)						
	N	Mean	P25	P50	P75	Std.
Ratings-Actual	1799	3.868	3.000	4.000	4.000	0.916
Ratings-Expected	1799	2.506	2.000	3.000	3.000	0.943
Int_Cov	1799	13.477	3.729	6.289	11.511	34.366
OperInc_Rev	1799	0.228	0.131	0.208	0.278	0.237
Ltd_Assets	1799	0.243	0.153	0.227	0.323	0.122
Td_Assets	1799	0.301	0.215	0.294	0.383	0.129
Size (billion)	1799	25.87	2.40	8.33	27.77	41.37
Beta	1799	0.928	0.617	0.900	1.170	0.452
SE	1799	0.016	0.012	0.015	0.018	0.005
T_Spread	1799	1.731	0.880	1.430	2.150	1.310
Mat	1799	12.370	5.110	10.140	10.360	11.547
Proc	1799	0.433	0.150	0.300	0.520	0.442
Sub	1799	0.033	0.000	0.000	0.000	0.180
Call	1799	0.636	0.000	1.000	1.000	0.481
Utility	1799	0.113	0.000	0.000	0.000	0.316
R415	1799	0.895	1.000	1.000	1.000	0.307
R144a	1799	0.030	0.000	0.000	0.000	0.171
Riksprem	1799	1.328	0.900	1.270	1.660	0.483
Splitrated	1799	0.122	0.000	0.000	0.000	0.328
Panel C. Treasury spread model. Actual ratings equal to the expected ratings (AR=ER)						
	N	Mean	P25	P50	P75	Std.
Ratings-Actual	1452	3.154	3.000	3.000	4.000	1.016
Ratings-Expected	1452	3.154	3.000	3.000	4.000	1.016
Int_Cov	1452	8.587	4.194	6.417	9.550	8.200
OperInc_Rev	1452	0.121	0.130	0.178	0.244	2.744
Ltd_Assets	1452	0.258	0.166	0.251	0.327	0.133
Td_Assets	1452	0.324	0.232	0.312	0.401	0.141
Size (billion)	1452	15.89	2.26	6.06	16.24	29.03
Beta	1452	0.837	0.583	0.773	1.050	0.421

Table 2.3 (continued)

	N	Mean	P25	P50	P75	Std.
SE	1452	0.019	0.014	0.018	0.023	0.007
T_Spread	1452	1.268	0.640	0.950	1.530	1.063
Mat	1452	12.718	5.090	10.140	12.190	11.285
Proc	1452	0.220	0.025	0.150	0.299	0.294
Sub	1452	0.018	0.000	0.000	0.000	0.133
Call	1452	0.468	0.000	0.000	1.000	0.499
Utility	1452	0.037	0.000	0.000	0.000	0.189
R415	1452	0.899	1.000	1.000	1.000	0.301
R144a	1452	0.038	0.000	0.000	0.000	0.191
Riksprem	1452	1.425	1.020	1.380	1.750	0.474
Splitrated	1452	0.131	0.000	0.000	0.000	0.337
Panel D. Treasury spread model. Actual ratings higher than the expected ratings (AR>ER)						
	N	Mean	P25	P50	P75	Std.
Ratings-Actual	316	3.016	2.000	3.000	4.000	1.199
Ratings-Expected	316	4.212	3.000	4.000	6.000	1.276
Int_Cov	316	5.612	3.844	4.802	6.729	3.554
OperInc_Rev	316	0.154	0.099	0.159	0.224	0.298
Ltd_Assets	316	0.319	0.235	0.290	0.364	0.154
Td_Assets	316	0.394	0.299	0.371	0.429	0.145
Size (billion)	316	7.07	0.88	2.50	11.34	9.34
Beta	316	0.830	0.477	0.747	1.022	0.534
SE	316	0.024	0.015	0.022	0.028	0.015
T_Spread	316	1.617	0.725	1.115	2.260	1.341
Mat	316	12.707	7.100	10.140	10.185	12.011
Proc	316	0.178	0.040	0.150	0.250	0.167
Sub	316	0.019	0.000	0.000	0.000	0.137
Call	316	0.516	0.000	1.000	1.000	0.501
Utility	316	0.035	0.000	0.000	0.000	0.184
R415	316	0.911	1.000	1.000	1.000	0.285
R144a	316	0.022	0.000	0.000	0.000	0.147
Riksprem	316	1.518	1.060	1.520	1.920	0.490
Splitrated	316	0.250	0.000	0.000	0.500	0.434

Table 2.4: Univariate Analysis

This table reports the univariate analysis of our sample. To facilitate comparison, we divide the entire sample into three sub-samples. The first sub-sample, which is the base case and is denoted as AR=ER, consists of the observations for which the rating assigned by CRAs (for stylistic convenience, we label these ratings as ‘actual ratings’) are equal to those predicted based on publically available financial information (for stylistic convenience, we label these ratings as ‘expected ratings’). The second sub-sample consists of observations where actual ratings are higher than the expected ratings (AR>ER). The final sub-sample consists of the bonds where the actual ratings are lower than the expected ratings (AR<ER). We further divide thesis sample into sub-samples on the basis of the level of difference between the actual and expected ratings. The Treasury spread is the difference between initial bond spread and the yield of a similar maturity Treasury security. The independent sample *t*-test is used to test for the equality of means across base case and other sub-samples. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Panel A

	(AR=ER)	Actual ratings are higher than the expected ratings. (AR>ER)			Actual ratings are 1 letter level higher than the expected ratings.			Actual ratings are 2 letter level higher than the expected ratings.		
Ratings level (A)	Treasury spread (B)	Treasury spread (C)	Difference (B-A) (D)	N (E)	Treasury spread (F)	Difference (D-A) (G)	N (H)	Treasury spread (I)	Difference (F-A) (J)	N (K)
AAA	0.652	0.885	0.233***	15	0.593	-0.059	4	0.991	0.339***	11
AA	0.595	0.834	0.239***	118	0.834	0.238***	115	0.837	0.241*	3
A	1.013	1.362	0.342***	85	1.293	0.274***	79	2.270	1.257***	6
BBB	1.686	2.096	0.411**	49	1.563	-0.123	23	2.568	0.883***	26
BB	2.920	3.398	0.478*	43	3.451	0.531**	42	1.180	-1.740	1
B	4.098	5.743	1.646***	6	5.743	1.646***	6			
CCC	5.005									

Panel B

	(AR=ER)	Actual ratings are lower than the expected ratings. (AR<ER)			Actual ratings are 1 letter level lower than the expected ratings.			Actual ratings are 2 letter level lower than the expected ratings.		
Ratings level (A)	Treasury spread (B)	Treasury spread (L)	Difference (M) (H-A)	N (N)	Treasury spread (O)	Difference (P) (J-A)	No (Q)	Treasury spread (R)	Difference (S) (L-A)	N (T)
AAA	0.652									
AA	0.595	0.839	0.244***	116	0.839	0.244***	116			
A	1.013	1.307	0.288***	417	1.280	0.267***	244	1.346	0.326***	173
BBB	1.686	1.543	-0.142**	964	1.468	-0.215***	776	1.849	0.163*	188
BB	2.920	2.784	-0.136	206	2.988	0.068	90	2.625	-0.295	116
B	4.098	3.948	-0.149	82	4.820	0.722*	7	3.867	-0.231	75
CCC	5.005	6.071	1.066	14	6.058	1.053	11	6.117	1.112*	3

Table 2.5: Ordered Probit Regression

This table reports the results of the ordered probit regression model based on a 2098 non split-rated Moody's and S&P jointly rated bonds issued between years 1983-1994. The p-values in Model 1 are based on the standard errors while p-values in Model 2 are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. The dependent variable for both probit regression models is *S&P_Rating*. *S&P_Rating* presents letter level ratings assigned by S&P to a bond issue. *S&P_Rating* is an ordinal variable while S&P assigns letter ratings to bond issues. We convert these letter ratings into numerical ratings following existing literature. Namely, we convert letter rating AAA to numerical rating 1, letter rating AA to 2, letter rating A to 3 and so on. The control variables, except for *Int_Cov*, are based on Blume et al. (1998). With respect to *Int_Cov*, Blume et al. (1998) divide the interest coverage ratio of an issuer into four categories based on whether the interest coverage ratio is less than 5, between 5 and 10, between 10 and 20 and 20 and 100. We do not use such categories. The variable definitions are provided in Panel A of Table 2.1.

	Model 1			Model 2	
Variables	Coefficient	Standard Errors	P>|z|	Robust Standard Errors	P>|z|
Int_Cov	-0.020	0.004	0.000	0.012	0.098
OperInc_Rev	-2.608	0.263	0.000	0.660	0.000
Ltd_Assets	4.058	0.329	0.000	0.917	0.000
Td_Assets	0.131	0.276	0.636	0.621	0.833
Size	-0.000	0.000	0.000	0.000	0.000
Beta	-0.235	0.069	0.001	0.158	0.136
SE	124.451	6.374	0.000	20.847	0.000
N	2098				
Rating boundaries					
AAA	<-0.641			0.398	
AA	-0.641<>0.921			0.363	
A	0.921<>2.675			0.391	
BBB	2.675<>4.044			0.448	
BB	4.044<>4.479			0.471	
B	4.479<>9.886			1.931	
CCC	>9.886			1.931	

Table 2.6: Actual versus Expected ratings

This table tabulates the actual ratings against the expected ratings for the bonds issued between years 1995-2008. The actual ratings are the initial ratings assigned to these bonds by S&P. The expected ratings present the ratings that are predicted for these bonds on the ordered probit model in Table 2.5. The tabulated ratings serve as a measure of the goodness of fit of model presented in Table 2.5. This table, for instance, shows that 117 bonds are jointly rated as AAA by S&P and Moody. The model in Table 2.5 correctly predicts AAA ratings for 103 of those bonds whereas 3 of these bonds are expected as AA, 7 as A, 2 as BBB and another 2 as B rated bonds.

	Actual ratings							
Expected ratings	AAA	AA	A	BBB	BB	B	CCC	Total expected
AAA	103	119	208	58	1	1	0	490
AA	3	122	229	149	2	3	0	508
A	7	109	841	765	115	22	2	1861
BBB	2	1	60	299	89	47	1	499
BB	0	2	1	22	19	10	0	54
B	2	0	5	23	39	66	11	146
CCC	0	0	0	0	1	6	2	9
Total Actual	117	353	1344	1316	266	155	16	3567

Table 2.7: Treasury Spread Regression controlling for the difference between actual and expected ratings

This table presents the results of the treasury spread regression that examines whether the difference between the ratings assigned by CRAs (actual ratings) and those that are predicted based on publically available financial information (the expected ratings) effects the bond yield. The dependent variable, for all the models reported in this table, is the *T_Spread*. *T_Spread* is defined as the difference between the 'offer yield to maturity' (Y) of a bond less 'yield on comparable treasury at offer date' (COMPTY). The control variables are based on Livingstone and Zhou (2010). Model 1 examines whether the difference between the actual ratings and expected ratings affects the required bond yield. In Model 1, apart from the control variables used in Livingstone and Zhou (2010), we also include indicator variables *Higher* and *Lower* in the treasury spread regression. The variable *Higher* equals 1 when the actual ratings are higher than the expected rating and 0 otherwise. The variable *Lower* is set equal to 1 when actual ratings are lower than the expected ratings and 0 otherwise. Model 2 and Model 3 are similar to Model 1 and presents the results for investment and non- investment grade bonds separately. Model 3 examines the effect of the magnitude of the difference between the actual and expected ratings on bond yield. For this purpose, apart from the control variables used in Livingstone and Zhou (2010), we include indicators variables *Dh2, Dh1, Dl2* and *Dl1* in the treasury spread regression. The variable *Dh2* equals 1 when the actual ratings are higher than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dh1* equals 1 when the actual ratings are higher than the expected ratings by one rating level and 0 otherwise. The variable *Dl2* equals 1 when the actual ratings are lower than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dl1* equals 1 when the actual ratings are lower than the expected ratings by one rating level and 0 otherwise. Model 3 examines the trend in use of in house credit risk analysis by investors. The variable definitions are provided in Panel B of Table 2.1. The *p*-values in are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Variables	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Model 3 Coefficients (p-values)	Model 4 Coefficients (p-values)
Mat	0.008***	0.007***	-0.014	0.008***
	(0.000)	(0.000)	(0630)	(0.000)
Proc	0.000**	0.000**	0.000	0.000***
	(0.024)	(0.026)	(0.119)	(0.008)
Sub	-0.033	0.167	0.019	-0.020
	(0.842)	(0.112)	(0.920)	(0.901)
Call	0.111***	0.098**	0.437***	0.107***
	(0.005)	(0.021)	(0.004)	(0.009)
Utility	-0.013	-0.032	-0.051	0.012
	(0.832)	(0.535)	(0.885)	(0.846)
R415	-0.350***	-0.040	-0.817***	-0.334***
	(0.000)	(0.508)	(0.000)	(0.000)
R144a	-0.433***	-0.211***	0.631	-0.420***
	(0.000)	(0.007)	(0.269)	(0.000)
Rikspremium	0.998***	0.920	1.977***	1.003***
	(0.000)	(0.000)***	(0.002)	(0.000)
AAA	-5.467***	-1.273***		-5.497***
	(0.000)	(0.000)		(0.000)
AA	-5.019***	-0.853***		-5.014***
	(0.000)	(0.000)		(0.000)
A	-4.731***	-0.569***		-4.716***
	(0.000)	(0.000)		(0.000)
BBB	-4.157***			-4.171***
	(0.000)			(0.000)
BB	-2.884***		-2.464***	-2.809***
	(0.000)		(0.000)	(0.000)
B	-1.725***		-1.502***	-1.641***
	(0.000)		(0.002)	(0.000)
Splitrated	0.142***	0.180***	-0.103	0.137***
	(0.004)	(0.001)	(0.545)	(0.006)

Table 2.7 (continued)

Higher	0.222***	0.162**	0.565**	
	(0.001)	(0.010)	(0.022)	
Lower	-0.235***	-0.232***	-0.196	
	(0.000)	(0.000)	(0.317)	
Dh2				0.635***
				(0.000)
Dh1				0.148**
				(0.027)
Dl1				-0.185***
				(0.000)
Dl2				-0.414***
				(0.000)
constant	4.735***	4.721***	4.701***	4.695***
	(0.000)	(0.000)	(0.000)	(0.000)
N	3567	3130	437	3567
Adj. R^2	62.37%	63.48%	64.52%	64.97%

Table 2.8: The difference between actual and expected ratings and information content of ratings

This table presents the results of the analysis that examines whether the difference between the actual and expecting ratings has a bearing on the information content of credit ratings. The dependent variable in Model 1, Model 2 and Model 3 is the *T_Spread* which is defined as the difference between the 'offer yield to maturity' (Y) of a bond less 'yield on comparable treasury at offer date' (COMPTY). The control variables in Model 1 are based on Livingstone and Zhou (2010) expect that we use the ordinal variable *S&P_Rating* instead of a dummy variable for each rating category. In Model 2, we indicator variable Equal which takes a value 0 when actual ratings are equal to expected ratings and 0 otherwise. In this model we also include an interaction term, *S&P_Rating*Unequal*, between *S&P_Rating* and Equal. Model 3 regresses *T_Spread* on all control variables used in Model 1 except for *S&P_Rating*. Model 4 and Models regresses the residuals from Model 3 on credit ratings. Model 4 is based on bonds for which actual ratings differ from the expected ratings while Model 5 uses the sample bonds for which actual ratings are equal to the expected ratings. The variable definitions are provided in Panel B of Table 2.1. The *p*-values in are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Variables	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Model 3 Coefficients (p-values)
Mat	0.000144		
	(0.906)		
Proc	-0.000118		
	(0.227)		
Sub	1.782***		
	(0.000)		
Call	0.378***		
	(0.000)		
Utility	-0.0668		
	(0.621)		
R415	-1.142***		
	(0.000)		
R144a	-1.432***		
	(0.000)		
Riksprem	0.873***		
	(0.000)		
S&P_Rating		0.499***	0.495***
		(0.000)	(0.000)
Splitrated	0.122*		
	(0.076)		
Constant	1.188***	-1.689***	-1.773***
	(0.000)	(0.000)	(0.000)
N	3,567	1,452	2,115
R-squared	40.53%	32.87%	25.41%

Table 2.9: Split rated bond analysis

This table presents the results of the analysis that examines the difference between the ratings assigned by CRAs (actual ratings) and those that are predicted based on publically available financial information (the expected ratings) on the split rated bonds yield. The dependent variable for these treasury spread regressions is the *T_Spread*. *T_Spread* is defined as the difference between the 'offer yield to maturity' (Y) of a bond less 'yield on comparable treasury at offer date' (COMPTY). Model 1 is the base model that examines the effect of several control variables, including the split rating identifier, *Splitrated* on bond yield. Model 2 presents the results of the analysis where, apart from the variables included in the Model 1, we also control for the difference between actual and expected ratings on bond yield. Model 3 is an extension of Model 2 with the inclusion of the interaction term, *Higher*Splitrated* between *Splitrated* and *Higher*. *Splitrated* is a dummy variable that identifies bonds for which Moody's and S&P differ in their ratings by at least one letter rating. *Higher* in a dummy variable that equals 1 when the actual ratings are higher than the expected rating and 0 otherwise. The rest of the control variables are based on Livingstone and Zhou (2010). The variable definitions are provided in Panel B of Table 2.1. The *p*-values in are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Variables	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Model 3 Coefficients (p-values)
Mat	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)
Proc	0.000	0.000**	0.000**
	(0.437)	(0.024)	(0.020)
Sub	-0.081	-0.033	-0.039
	(0.632)	(0.842)	(0.815)
Call	0.121***	0.111***	0.112***
	(0.004)	(0.005)	(0.005)
Utility	-0.053	-0.013	-0.017
	(0.513)	(0.832)	(0.792)
R415	-0.379***	-0.350***	-0.346***
	(0.000)	(0.000)	(0.000)
R144a	-0.487***	-0.433***	-0.437***
	(0.000)	(0.000)	(0.000)
Riksprem	1.003***	0.998***	0.996***
	(0.000)	(0.000)	(0.000)
AAA	-5.274***	-5.467***	-5.481***
	(0.000)	(0.000)	(0.000)
AA	-4.814***	-5.019***	-5.035***
	(0.000)	(0.000)	(0.000)
A	-4.591***	-4.731***	-4.743***
	(0.000)	(0.000)	(0.000)
BBB	-4.114***	-4.157***	-4.167***
	(0.000)	(0.000)	(0.000)
BB	-2.837***	-2.884***	-2.886***
	(0.000)	(0.000)	(0.000)
B	-1.628***	-1.725***	-1.731***
	(0.000)	(0.000)	(0.000)
Splitrated	0.164***	0.142***	0.109**
	(0.003)	(0.004)	(0.040)
Higher		0.222***	0.169**
		(0.001)	(0.023)
Lower		-0.235***	-0.236***
		(0.000)	(0.000)
*Higher*Splitrated*			0.229*
			(0.069)

Table 2.9 (continued)

Constant	4.551***	4.658***	4.744***
	(0.000)	(0.000)	(0.000)
Year dummy	Yes	Yes	Yes
N	3567	3567	3567
Adj. R^2	64.17%	64.62%	64.76%

Table 2.10: Conservativeness of Moody's and S&P

This table presents the results of the analysis where we compare ratings assigned by Moody's and S&P (actual ratings) with the ratings predicted based on publically available information (expected ratings) information. The sample for this analysis consists of 791 split rated bonds. This table, for instance, reveals that 157 of the split rated bonds received higher than expected ratings and 315 bonds received lower than expected ratings from S&P. For 319 bonds, the ratings assigned by S&P are equal to the expected ratings.

	S&P	Moody's
Actual ratings > Expected ratings	157 (19.85%)	120 (15.17%)
Actual ratings = Expected ratings	319 (40.33%)	266 (33.63%)
Actual ratings < Expected ratings	315 (39.82%)	405 (51.20%)
Total	791	791

Table 2.11: Univariate analysis - The difference between actual and expected ratings and subsequent rating revision

This table presents the statistics about the number of days after which the sample of bonds included in our study received a rating revision subsequent to the initial ratings. The full sample is divided into two sub-samples based on whether the ratings assigned by CRAs (actual ratings) are equal to the ratings predicted based on publically available information (expected ratings). The sub-samples are further divided in the different samples bases on whether the actual ratings and higher or lower than the expected ratings and based on the magnitude of the difference between the actual and expected ratings. The sub-sample for which the actual ratings are equal to the expected ratings is our base case. The independent sample t-test is used to test for the equality of means across base case and other sub-samples. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Rating agency		Equal (Days)	Not equal (Days)	Higher (Days)	Lower (Days)	Higher by 1 notch (Days)	Higher 1+ notch (Days)	Lower by 1 notch (Days)	Lower by 1+ notch (Days)
Moody's	Average	1032	854***	1,075	814***	1,108	797	851***	738***
	Median	831	686	1,053	642	1,087	650	635	682
	N	461	794	123	671	110	13	449	222
S&P	Average	726	779*	1,151***	714	1,184	969**	731	684
	Median	532	604	838	564	957	718	518	570
	N	512	768	255	513	209	46	357	156

Table 2.12: Rating revision regression controlling for the difference between actual and expected ratings

This table presents the results of the analysis that examines whether the difference between the ratings assigned by CRAs (actual ratings) and those that are predicted based on publically available financial information (the expected ratings) leads to an early rating revision by CRAs. The dependent variable of the regression analysis is 'Days' which is defined as the difference, in number of days, between the date of initial bond ratings and the date of first subsequent rating change. The independent variables are based on Livingston et al. (2008). In Model 1 the dependent variable 'Days' is calculated based on the initial and first subsequent bond rating changes by Moody's. In Model 2 the dependent variable 'Days' is calculated based on the initial and first subsequent rating change by S&P. The analysis consists of a subsample of all bonds including in our main analysis for which the credit rating history is available through Bloomberg Finance. The *p*-values in are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. The variable definitions are provided in Panel C of Table 2.1. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Variables	Model 1 Coefficients (p-values)	Model 1 Coefficients (p-values)
Higher	335.051**	342.364*
	(0.042)	(0.070)
Lower	-164.868	127.266
	(0.183)	(0.214)
High_Yield	-220.803*	-98.0369
	(0.077)	(0.261)
Higher Yield_High*	-540.629**	-55.411
	(0.022)	(0.748)
Lower Yield_Low*	153.578	91.702
	(0.266)	(0.398)
Splitrated	-81.246	-108.073
	(0.290)	(0.102)
Peak	725.995***	301.947*
	(0.000)	(0.052)
Trough	-160.653*	-138.149
	(0.089)	(0.143)
AA	-967.964***	-510.274
	(0.000)	(0.214)
A	-813.945***	-795.909**
	(0.001)	(0.014)
BBB	-725.953***	-643.074**
	(0.002)	(0.043)
BB	-1122.562***	-964.025***
	(0.000)	(0.003)
B	-1078.579***	-832.758***
	(0.000)	(0.010)
CCC	-1088.659***	-956.482***
	(0.000)	(0.007)
Constant	-1826.868***	1329.726***
	(0.000)	(0.000)
Year dummy	Yes	Yes
N	1110	1178

Table 2.13: Robustness test based on random samples

This table presents the results of the robustness tests of the main findings. The dependent variable, for all the models reported in this table, is the *T_Spread*. *T_Spread* is defined as the difference between the 'offer yield to maturity' (Y) of a bond less 'yield on comparable treasury at offer date' (COMPTY). The control variables are based on Livingston and Zhou (2010). In Model 1, apart from the control variables used in Livingston and Zhou (2010), we also include indicator variables *Higher* and *Lower* in the treasury spread regression. The variable *Higher* equals 1 when the actual ratings are higher than the expected rating and 0 otherwise. The variable *Lower* is set equal to 1 when actual ratings are lower than the expected ratings and 0 otherwise. In Model 1, the p-values are based on two-way clustering based on the year and the issuer of the bond. Model 2 presents the average coefficients values of control variables that result from 1121 bond yield regressions that are carried on 1121 random sample taken out of the main sample to examine whether the difference between the ratings assigned by CRAs (actual ratings) and those predicted based on the publically available information (expected ratings) affects the required bond yield. Model 3 examines the effect of the magnitude of the difference between the actual and expected ratings on bond yield. For this purpose, apart from the control variables used in Livingston and Zhou (2010), we include indicators variables *Dh2, Dh1, Dl2* and *Dl1*in the treasury spread regression. The variable *Dh2* equals 1 when the actual ratings are higher than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dh1* equals 1 when the actual ratings are higher than the expected ratings by one rating level and 0 otherwise. The variable *Dl2* equals 1 when the actual ratings are lower than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dl1* equals 1 when the actual ratings are lower than the expected ratings by one rating level and 0 otherwise. For Model 2 and Model 3, the *p*-values are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. The variable definitions are provided in Panel B of Table 2.1. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Variables	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Model 3 Coefficients (p-values)
Mat	0.006***	0.008***	0.006***
	(0.000)	(0.000)	(0.000)
Proc	0.000*	0.000**	0.000
	(0.083)	(0.024)	(0.116)
Sub	-0.132	-0.033	-0.150
	(0.321)	(0.842)	(0.266)
Call	0.069	0.111***	0.074*
	(0.103)	(0.005)	(0.083)
Utility	-.0388	-0.013	-0.043
	(0.538)	(0.832)	(0.513)
R415	-0.262***	-0.350***	-0.266***
	(0.000)	(0.000)	(0.000)
R144a	-0.396***	-0.433***	-0.408***
	(0.000)	(0.000)	(0.000)
Riksprem	0.867***	0.998***	0.866***
	(0.000)	(0.000)	(0.000)
AAA	-5.183***	-5.467***	-4.937***
	(0.000)	(0.000)	(0.000)
AA	-4.912***	-5.019***	-4.716***
	(0.000)	(0.000)	(0.000)
A	-4.619***	-4.731***	-4.446***
	(0.000)	(0.000)	(0.000)
BBB	-4.070***	-4.157***	-3.902***
	(0.000)	(0.000)	(0.000)
BB	-2.614***	-2.884***	-2.496***
	(0.000)	(0.000)	(0.000)
B	-1.334***	-1.725***	-1.446***
	(0.000)	(0.000)	(0.000)
Splitrated	0.0904***	0.142***	0.086**
	(0.008)	(0.004)	(0.013)

Table 2.13 (continued)

Higher		0.222***	0.125**
		(0.001)	(0.011)
Lower		-0.235***	-0.119**
		(0.000)	(0.019)
Dh2	0.217		
	(0.155)		
Dh1	0.141***		
	(0.003)		
Dl1	-0.128***		
	(0.008)		
Dl2	-0.392**		
	(0.013)		
Constant	4.424***	4.735***	4.312***
	(0.000)	(0.000)	(0.000)
N	3567	3567	3567

Table 2.14: Detailed results of robustness tests

This table provides the detailed results of the robustness test where we run the bond yield regression for 1121 times based on the random sub-samples taken out of the main sample. The results in this table, for instance, reveal that in 1064 of these regressions the coefficient on variable *Higher* is positive and significant at p=0.05 level and in 1112 of these regression the coefficient on *Higher* is positive and significant at p=0.100. Further, the results also reveal that in 1 out of 1121 regressions, the coefficient on variable *Higher* is negative. The dependent variable in all treasury regression is the *T_Spread*. *T_Spread* is defined as the difference between the 'offer yield to maturity' (Y) of a bond less 'yield on comparable treasury at offer date' (COMPTY). The control variables that are based on Livingston and Zhou (2010). In the treasury spread regression that examines whether the difference between the actual ratings and expected ratings affects the required bond yield, apart from the control variables used in Livingston and Zhou (2010), we also include indicator variables *Higher* and *Lower* in the treasury spread regression. The variable *Higher* equals 1 when the actual ratings are higher than the expected rating and 0 otherwise. The variable *Lower* is set equal to 1 when actual ratings are lower than the expected ratings and 0 otherwise. In the treasury spread regression that examines the effect of the magnitude of the difference between the actual and expected ratings on bond yield, apart from the control variables used in Livingston and Zhou (2010), we include indicators variables *Dh2*, *Dh1*, *Dl2* and *Dl1* in the treasury spread regression. The variable *Dh2* equals 1 when the actual ratings are higher than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dh1* equals 1 when the actual ratings are higher than the expected ratings by one rating level and 0 otherwise. The variable *Dl2* equals 1 when the actual ratings are lower than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dl1* equals 1 when the actual ratings are lower than the expected ratings by one rating level and 0 otherwise.

Variables	No. of simulations	P-values <0.05	P-values <0.100	Unexpected sign
Higher	1,121	1,064 (94.92%)	1,112 (99.20%)	1
Lower	1,121	950 (84.74%)	1,098 (97.95%)	0
Dh2	1,121	90 (8.04%)	338 (30.10%)	0
Dh1	1,121	1,059 (94.47%)	1,105 (98.56%)	0
Dl1	1,121	971 (86.57%)	1,067 (95.12%)	0
Dl2	1,121	934 (83.26%)	1,047 (93.32%)	0

Table 2.15: Robustness test. The treasury spread regression for each rating category

This table presents the results of the treasury spread regression that, for each credit rating category, examines whether the difference between the ratings assigned by CRAs (actual ratings) and those that are predicted based on publically available financial information (the expected ratings) effects the bond yield. For this purpose we estimate a separate treasury spread regression for each rating category. The dependent variable for these treasury spread regressions is the *T_Spread*. *T_Spread* is defined as the difference between the 'offer yield to maturity' (Y) of a bond less 'yield on comparable treasury at offer date' (COMPTY). The control variables are based on Livingston and Zhou (2010). We examine whether the difference between the actual ratings and expected ratings affects the required bond yield by, apart from the control variables used in Livingston and Zhou (2010), including indicator variables *Higher* and *Lower* in the treasury spread regression. The variable *Higher* equals 1 when the actual ratings are higher than the expected rating and 0 otherwise. The variable *Lower* is set equal to 1 when actual ratings are lower than the expected ratings and 0 otherwise. To examine the effect of the magnitude of the difference between the actual and expected ratings on bond yield, apart from the control variables used in Livingston and Zhou (2010), we include indicators variables *Dh2*, *Dh1*, *Dl2* and *Dl1* in the treasury spread regression. The variable *Dh2* equals 1 when the actual ratings are higher than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dh1* equals 1 when the actual ratings are higher than the expected ratings by one rating level and 0 otherwise. The variable *Dl2* equals 1 when the actual ratings are lower than the expected ratings by two or more ratings level and 0 otherwise. The variable *Dl1* equals 1 when the actual ratings are lower than the expected ratings by one rating level and 0 otherwise. We do not report control variables for brevity. The *p*-values in are based on robust standard errors that have been adjusted for potential clustering problem caused by issuance of multiple bonds by the same firm. ***,**,* show the significance of difference at 0.01, 0.05 and 0.10 level, respectively.

Rating category	*Dh2*	*Dh1*	*Higher*	*Dl2*	*Dl1*	*Lower*
1	0.596***	0.376***	0.104			
	(0.000)	(0.000)	(0.478)			
2	0.384***	0.167***	0.171**		-0.100	-0.032
	(0.000)	(0.002)	(0.017)		(0.240)	(0.611)
3	0858**	-0.001	0.0406	0.309***	-0.110*	-0.301***
	(0.033)	(0.994)	(0.507)	(0.000)	(0.078)	(0.001)
4	0.653**	-0.282***	0.494*	-0.332***	-0.289***	-0.040
	(0.030)	(0.008)	(0.078)	(0.003)	(0.000)	(0.471)
5	-1.352***	0.497**	0.134	-0.522*	0.120	-0.619***
	(0.000)	(0.036)	(0.709)	(0.064)	(0.594)	(0.005)
6		1.632**	1.972***	-0.445**	0.289	0.0511
		(0.029)	(0.003)	(0.045)	(0.680)	(0.826)
7				0.830**	0.611	0.737
				(0.014)	(0.335)	(0.174)

Chapter 3

The quality of financial reporting under IFRS: evidence from credit ratings

3.1 Introduction

n this study we examine whether or not firms that report under International Financial Reporting Standards (IFRS) receive higher credit ratings than firms who do not report under IFRS, and whether or not the application of IFRS is associated in those firms with lower instances and levels of rating disagreements among the credit rating agencies (CRAs).[1] IFRS are issued by The International Accounting Standard Board (IASB) who aims to develop a single set of high quality, understandable, and internationally comparable financial reporting standards for general purpose financial statements.[2] Currently, more than 100 countries across the world require or allow firms to prepare their financial statements in accordance with IFRS (Ball, 2006). From 2005 onwards, firms in EU member states are mandatorily required to prepare their financial statements by following IFRS. The Security and Exchange Commission (SEC) is also currently deliberating on whether or not to allow firms to report under IFRS in the US. The adoption of IFRS is expected to enhance transparency, comparability and quality of financial statements presented by European firms. This, in turn, is expected to contribute to a more efficient functioning of the capital and internal markets (EC Regulation No. 1606/2002).

The worldwide adoption of IFRS in the recent years has motivated many researchers to investigate quality differentials between IFRS and the set of standards they replace. These studies focus on a range of accounting quality attributes such as value relevance (e.g., Barth et al. 2008), timeliness of loss recognition (e.g., Barth et al. 2008; Van der Muelen 2007), accrual quality, predictability (e.g., Ashbaugh and Pincus, 2001; Van Tendeloo and Vanstraelen, 2005) and more. While most of the studies concentrate on the equity market effects of IFRS, a relatively small number of studies examine the change in accounting quality from the perspective of the debt market. The debt market is a much bigger and important source of finance for public firms compared to the equity market (Henderson et al. 2006) as about 2/3rd of the assets of an

[1] We use the term IFRS and IAS interchangeably throughout our paper.
[2] http://www.ifrs.org/The+organisation/IASCF+and+IASB.htm

average firm in big economies (e.g. the US, UK, Japan etc.) are financed through debt instruments (see for example Rajan and Zingales, 1995).

Firms typically approach the debt market by issuing fixed-income securities such as bonds. The issuance of a new bond is a complex process that is facilitated by different financial intermediaries including CRAs. The role of CRAs in a bond issuance process is to assess if the bond issuer will be able to meet its contractual and financial obligations when they become due. These risk assessments provided by CRAs are of immense importance as they decrease the information asymmetry between borrowers and lenders and thus enhance firms' access to new funding sources and new markets (Strahan, 1999; Susan and Rechtschaffen, 1998). Fundamentally, credit ratings are based on the analysis of current and historical information so as to draw opinion about the events and developments that are likely to happen in future. Since the occurrence of future events is hard to predict with conviction, a degree of uncertainty is always associated with the credit rating process. Morgan (2002) argues that the uncertainty in the credit rating process relates directly to the information asymmetry that exists between a firm and the outside world, and the difficulty involved in the valuation of a firm's assets. The uncertainty and information asymmetry in the credit rating process might have two important consequences on rating decisions. Firstly, as argued by Pagratis and Stringa (2009), if CRAs act conservatively and err on the side of safety, then information asymmetry and uncertainty about the firm's true risk might lead CRAs to assign lower ratings compared to what might have been assigned otherwise. Secondly, depending on the level of uncertainty, if a bond is rated by two (or more) CRAs and one rater acts more conservatively than the other, then the two raters might assign different ratings to same bond, Hence, the bond might be split rated.

The discussion above shows that information asymmetry and uncertainty are associated with levels of assigned ratings and the occurrence of split ratings. In other words, rating levels and split ratings reveal the presence of information asymmetry and uncertainty in the rating process and thus can be reasonably used as a proxy for information asymmetry and uncertainty. From the point of view of a firm, both lower ratings and split ratings are costly. Prior research shows that bond yields exhibit an inverse relation with credit ratings, for example bonds with lower credit ratings have higher yield spreads (Allen et al. 1990; Mitchell 1991). Similarly, bonds that are split rated have bigger yield spreads (Billingsley et al. 1985; Ziebart, 1991; Jewell and Livingston, 1998) and carry higher issuing costs measured in terms of underwriters' spread (Jewell and Livingston, 1998).

Academic literature provides consistent evidence that credit ratings are largely based on the debt issuer's accounting information. For example, Horrigan (1966) reports that about 2/3rd of the credit ratings assigned by CRAs can be correctly predicted on the basis of an issuer's accounting ratios. Pogue and Soldofsky (1969) find that up to 80% of the variation in credit ratings can be explained using accounting information based models. Other studies that report accounting information as an important input of the credit rating process include Blume *et al.* (1998), Chan and Jegadeesh (2001), Kamstra, Kennedy, and Suan (2001). Most importantly, CRAs such as S&P also acknowledge that the financial risk of debts issuers is largely determined based on the accounting information extracted through an entity's financial statements.

Since accounting information plays a vital role in the determination of financial risk, accounting information that is transparent, comparable, and provides more disclosures is likely to decrease the information asymmetry and the ambiguity about the financial health of a firm. As discussed earlier, the rise in information asymmetry might lead to lower ratings and greater rating disagreements and vice versa. If this is true, then firms that provide higher quality information are, on average, more likely to receive higher credit ratings and experience lower instances of rating disagreements. At least one empirical study supports this hypothesis: Jorion *et al.* (2007) document that CRAs tend to issue lower ratings to firms that have lower accounting quality and the other way round. Mansi et al. (2004) provide indirect evidence of the influence of quality of accounting information on the ratings assigned by CRAs by showing that firms audited by a Big 4 auditor (usually taken as a proxy for quality of information) on average receive higher ratings compared to those audited by smaller audit firms.

In this study we investigate whether the application of IFRS reduces information asymmetry and uncertainty about the financial risk of a firm. We do so by examining that whether bonds issued by European financial firms (banks and insurance companies) that report under IFRS receive higher credit ratings compared to those issued by firms reporting under other sets of accounting standards. Further, we examine whether CRAs (specifically Moody's and S&P, two of the most prominent CRAs), disagree less frequently when assigning ratings to the bonds issued by firms that report under IFRS as compared with those who do not report under IFRS. We also examine whether reporting under IFRS influences the magnitude of rating disagreements between Moody's and S&P when split ratings occur. As an additional source of evidence, we observe the pattern of lopsidedness of rating disagreements for bonds issued by IFRS and non-IFRS sample firms. Lopsidedness is a term used in the literature to refer to the situation where one CRA consistently issues lower ratings to bonds as compared with other CRAs' ratings. The level of lopsided ratings is also argued to be associated with information asymmetry and uncertainty involved in the assessment of the financial risk of a firm (see Livingston et al., 2007; Morgan, 2002).

We limit our analysis to a sample of European financial firms for a number of reasons. First, the financial reporting changes brought by IFRS have had a bigger impact on financial firms than on non-financial firms (Ammer et al., 2004).[1] Further, the assets of financial firms are more difficult to value compared to those of non-financial firms (e.g., Morgan, 2002; Innotta 2006). Therefore, the effects of IFRS are expected to be more pronounced for financial firms. Second, most of the bonds issued by European non-financial firms are rated by only one CRA, which means that they will not have split ratings. Third, financial firms issue more bonds than do non-

[1] For example, the differences in reporting assets and liabilities at fair value and the treatment of financial derivatives and hedges as required under IFRS are argued to be larger for financial firms compared to non-financial firms (see Moody's Investor Service ―Expected Impact of International Financial Reporting Standards (IFRS) on European Banks February, 2004).

financial firms (e.g., about 85% of the bonds included in Innotta (2006) are issued by financial firms); hence, focusing on financial firms gives more power to our tests due to a larger sample size. Finally, while firms in many other countries report under IFRS, we focus on European firms to avoid the heterogeneity issues that may exist in different financial markets.

Based on the results of the univariate and multivariate tests that we performed on a sample of 788 bonds issued by European financial firms during the period 1996-2008, we find that bonds issued by firms reporting under IFRS, on average, receive higher credit ratings by about 0.38 of a notch compared to those issued by firms that report under other sets of accounting standards. Next, consistent with previous research, we find that a high proportion (68.53% in aggregate terms) of bonds jointly rated by Moody‘s and S&P are split rated. However, our results provide strong evidence that the probability of getting a split rating lowers by about 17% after firms start to report under IFRS. Monetarily, this lower probability of split rating for firms reporting under IFRS saves about $91,000 dollars in terms of lower yield spread.[2] Further, we document that the level of absolute disagreement between raters also declines (by approximately 0.42 of a notch) for IFRS sample firms in instances when a split rating occurs. With respect to the lopsidedness of ratings, we document the existence of this pattern for both pre and post IFRS sample firms. Nonetheless, our results show that there is at least a slight decrease in this phenomenon once firms start to report under IFRS. We attribute these results to higher quality and more transparent accounting information under IFRS. Our results do not materially change when we use a constant sample, a matched sample, or a constant sample of mandatory adopters of IFRS only.

Our study contributes to literature that examines the potential benefits of IFRS adoption by focusing on debt market perspective. While the number of studies that examine the impact of IFRS on equity markets has grown considerably, the evidence from the perspective of the debt market is relatively scarce. Evidence from debt markets in the presence of evidence from equity markets is still important since the debt market is a much bigger source of finance for listed firms and because the results obtained from the analysis of equity markets might not hold for the debt market (Ball et al., 2009). Another reason evidence from the debt market is relevant is that the results of equity market based studies, such as those focusing on value relevance, might have reliability issues because of the imprecision of the stock pricing models used (e.g. Mansi et al., 2003). These studies are also criticized on the grounds of econometrics (Lambert, 1996; Lys, 1996; and Skinner, 1996, 1999) as well as on the basis of the validity of the proxies used to measure the quality of financial reporting (Holthausen and Watts, 2001).

Focusing on an important information intermediary of the debt market, CRAs, to gather evidence of any change in the quality of accounting information associated with IFRS) also gives our study several advantages over other studies. For instance, CRAs form their rating opinions based on a detailed analysis of individual components of accounting information rather than simply relying on bottom line figures such as net income or book values.[3] Consequently, credit

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[2] See footnote 21 for detailed calculations.

[3] This is evident from the S&P document “Corporate Credit Ratings 2008” which states “…we believe it is critical to analyze each type of business and asset class in its own right.”

ratings may capture and reflect changes in accounting quality also occurring at the individual accounts level. Additionally, CRAs are expected to gather sufficient support before they assign a particular risk level to a bond issue since any incorrect rating could be costly for the debt issuers, investors, and for the rating agencies themselves. This is mainly due to the fact that investors and regulators heavily rely on these ratings and in many cases these ratings are integrated into the regulations. In such cases, a change in credit rating necessitates inventors adjust their portfolio of investments or requires supervisory bodies to initiate regulatory actions.[4] Based on these factors we assume that the ratings opinions given by CRAs are less likely to be affected by noise in the information environment. We also contribute to the literature by using a much cleaner and more directly observable set of proxies for the information asymmetry, such as credit rating levels and split ratings, compared to other proxies that are often hard to quantify and difficult to measure, such as firm size, intangible assets, or analyst forecast dispersion (Livingston and Zhou, 2010). Apart from our contribution to the literature of IFRS, we also contribute to literature that examines the effect of the quality of accounting information on credit ratings decisions by showing that high quality accounting information may lead to better ratings and lower instances of rating disagreements.

The remainder of the paper is organized as follows: Section 2 builds and explains our hypothesis, Section 3 discusses the existing literature on IFRS and credit ratings, Section 4 and 5 describe the dataset and the methodology used respectively, Section 6 presents the results of our analysis, Section 7 performs robustness tests and Section 8 discusses the findings and conclusions.

3.2 Hypothesis development

The credit rating of a bond is a function of the business and the financial risk. Whereas information about business risk comes from a consideration of general economic and industry specific conditions, the information about the financial risks is largely based on the accounting information periodically released by the firm in the form of financial statements. S&P acknowledges the utility of accounting information in a credit rating process by stating "financial statements and related disclosures serve as our primary source of information regarding financial condition and financial performance…," and that "financial risk is portrayed largely through quantitative means, particularly by using financial ratios". [5]

Existing literature also provides evidence of usage and significance of accounting information in bond ratings process. For example, the rating prediction model proposed by Horrigan (1966), which consists of five financial ratios, could correctly explain 65% of the variation in bond

[4] For example, according to the "International convergence of capital measurement and capital standards a revised framework" of the Basel Committee for Banking Supervision, the capital charge on the debt issued by banks depends on the ratings assigned to the bonds. A decline in ratings requires banks to issue extra capital or limit their borrowings.

[5] Standard and Poor's Corporate Ratings Criteria 2008, page.23.

ratings issued during 1961-1964. The model could also correctly predict up to 58% of new ratings and 57% of the rating changes. With a slightly different combination of accounting variables Pogue and Soldofsky (1969) are able to predict 80% of the ratings assigned by CRAs. Many other studies including Blume et al. (1998), Chan and Jegadeesh (2001), Kamstra et al. (2001), and Jorion and Zhang (2007) either use accounting information to predict credit ratings or provide evidence of usage of accounting information in the credit rating process. Importantly, not only academia, but also regulators and firms trust and utilize the results of these studies. For instance, the findings of Blume et al. (1998), which shows that the CRAs have tightened their rating standards over time, have been cited in well over 100 scientific articles. Notably, the same paper is also referred to by the Federal Reserve Board in its comment letter on the proposal of Draft Standard and Basis Conclusions-Financial Instruments and Similar Items issued by the International Accounting Standards Committee and in its research report on the U.S. banking sector issued in 2003. Highlighting the importance of these studies, some researchers (for example, Kamstra et al., 2001) believe that companies use the results of these studies to predict initial bond ratings or subsequent changes to them.

The estimation of credit risk, however, is not an exact science and requires subjective judgments.[6] The subjective nature of the rating process makes it difficult for CRAs to precisely determine the credit risk of a bond. Instead, under such circumstances, CRAs are more likely to determine a range within which the credit risk for a bond may fall. The more uncertain the CRAs are about the risk of a firm, the broader the range of possible risk. The width of a credit risk range might have two consequences. First, if CRAs prefer to err on the lower rather than upper side and i.e., act conservatively, then they are likely to assign ratings that correspond to the higher side of the possible credit risk range while the level of actual credit risk might lie on the lower end of the credit risk range. This means that when CRAs are less confident about the true value of the assets of a firm, they might prefer to issue lower credit ratings and vice versa (Morgan, 2002). Consistent with this notion, Jorion and Zhang (2007) finds that the decline in the quality of accounting information overtime has, in fact, led CRAs to issue lower ratings to US corporate bonds. CRAs also admit that they consider the quality of accounting information during the credit rating process. For example, S&P states that:

> Ratings rely on audited data, and the rating process does not entail auditing a company's financial records. Analysis of the audited financials begins with a review of accounting quality. The purpose is to determine whether ratios and statistics derived from financial statements can be used accurately to measure a company's performance and position relative to both its peer group and the largest universe of industry or utility companies.[7]

Among the factors that influence the quality of accounting information are the accounting standards since they provide a collection of rules, procedures, and conventions that determine the

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[6] Standard and Poor's Corporate Ratings Criteria 2008, page.20.
[7] Standard and Poor's Corporate Ratings Criteria 2003, page 22.

treatment of various transactions that make up the financial statements of a firm. S&P describes the importance of accounting standards in their rating process in the following words: "Understanding the implications of the accounting basis used—e.g., International Financial Reporting Standards, U.S. Generally Accepted Accounting Principles, or other local or statutory GAAP basis—is highly germane to our corporate rating methodology."[8] IFRS are issued by IASB that has an objective to issue high quality accounting standards that result in transparent and comparable financial statements. The salient features that are attributed to IFRS are that they are forward looking, focus on fair value reporting of assets and liabilities, require higher levels of disclosures (Daske and Gebhardt, 2006), and limit allowed alternate accounting treatments (Barth et al. 2008). The IFRS are also considered to be more comprehensive than most of the local GAAP (Bae et al. 2008). Regulators also expect IFRS to enhance comparability of accounting information and make accounting information more transparent (EC Regulation No. 1606/2002). Incidentally, these features are closely relevant to the credit rating process. For example, as credit ratings essentially provide forward looking information, it would be more helpful if they were determined using forward looking information (as presumably provided by IFRS). Similarly, IFRS puts more emphasis on fair values, thus IFRS reported figures are likely to be closer to the true economic values of assets and liabilities and hence be more decision relevant compared to the historical costs that become increasingly irrelevant with the passage of time. IFRS based figures of income and loss are also believed to be more informative compared to those reported under the local GAAP.[9] The amount of information disclosed through financial statements also has important implications on a firm's credit risk. This is because higher disclosure levels tend to reduce estimation risks (Verrecchia, 2001) whereas lower disclosure levels could, as suggested by S&P, lead to lower ratings.[10] Limiting managerial discretion is important as it enhances the transparency and quality of accounting information by restricting managers' opportunistic discretions (Ashbuagh and Pincus, 2001). Finally, reporting under the same set of standards facilitates the credit rating process by making it easier to compare financial performance of a bond issuing firm with the performance of its peers. The comparability of financial statements is important in the credit rating process as S&P admits that "the rating process is, in part, one of comparisons, so it is important to have a common frame of reference."[11] As the features discussed above are closely relevant to the credit rating process and are perceived to be associated with reporting under IFRS, their realization is expected to lower uncertainty in the rating process and lessen the need to issue conservatively lower ratings. This leads us to our first hypothesis:

> Hypothesis 1: Bonds issued by firms reporting in accordance with IFRS receive higher credit ratings compared to bonds issued by firms reporting under non-IFRS.

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[8] Standard and Poor's Corporate Ratings Criteria 2008, page 37.
[9] Bank of England, Financial Stability Review, December 2005, page 42.
[10] S&P define the benefits of disclosure by stating that "to the extent we believe information risk exists, it can influence our decision to maintain a rating, assign a rating in the first place, or the level of the rating assigned."
[11] Standard and Poor's Corporate Ratings Criteria 2008, page.23.

Another implication of the inability of CRAs to determine credit risk with precision arises when a bond is rated by two (or more) CRAs. In such a case, if the range of possible credit risk determined by CRAs remains within the boundaries of a particular credit rating, then both CRAs would assign similar ratings to the bond. However, if the range of credit risk determined by CRAs is so wide that it crosses the boarders of two or more adjacent credit ratings, then the bond may get a split rating. High quality accounting information is expected to help CRAs to determine the possible financial risk of a firm within a narrow range. High quality accounting information is also likely to lead CRAs to place more reliance on and come up with a similar interpretation of accounting information. These factors are expected lower the frequency of rating disagreements between CRAs. This leads us to our second hypothesis:

> Hypothesis 2: Bonds issued by firms reporting under IFRS are less likely to be split rated compared to bond issued by firms reporting under non-IFRS.

In many cases the determination of credit risk is so difficult that the credit rating issued by CRAs differs by more than one notch. For example, more than 18% of the bonds in the sample used in Morgan (2002) are split rated by two or more notches. Although the implementation of IFRS is expected to help CRAs to determine credit risk more accurately, IFRS are not expected to completely eliminate the uncertainty and information asymmetry from the rating process. Therefore, a good proportion of bonds might still be split rated even after firms start to report under IFRS. Nevertheless, we expect that improved accounting quality would reduce the absolute magnitude of rating disagreements when a split rating occurs. Our third hypothesis is as follows:

> Hypothesis 3: The magnitude of rating disagreement between CRAs is lower for bonds issued by firms reporting under IFRS compared to bonds issued by firms reporting under non-IFRS.

Based on both the perceived and empirically tested characteristics of IFRS, we expect to find empirical support for our hypothesis. Nonetheless, our results may indicate no, or even negative effects of IFRS on our chosen proxies. This can happen on the following grounds: First, although the fair values of assets and liabilities provide superior information to the user of financial statements, the management discretion and assumption applied in determination of the fair values make them questionable (Nissim, 2003). Second, despite several associated benefits, limiting managerial discretions in accounting reporting could hinder managements' ability to reflect the true performance and financial position of a firm in its financial statements (Barth et al. 2008). Third, although reporting under the same set of accounting standards increases the harmonization of accounting information, provision of options in some accounting standards and the room for varied interpretations, especially in the case of IAS32 and IAS 39, may still reduce the comparability of accounting information.[12] Finally, the possible increase in the volatility of financial results resulting from application of IFRS as suggested by Ball (2006) could also lead to the issuance of lower ratings and higher rating disagreements.

3.3 Literature Review

Two streams of literature are relevant to this study, one examines the difference between the quality of accounting information produced under IFRS and other GAAPs, and the other investigates the role of accounting information in the credit rating process.

3.3.1 IFRS and the quality of accounting information

Studies examining the effect of adoption of IFRS largely focus on value relevance, earnings management, and the cost of capital. The papers comparing IFRS and GAAP based on value relevance or earnings management provide mixed evidence. For example, Van Tendeloo and Vanstraelen (2005) and Goncharov (2005) do not find any conclusive evidence as to whether firms reporting under IFRS engage in lower earnings management. Similarly, Hung and Subrananyam (2007) do not find a significant difference between the value relevance of accounting numbers such as book value and net income prepared under IFRS and the German GAAP. Bartov et al. (2005), however, find evidence of higher quality reporting under IFRS as compared to the German GAAP in terms of earnings association with a 12 month stock return. Consistent with Bartove et al. (2005), findings in Barth et al. (2008) also suggest that voluntary adopters of IFRS produce high quality earnings information in terms of their value relevance, level of earnings management, and timely recognition of losses in comparison to a matched sample of firms following the local GAAP. The evidence of high quality reporting is also provided by Gassen (2006) and Daske and Gebhardt (2006). The results of studies investigating the effect of adoption of IFRS on the cost of equity are also not consistent. Whereas Cuijpers and Buijink (2005) and Daske (2006) do not find evidence of a decrease in the cost of capital for IFRS adopting firms, Daske el al. (2007a), Vogler (2008), and Kim and Shi (2007) find evidence of a reduction in the cost of capital after firms switch to IFRS. A final set of studies gathers evidence of expected benefits of IFRS by looking at the market reaction to the news of an increase or decrease in the likelihood of IFRS adoption in Europe. The results of these studies also point in both directions. Comprix et al. (2003) report a weak but negative reaction of the

[12] Banque De France document “The impact of the transition to IFRS for French banking groups”. Pp. 1. Available at http://bdfbs-ws01.heb3.fr.colt.net/gb/supervi/telechar/arcb2005-the-impact-of-the-transition-to-ifrs-for-french-banking-groups.pdf

market to the news of IFRS adoption in Europe, while Armstrong et al. (2007) report a positive market reaction to events indicative of IFRS adoption in Europe.

3.3.2 The role of accounting information in credit rating process

Researchers over a long period of time have been interested in exploring whether accounting information can be used to predict ratings assigned by Moody's and S&P. In one of the pioneer studies, Horrigan (1966) examines whether accounting data, especially when transformed into accounting ratios, can be used to explain the credit ratings issued by S&P. He finds that a regression model built almost entirely on accounting information such as liquidity, solvency, and capital turnover ratio can correctly predict over half the ratings assigned by S&P to US corporate bonds. Pogue and Soldofsky (1969) also examine role of publically available information in the credit rating process. They find financial information such long-term debt to total assets, the coefficient of variation of earnings, and total assets to be highly relevant in the credit rating process. With the addition of a few other accounting variables, their model was able to correctly predict credit ratings for 80% of the bonds included in the sample. Many other studies such as Altman and Katz (1976), Ang and Patel (1975), Bhandari et al. (1979), and Martin et al., (1984) build accounting information based statistical models to predict bond ratings. Jegadeesh and Chan (2001) compare the relative strength of different statistical models and conclude that the prediction power of these models reaches up to 85%. Belkaoui (1980) consider that the rating prediction models are a significant help to firm managers. These rating models facilitate managers to get an approximation of the risk premium of a bond before its issue, and therefore help managers in financial decisions. A few recent studies use these accounting information based statistical models to try to answer the concerns raised about the accuracy of the credit ratings issued by CRAs. Blume et al. (1998) is one of the most important studies in this respect. In the study, researchers, in order to explain the visible downward trend in the credit ratings assigned to the US corporate debt, compare the actual bond ratings with ratings predicted based on accounting information. On the basis of this comparison they conclude that CRAs have, over the time, become more stringent in their risk assessment approach. Findings in Jorion and Zhang (2007) provide more direct evidence of the importance of accounting information in the credit rating process. They show that the apparent stringent standards of CRAs, as reported by Blume et al. (1998), are in fact largely caused by the decline in the quality of accounting information over time. Poon (2003) analyze a set of accounting based ratios to conclude that the unsolicited ratings issued by CRAs are lower than the ratings issued at the request of the issuers.

The next set of studies relevant to our work is directed towards the causes and consequences of rating disagreements. Ederington (1986) is one of the first studies that investigate the causes of the occurrence of split ratings. In his study Ederington examines whether split ratings occur due to a) a difference between the respective rating categories used by different CRAs, b) different CRAs giving asymmetric importance to various determinants of credit ratings, or c) whether or not the subjectivity involved in evaluation of credit worthiness of various firms becomes the basis for split ratings. Based on the analysis of 493 industrial bonds jointly rated by Moody's and S&P issued between January 1975 and December 1980, his study largely rules out the possibility of any systematic difference between rating criteria used by Moody's and S&P and concludes that split ratings are mainly caused by the random difference of opinion between CRAs. A few studies, however, argue that split ratings do not occur from random errors by CRAs; rather, they occur due to the opaqueness of assets held by bond issuing firms. Morgan (2002), for example, finds that bonds issued by banking firms (possessing more opaque assets) are more likely to be split rated compared to bonds issued by industrial firms. Iannotta (2006) also reports similar results for a study carried out on European markets. The asset opaqueness hypothesis is also supported by Livingston et al. (2007).

Finally, a number of studies closely associated with the split ratings literature also investigate whether split ratings matter to the market. On the one hand, Bilingsley (1985), Liu and Moore (1987), and Perry et al. (1988) examine the consequences of split ratings on bonds yields and report that the yield on split rated bonds lies close to the yield on the lower of the two ratings making a split. On the other hand, Hsueh and Kidwell (1988) find that split rated bonds trade as a separate rating category different from the upper and lower rating, and that the split rated bonds experience a lower issuing cost compared to a similar single rated bond. Reiter and Ziebart (1991) investigate the effect of split ratings on bond yields by taking into account various factors known to affect the bond yield. The results of their study led them to conclude that the market gives more value to the higher of two ratings in the pricing of split rated bonds. Jewell and Livingston (1998) take a larger sample compared to most of the previous studies and find that the bond yield on split rated bonds is approximately equal to the average yield generally associated with upper and lower ratings. They further report a higher underwriters spread for high yield split rated bonds.

3.4 Data

We use three different databases to construct our sample, the Securities Data Company (SDC) database, Institutional Brokers' Estimate System (I/B/E/S) database, and Thomson One Banker database. We use SDC to gather the issue specific (face value, maturity date, issue type, Moody's and S&P ratings, etc.) and issuer specific (nationality, industry, ultimate parent, etc.) information for newly issued bonds. The accounting information required for our analysis is retrieved from Thomson One Banker, whereas the information about the number of analyst followings and the standard deviation of their forecast is taken from I/B/E/S database.

We start by retrieving bond specific information from SDC. Together with bond specific information, we also retrieve the ticker and issuer name for each bond. We use tickers to match our dataset to Thomas One Banker and I/E/B/S. Our data set includes publically issued bonds by European financial institutions from 1996-2008. Our sample period starts in 1996, which when a set of revised International Accounting Standards (IAS) became effective. The IAS before this revision were mostly descriptive and were criticized for allowing a number of alternative accounting treatments (Van Tendeloo and Vanstraelen, 2005). Therefore, including bonds issued by firms reporting under IASs of potentially questionable quality might bias our results against finding any results that support IFRS quality. Our sample period ends in 2008 due to the availability of required data at the time of our analysis. Following Iannotta (2006) we only include fixed rate, non-convertible, non-perpetual, and non-callable bonds in our analysis. We also exclude bonds issued by central banks, supranational institutions, central governments, or government owned firms. We start with 2330 newly issued bonds and delete bonds that are not jointly rated by Moody's and S&P and bonds with missing information (most bonds were deleted from our sample because they were not jointly rated by Moody's and S&P). Our final sample consists of 788 bonds issued by 58 distinct financial firms. For the purpose of analysis, we only take into account the initial bond ratings issued by Moody's and S&P. The inclusion of ratings subsequent to initial ratings may bias results because of the possibility of asynchronous ratings revision by Moody's and S&P (Livingston et al., 2007).

3.5 Methodology

3.5.1 IFRS and the credit rating levels

To test our first hypothesis, we use an ordered probit model and regress the dependent variable *S&P_Rating* on a set of variables that are associated with the credit risk of a firm. The dependent variable *S&P_Rating* presents the S&P ratings assigned to a bond. *S&P_Rating* is an ordinal variable and since S&P assign letter ratings to bonds, we convert these letter ratings into numerical ratings. Namely, we convert letter rating AAA to numerical rating 1, letter rating AA to 2, letter rating A to 3, and so on. Defining our dependent variable in this way means that a lower value of *S&P_Rating* corresponds to a better rating. The independent variables of our ordered probit regression include the pre-tax interest coverage ratio *(Int_Cov)*, operating income to revenue ratio *(OperInc_Rev)*, long term debt to assets ratio *(Ltd_Assets)*, and total debt to assets ratio *(Td_Assets)*. Apart from these accounting information based ratios, we also include total assets *(TA)* as a proxy for firm size, the firm beta *(Beta)*, and standard errors from market model *(SE)* in order to control for the equity risk of a firm. Finally, we include an IFRS *(IFRS)* dummy in our regression analysis to capture the effect of IFRS on the credit rating decisions. Table 3.1 contain the detailed description and definitions of these variables.

The expected impact of variables described above on the level of credit ratings assigned to a bond is as follows: the pre-tax interest coverage, which is ratio of a firms operating income before interest and tax to the interest expenses, is a measure of a firm's ability to pay the interest on its outstanding debt. A firm with a high pre-tax interest coverage ratio is expected to service its debts with more ease and is likely to have less chance of defaulting. Therefore, the pre-tax interest coverage ratio is expected to have a positive relation with the assigned ratings. The operating income to revenue is a ratio that indicates the strength of a firm's operating activities. In essence, this ratio indicates the percentage of sales revenue that is left (after payment of the direct costs of a company) to pay its fixed costs including the interest and capital repayment of outstanding debt. Therefore, higher operating income to sales ratio is a sign of good financial health of a company and should lead to higher credit ratings. The next two ratios, long term debt to assets ratio and total debt to assets ratio, relate to the gearing of a firm. Gearing reveals the extent to which a firm is financed by external sources that require a fixed return. Therefore gearing is an important measure of risk of a firm. A higher gearing may be used to increase returns to equity owners, however, it also increases the financial burden of a firm and thus the likelihood of default. Therefore, we expect an inverse relation between gearing ratios and the assigned credit ratings. The firm size is expected to be positively related to the level of credit ratings since larger firms tend to be more diversified and competitive. Also, larger firms in general reveal more information to the market, have greater analyst following, and are more visible to the market. Both the equity beta and standard error of residuals represent a firm risk with respect to the market. Prior studies (e.g., Kaplan and Urwitz, 1979 and Blume, et al., 1998) document a negative relation between credit rating level and firm risk with respect to the market. Finally, as argued in previous sections, we expect *IFRS* to have a positive influence on the level of ratings assigned by CRAs. In all the models (i.e., equation (1) and equation (2 & 3) below), we also include regional dummies in our analysis to control for any differences in the accounting information environment due to variation in the legal and political system, law enforcement, investors' protections, and ownership structure. These regional dummies are based on La Porta et al. (1998). The ordered probit model to test our first hypothesis is defined as:

$$\begin{aligned} S\&P\_Rating = {} & \beta_0 + \beta_1 IFRS_{i,t} + \beta_2 Int\_Cov_{i,t} + \beta_3 OperInc\_Rev_{i,t} \\ & + \beta_4 Ltd\_Assets_{i,t} + \beta_5 Td\_\ Assets_{i,t} + \beta_6 TA_{i,t} \\ & + \beta_7 Beta_{i,t} + \beta_8 SE_{i,t} + \beta_9 Region\_dummies \end{aligned} \tag{1}$$

The detailed description and definitions of control variables used in model 1 is presented in Table 3.1.

3.5.2 IFRS and the split ratings

We test our second and third hypothesis by using a set of probit and ordered probit models. In these models we regress dependent variables *Split* and *Abs_Split* on *IFRS* dummy and various control variables as suggested by prior literature. The dependent variable *Split* is a binary variable which is equal to 0 when both Moody's and S&P assign the same notch level rating to a new bond and 1 when they (Moody's and S&P) assign different ratings. *Abs_Split* is an ordinal variable which is equal to 0 when both Moody's and S&P assign the same rating to a new bond; *Abs_Split* is equal to 1 when Moody's and S&P rating differ by one notch; *Abs_Split* is equal to 2 when Moody's and S&P rating differ by two notches and so on. The control variables used in this analysis include both bond and firm specific characteristics.[13] Starting with the bond specific characteristics, the first control variable is the bond maturity *(Mat)* which represents the number of months from issue date of bond till date of final maturity. Intuitively, it is easier to predict the outcome of events likely to occur in the near future as compared to those in the distant future. Accordingly, CRAs are likely to determine the credit risk of shorter maturity bonds with more certainty compared to bonds with longer maturity. Previous studies such as Flanner (1996) also find a positive association between uncertainty and bond maturity. Therefore, as the probability of split rating increases with uncertainty, the bonds with longer maturity are more likely to be split rated than bonds with shorter maturity. The level of default risk of a bond is another indicator of uncertainty. We use the S&P rating *(S&P_Rating)* assigned to a bond as a proxy for its default risk. Since uncertainty increases with risk, bonds with lower ratings are more likely to be split rated than bonds with higher ratings. Face value *(FV)* represents the total value of a bond measured in millions of dollars. High face value bonds are normally issued by bigger firms; since bigger firms have lower information asymmetry problem, high face value bonds are less likely to be split rated. Moving towards the accounting variables used in our analysis, loan and leases *(Loans&Leases)* represents the ratio of the total amount of money loaned to customers (net of the reserves for loan losses) and loans made by the banks in order to finance leases to the firm's total assets. The amount of outstanding loans and leases raises the opaqueness of banks assets because of the problems associated with their valuation (Guthman, 1953). Loans and leases also give rise to the agency problem especially when they are extended to a large number of small borrowers (Diamond, 1984). Consequently, bonds issued by firms with a higher proportion of loans and leases are more likely to be split rated. Cash and Deposits *(Cash&Deposits)* represents the ratio of the total amount of money available for use in normal operations and the value of money held by the bank or financial company on behalf of its customers to the firm's total assets. The cash and deposits rank among the most certain assets held by a firm. Thereby, their presence is expected to lower the overall opaqueness of the firm's assets. Conversely, the cash and deposits could make it difficult to assess the credit risk of a firm because of the uncertainty about their expected disposal by the manager (Jensen, 1986). Fixed assets *(FA)* are defined as the ratio of the total value of the property, plant, and equipment (net of depreciation) to the firm's total assets. Fixed assets are the least uncertain assets held by any bank thus their presence is likely to reduce the overall opaqueness of a bank's assets. Therefore, bonds issued by banks with a bigger portion of fixed assets are less likely to be split rated. The valuation problems associated with intangible assets *(Int)* make such assets hard to value, and thus presence of intangible assets is expected to contribute to the overall opaqueness of a firm's assets. Other assets *(OA)* represents the ratio of

[13] The variable definition and explanation of their possible impact of split ratings are based on Morgan (2002) and Livingston et al. (2007).

assets other than those included in the different asset definition of our study to the fixed assets of a firm. *CapTA* is defined as the capital to total asset ratio. Banks with a high capital level tend to have good asset quality;[14] hence, a higher capital to asset ratio should lead to lower rating disagreements. Firm size, measured as the total assets *(TA)* of a firm, is expected to enter negatively in our equation. This is because big firms have more media and analyst following and thus are more visible to the market. As a result bigger firms are likely to have lower information asymmetry and asset opaqueness problems. As a robustness check, we include additional variables in our analysis that have been used in other studies as proxies for information asymmetry. These variables are based on Livingston et al. (2007) and include the number of analyst following a firm *(N_Analysts)*, standard deviations of analyst forecast *(Std_Forecast)*, and market to book ratio *(MB)*. Analyst following reduces the asset opaqueness (Brennan and Subrahmanyam, 1995); hence, bonds issued by firms with higher analyst following are less likely to be split rated. Standard deviation of analyst forecast is a measure of the level of consensus among analysts. Since consensus among analysts is likely to decline with the level of opaqueness of a firm's assets, the bonds issued by firms with higher deviation of analyst forecast are more likely to be split rated than the bonds issued by other firms. Market to book value has been used in previous studies, for example McLaughlin et al. (1998), as a proxy for information asymmetry. Consequently, bonds issued by firms with a higher market to book ratio are more likely to be split rated as compared to bonds issued by firms with a lower market to book ratio. Finally, *IFRS* is a dummy variable which is equal to 1 for firms reporting under IFRS and 0 otherwise. A negative sign on *IFRS* means would mean that reporting under IFRS reduces the instances of rating disagreements between raters while a positive sign on *IFRS* provides evidence to the contrary. The probit model that investigates whether there is a quality difference between IFRS and other standards measured in terms of the frequency of split ratings is defined as:

$$\begin{aligned} Split =\ & \beta_0 + \beta_1 IFRS_{i,t} + \beta_2 Mat_{i,t} + \beta_3 S\&P\_Rating_{i,t} + \beta_4 FV_{i,t} \\ & + \beta_5 Laons\&Leases_{i,t} + \beta_6 Cash\&Deposits_{i,t} + \beta_7 FA_{i,t} \\ & + \beta_8 Int_{i,t} + \beta_9 OA_{i,t} + \beta_{10} CapTA_{i,t} + \beta_{11} TA_{i,t} + \beta_{12} TA^2_{i,t} \\ & + \beta_{13} Region\_dummies + \varepsilon \end{aligned} \tag{2}$$

Our ordered probit model takes the following form:

$$\begin{aligned} Abs\_Split =\ & \beta_0 + \beta_1 IFRS_{i,t} + \beta_2 Mat_{i,t} + \beta_3 S\&P\_Rating_{i,t} + \beta_4 FV_{i,t} \\ & + \beta_5 Laons\&Leases_{i,t} + \beta_6\ Cash\&Deposits_{i,t} + \beta_7 FA_{i,t} \\ & + \beta_8 Int_{i,t} + \beta_9 OA_{i,t} + \beta_{10} CapTA_{i,t} + \beta_{11} TA_{i,t} + \beta_{12} TA^2_{i,t} \\ & + \beta_{13}\ Region\_dummies + \varepsilon \end{aligned} \tag{3}$$

[14] Moody's special comment, 1993, p.5.

The detailed description and definitions of control variables used in model 2 and model 3 are presented in B of Table 3.1.

3.5.3 Kappa Statistics

We also compare the probability and level of split ratings for IFRS and non-IFRS samples using kappa statistics. Kappa is a statistical tool that is often used in scientific studies and in daily situations where one needs to assess the level of consensus between two raters. Although kappa statistics do not entail complex calculations, the important feature of kappa statistics that it takes into account the probability that the consensus between raters may occur simply by chance makes it superior to the other univariate tests. Kappa statistics are defined as:

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}$$

Pr(a) is the percentage of bonds with consensus Moody's and S&P ratings. Pr(e) is the probability of occurrence of the rating consensus by chance. Since kappa statistics do not give weight to the level of rating disagreements, it can only be used to test whether reporting under IFRS lowers the probability of rating disagreements between CRAs. To test whether reporting under IFRS also lowers the level of rating disagreements between CRAs, we use a more advanced form of kappa statistics called weighted kappa. Kappa statistics determine the level of agreement between raters on a -1 to +1 scale (-1 refers to the least agreement while +1 means perfect agreement).

3.6 Results

3.6.1 Descriptive statistics

Table 3.2 provides comparative statistics of the dataset that is used to test the three hypotheses of this study. The dependent variables, Panel A in Table 3.2, show that the bonds issued by IFRS sample firms, on average, received about $1/3^{rd}$ of a notch higher ratings than did the bonds issued by non-IFRS sample firms. This difference is significant at p=0.01 level. With regard to the rating disagreements, Panel B reveals that about 60.99% of the IFRS sample bonds are split rated whereas the percentage of split rated bonds stands at a much higher level of 76.5% for the non-IFRS sample. The statistics in Panel C further reveal that not only the instances but also the average level of rating disagreements between CRAs are lower in the case of the IFRS sample (0.87 of a notch) as compared to the non-IFRS sample (1.10 of a notch).

With respect to the control variables used in the model to test the first hypothesis, the descriptive statistics reveal that both IFRS and non-IFRS sample have quite similar interest coverage ratios (*Int_Cov*: 1.545 vs. 1.586), whereas the IFRS sample has a slightly better operating income to revenue ratio (*OperInc_Rev*: 0.105 vs. 0.199). In terms of the gearing ratios, the IFRS sample has a significantly lower long term debt to the total assets ratio (*Ltd_Assets*: 0.216 vs. 0.137) as compared to the non-IFRS sample. However, The IFRS and non-IFRS samples do not differ in terms of total debt to total asset ratio (*Td_Assets*: 0.468 vs. 0.423). Finally, the equity beta (*Beta*: 0.959 vs. 0.915) of both the IFRS and non-IFRS sample is close to 1 which shows that the none of the sample's stocks are more volatile than the market as a whole. The standard errors calculated from the market model (*SE*: 0.000 vs. 0.000) for both samples are also similar and are not significantly different from 0.

The descriptive statistics for the control variables used to test the second and third hypothesis are reported in Panel D of Table 3.2. According to these statistics, the bonds issued by IFRS sample firms on average have shorter maturity (*Mat*: 50.40 vs. 46.08) but higher face value (*FV*: 328.07 vs. 532.19) compared to the bonds issued by non-IFRS sample firms. The issuer specific information shows higher analyst following (*N_Analysts*: 22.15 vs. 27.07), smaller standard deviation of forecast (*Std_Forecast*: 1.27 vs. 0.54), and a much higher average market to book ratio (*MB*: 8.72 vs. 26.75) for the IFRS sample. Descriptive statistics of the accounting variables show that the IFRS sample has a smaller percentages of loans and leases (*Loans&Leases*: 61.36 vs. 59.28) and cash and deposits (*Cash&Deposits*: 34.65 vs. 33.01) as compared to the non-IFRS sample. These statistics further reveal that the IFRS sample firms have a slightly lower percentage of fixed assets (*FA*: 1.42 vs. 1.17) but a significantly higher proportion of intangible assets (*Int*: 0.43 vs. 0.91) and other assets (*OA*: 2.14 vs. 5.63) in their assets mix as compared to that of the non-IFRS sample firms. Finally, the IFRS sample firms are bigger in terms of total assets *(TA)* and have a better capital to assets ratio (*CapTa*: 20.57 vs. 26.09) than the non-IFRS sample firms' ratio.

Taken together, the descriptive statistics reveal that the IFRS and the non-IFRS sample firms differ significantly in terms of the characteristics that influence the level and likelihood of split ratings and thus suggest the need to control for the differences in these firm characteristics.

3.6.2 Reporting under IFRS and the credit ratings levels

In this section we use the multivariate analysis to examine whether firms reporting under IFRS receive a better credit rating than firms reporting under other accounting standards. Our dependent variable *(S&P_Rating)* in this analysis is the S&P rating assigned to a bond. As explained in methodology section, *S&P_Rating* is constructed in such a way that a lower value on this variable actually reveals a better rating. For example, a bond with the *S&P_Rating* value of 5 has a better rating compared to a bond with the *S&P_Rating* value equal to 6. Accordingly, a negative sign on the coefficient of any independent variable indicates that that particular variable is positively associated with better credit ratings.

As discussed in the methodology section, we use an ordered probit model similar to the one used in Blume et al. (1998) and extend this model by including an *IFRS* dummy. The results, as reported in Table 3.3, show that the *IFRS* dummy enters with a negative sign in the ordered probit analysis and is significant at close to 0.01level. The magnitude of the coefficient for the *IFRS* dummy (-0.201), interpreted with the cut points of the ordered probit model as reported in the lower half of the Table 3.3, indicates that after controlling for other relevant variables, firms reporting under IFRS on average receive ratings of about 0.38 of a notch better than the firms reporting under other accounting standards. This result supports our first hypothesis that reporting under IFRS improves the ability of CRAs to measure the credit risk more accurately. Consequently, CRAs tend to act less conservatively in the rating process which results in firms getting better credit ratings for their debt on average.

With respect to control variables, the operating income scaled by the total revenue *(OperInc_Rev)* has the expected negative sign, although it is not significant at the conventional level. The variable representing the long term debt to assets ratio *(Ltd_Assets)* is positive and significant. This indicates that firms with larger long term debts tend be more risky and thus receive lower ratings. The coefficient on *TA*, used as a proxy for firm size, is negative and significant. This is consistent with the argument that larger firms reveal more information, have greater analyst following, and are generally more visible to the market. These factors lower the level of uncertainty for these firms and thus make them less risky. Also consistent with previous research, the firm beta *(Beta)*, used as a proxy for the firm equity risk, is positive and significant. Variables representing interest coverage ratio *(Int_Cov)*, total debt to assets ratio *(Td_Assets)*, and standard errors from market model *(SE)* take unexpected signs on their coefficients. Blume et al. (1998) also report a positive (though insignificant) sign on interest coverage ratio when it becomes extremely large (i.e., higher than 20 times). Similarly, Blume et al. (1998) also find a negative sign on the coefficient for the total debt to asset ratio *(Td_Assets)* and argue that apparently, after having controlled for the long term debt to asset ratio, firms with a higher proportion of short term debts are considered to be less risky by CRAs. Although the coefficient on *SE* is negative, it is not significantly different from zero.

3.6.3 Reporting under IFRS and the split ratings (univariate analysis)

Table 3.4 provides the results of various measures of disagreements between bond raters. The first of these measures is the kappa statistics. The kappa statistics for IFRS sample firms is 0.249 compared to 0.086 for non-IFRS sample firms. These figures indicate a comparatively higher level of rating agreements between CRAs for the IFRS sample. In absolute terms, however, these kappa values show a “fair” level of rating consensus between CRAs for IFRS sample firms where the level of agreement between CRAs for non-IFRS sample stands at only "slight" level.[15] The weighted kappa statistics, where the level of rating disagreements is also taken into account, also show greater agreement level between raters for the IFRS sample as compared to the non-IFRS sample. The weighted kappa statistics are 0.516 (moderate level of agreement) for IFRS sample and 0.363 (fair level of agreement) for non-IFRS sample. The supplementary kappa statistics reveal a significantly higher observed level of agreement for IFRS sample firms as opposed to non-IFRS sample firms (39.01 vs. 23.50), while the results do not show a significant difference between the IFRS and non-IFRS sample in terms of the possibility of chance rating agreement(18.76 vs. 16.31).

In terms of other agreement measures, the IFRS sample shows a higher level of correlation between the credit ratings assigned by Moody's and S&P as compared to the correlation for the non-IFRS sample (0.81 versus 0.66). The absolute average gap between the credit ratings assigned by Moody's and S&P is 0.87 for the IFRS sample and 1.10 for the non-IFRS sample. The difference between these two numbers is significant at 1% level. Finally, the IFRS sample has a lower percentage of bonds falling in each of the rating gap categories, i.e. an absolute rating gap ranging from 1 to 3+. Taken together, the preceding results show a higher level of rating agreement between rating agencies for IFRS sample firms as compared to the non-IFRS sample firms.

3.6.4 Reporting under IFRS and probability and level of rating disagreements (multivariate analysis)

We use a pair of closely related models to obtain formal evidence of whether or not reporting under IFRS is negatively associated with the frequency and level of disagreement between CRAs. We start with our base model (Model 1) where we regress *Split* on *IFRS* dummy and the variables identified in Morgan (2002) as associated with the occurrence of split ratings. According to the results of this model as reported in Table 3.5, the *IFRS* dummy is negative with a coefficient value of -0.468 and significant at 1% level. This indicates that reporting under IFRS is negatively associated with the occurrence of the split rating. The results for control variables are, in general, consistent with those reported in previous studies. For example, in line with Morgan (2002), we find that factors such as capital to total assets ratio *(CapTA)*, percentage of fixed assets *(FA)*, percentage of other assets *(OA)*, face value *(FV)* of the bonds, and proportion of cash and deposits *(Cash&Deposits*, though not significant*)* have a significantly negative association with split ratings. On the other hand, the credit risk measured in terms of S&P ratings *(S&P_Rating)* and the loans and leases *(Loans&Leases*, though not significant*)* have a positive association with the probability of split rating occurrence. Further, whereas Morgan (2002) does not report a significant relation between split ratings and percentage of intangible assets *(Int)*, we

[15] Based on the kappa statistics categories defined by Landis and Koch (1977). For a reference, these categories have been reproduced below in Table 3.4.

find that bonds issued by firms with a higher percentage of intangible assets are more likely to be split rated compared to bonds issued by firms with a lower percentage of intangible assets. This makes sense since, by their very nature, intangible assets are harder to value and therefore their presence increases the overall opaqueness of a firm's assets (Livingston et al. 2007). The size of a firm and its squared value have unexpected signs, but their coefficients are only marginally significant.

Model 2 includes three additional variables, the number of analysts *(N_Analysts)*, the standard deviation of analyst forecast *(Std_Forecast)*, and the market to book value *(MB)* of the issuer.[16] Livingston et al. (2007) report that these variables have a significant relation with split ratings. In Model 2, however, only the number of analysts *(N_Analysts)* is significant and that too has a coefficient sign opposite to what is expected. Standard deviation of analyst forecast *(Std_Forecast)* has an unexpected negative sign but is not significant as is the case with market to book ratio *(MB)*. Nonetheless, the *IFRS* dummy is still negative and significant at 1% and has a bigger coefficient compared to that in the previous model. Generally, the absolute value of the *IFRS* dummy remains close to 0.50 in both models. Based on the calculations (as presented in Table 3.5 column 4), this means that bonds issued by firms reporting under IFRS have approximately 17% lower probability of being split rated as compared to bonds issued by firms reporting under non-IFRS standards.

Next, we examine whether reporting under IFRS also affects the level of absolute rating disagreements between CRAs. To test this hypothesis, we replace the dependent variable *Split* with the variable *Abs_Split* and redo the analysis using ordered probit regression. In the results of this specification (Model 3) the *IFRS* dummy is again negative with a coefficient value of -0.410 and is significant at a level of 1%. The *IFRS* dummy still remains significant after the inclusion of additional control variables such as the number of analysts *(N_Analysts)*, the standard deviation of analyst forecast *(Std_Forecast)*, and market to book value *(MB)*. Based on the magnitude of the *IFRS* in Model 3 and the rating disagreement boundaries (see the bottom of the Table 3.5), these results indicate that the level of rating disagreement between CRAs is, on average, 0.42 of a notch lower for IFRS sample firms as compared to non-IFRS sample firms.

Taken together, our results suggest that firms reporting under IFRS receive higher credit ratings compared to firms reporting under non-IFRS. Further, reporting under IFRS not only reduces the probability of occurrence of split rating but also decreases the magnitude of split rating when it happens. We attribute these findings to the fact that the use of IFRS leads to more transparent and reliable accounting information which, in turn, sheds some of the information asymmetry and uncertainty involved in the credit rating process.

3.6.5 Lopsidedness of Rating Disagreements

[16] The smaller number of observations in this model aisre due to the fact that I/B/E/S has relatively low coverage for European firms as compared to its coverage for US firms.

Previous studies that examine the causes of the split ratings find a pattern of lopsided rating disagreements between CRAs. That is, these studies find that a particular rating agency (for instance, S&P in the case of US market based studies) consistently provides lower ratings compared to other raters when a split rating occurs. Researchers in previous studies such as Morgan (2002) and Livingston et al. (2007) believe that the pattern of lopsided ratings is also caused by asset opaqueness and uncertainty involved in the rating process. These studies argue that if CRAs differ with respect to their level of conservativeness then the uncertainty and asset opaqueness will lead a more conservative rater to issue lower ratings even more frequently.

We argue that if IFRS improve the quality of accounting information then their application should lessen the uncertainty and asset opaqueness and, consequently, the rating conservatism of the CRAs. The decline in rating conservativeness is expected to be larger in the case of a more conservative rater because a more conservative rater has more room to decrease its level of conservativeness. Consequently, the difference in the level of rating conservatism maintained by the *more conservative rater* and the *less conservative rater* is expected to be lower in the case of firms reporting under IFRS compared to that of firms reporting under other accounting standards. To determine whether this actually happens, we calculate the level of lopsided ratings for both IFRS and non-IFRS samples. The procedure is as follows: first, for each sample we determine the percentage of bonds rated higher by each of the raters (i.e., by Moody's and S&P). Then we calculate the difference between these percentages. This difference between percentages presents the level of lopsidedness. The outcome of these calculations is presented in Table 3.6 which reveals that the level of lopsided ratings is 53% for non-IFRS sample firms (65% bonds with better Moody's ratings and 12% bonds with better S&P ratings) and at 49% for IFRS sample firms (55% bonds with better Moody's ratings and 6% bonds with better S&P ratings). Hence, the IFRS sample shows a 4% lower pattern of lopsided ratings compared to the non-IFRS sample. Thus, this reduced level of rating lopsidedness provide us with further evidence of better quality accounting information under IFRS as compared to other accounting standards.

3.7 Robustness tests

In this section we test the robustness of our previous findings. Our robustness tests are largely based on the variation of the composition of our sample. The construction procedure of various samples are described below.

3.7.1 Reporting under IFRS and credit ratings levels

The results in the previous section provide evidence of better credit ratings and a lower frequency and level of split ratings for IFRS sample firms. However, these results might have been driven by the possibility that the bonds included in the non-IFRS sample are issued by more opaque firms compared to those included in IFRS sample. To overcome this problem we construct a constant sample, one that consists of only those firms that have issued bonds under both set of standards. Model 1 in Table 3.7 presents the results for this sample for the first hypothesis. The variable of interest *IFRS* is negative and significant with a coefficient bigger in absolute terms than the one reported in the main analysis in Table 3.3 (-0.398 vs. -0.201). The coefficient signs on most of the control variables are similar to the signs reported for the main analysis.

Constructing a sample in this way, however, has a potential problem since the number of bonds issued by each firm under non-IFRS and IFRS standards are not equal. For instance, it might be the case that firms that are more opaque have issued higher numbers of bonds when reporting under non-IFRS than when reporting under IFRS. In order to navigate this issue we construct a matched sample. In this matched sample, for each firm we include equal numbers of bonds issued under non-IFRS and IFRS reporting standards. The construction procedure of this sample is as follows: first, we count the number of bonds issued by each firm under each set of accounting standards. Then, if the number of bonds issued by a firm under non-IFRS is greater than the number of bonds issued by the same firm under IFRS, we delete the additional bonds issued under non-IFRS starting with the bonds with the shortest maturity at the issue date. We follow the same procedure when a firm has issued more bonds while reporting under IFRS. This process reduces our sample size to 300 bonds with an equal number of bonds included for each firm in the IFRS and non-IFRS sample. The results of this sample, reported in Model 2, are still in line with those of the main analysis. Once again, the variable of interest is negative and significant with a coefficient of -0.497 and a p-value <0.01 which is similar to the results reported for the constant sample and greater than the results for the main analysis.

About 1/4th of the bonds included in the main analysis belong to voluntary adopters of IFRS. Prior literature suggests that firms voluntarily reporting under IFRS have specific characteristics that distinguish them from average firms. For example, voluntary adopters of IFRS are less capital intensive, are much bigger (Dumontier and Raffournier, 1998), have a higher percentage of foreign sales (Murphy, 1999), maintain a lower debt to equity ratio, and have higher profitability compared to other firms (El-Gazzar et al. 1999). Factors such as the need to raise additional equity (El-Gazzar et al. 1999), the political cost, and outside market pressure (Dumontier and Raffournier, 1998) also motivate firms to voluntarily adopt IFRS. Mandatory adopters of IFRS do not have any particular incentives and do not have characteristics distinguishing them from other firms. Since voluntary adopters of IFRS are different in certain aspects from average firms, our previously reported results might be biased (both for or against) due to these distinguishing features of voluntary adopters.[17] Therefore, we exclude, from the constant sample used in Model 1 Table 3.7, all bonds issued by firms when they voluntarily reported under IFRS. The results as reported in Model 3 of Table 3.7 show that the *IFRS* dummy

[17] The lack of comparability of accounting information could be one reason that could potentially lessen the benefits of adoption of IFRS for voluntary adopters. This is especially true if only a limited number of firms in a particular industry voluntarily adopt IFRS.

is negative (-1.131) and significant at better than p=0.01 level whereas the coefficients on the other variables are largely similar to those reported in other models. These results show that our previously reported findings also hold in the case of constant samples of mandatory IFRS adopters.

3.7.2 Reporting under IFRS and probability and level of rating disagreements

We also perform a similar analysis to test the robustness of our results for the probability and level of rating disagreements. The results of these analyses are reported in Table 3.8. Model 1 to Model 3 show the influence of IFRS on the probability of rating disagreements for the constant, matched and constant set of mandatory adopters of IFRS respectively. For constant and matched samples, the coefficients on *IFRS* dummies are negative (-0.747 and -0.681) and highly significant at the $p<0.01$ level while for constant samples of mandatory adopters, the coefficient on *IFRS* dummy (-0.135) is significant at the $p<0.05$ level. Similarly, Model 4 to Model 6 presents the results of the ordered probit regressions to find additional evidence of whether reporting under IFRS reduces the level of rating disagreements between Moody's and S&P. Again, the *IFRS* dummy is negative for all three models though it is marginally insignificant for the constant sample IFRS mandatory adopters.

Taken together, the results of our robustness test are consistent with those of our main findings, that bonds issued by firms that report under IFRS receive better credit ratings and are less likely to be split rated. Further, these results support our findings that the absolute level of rating disagreements between CRAs is also smaller for the IFRS sample.

3.8 Economic significance of switching to IFRS

For firms that adopt them, IFRS brings potential economic benefits and better implementation costs. The implementation costs of IFRS include, for example, the deployment of new IT sources and the overhauling of existing IT infrastructure (Jermakowicz and Gornik-Tomaszewski, 2006). Firms might also need to spend a significant amount of time and money to make their accounting staff familiar with IFRS. A PwC survey of FTSE 350 firms reveals that most of these firms actually had to hire extra staff during the implementation stage of IFRS.[18]

Our results could also be used to measure the approximate costs firms can potentially save by reporting under IFRS. For example, the non-IFRS firms in our sample have a median face value debt of $92.42 million. Assuming that IFRS lowers the probability of split rating by approximately 17% (see Table 3.6), this translates into savings of $91,000 in terms of a lower

[18] Price WaterhouseCoopers (2006a). IFRS: Embracing Change, July, London, PWC, page, 27.

yield spread for a bond with a maturity of 3.89 years.[19] Similarly, as documented in this study, firms reporting under IFRS also benefit from the lower yield spread because such firms, on average, receive higher bond ratings, compared to firms reporting under other standards. This cost saving can be compared to the various costs of switching to IFRS as identified in prior literature. These cost saving figures are important for firms in the process of deciding whether to switch to IFRS voluntarily in countries that have not yet adopted IFRS.

3.9 Conclusion

The move toward IFRS is a global trend. The recent adoption of IFRS in various countries and regions including the EU motivated many researchers to compare the difference in accounting quality before and after the adoption of IFRS. Most of these studies focus on the capital market effects of adoption of IFRS and only a few studies gather evidence of the accounting quality differential from the debt market. Although studies based on the equity market consequence of IFRS provide valuable information about the changes in accounting quality brought by IFRS adoption, evidence from the debt market is also important since the results obtained from the analysis of equity market might not hold for the debt market because of the fundamental differences between these markets (Ball et al., 2009). Furthermore, compared to the equity market, the debt market is a much bigger source of finance for firms (Henderson et al., 2006). Therefore, regulators around the world should be interested in looking at the evidence of reporting under IFRS from the perspective of the debt market.

In this study we examine and compare the accounting information quality prepared under IFRS and other local GAAP used in the EU from the perspective of an important information intermediary of the debt markets, CRAs. CRAs play a vital role in the debt market as they provide an independent opinion about the credit worthiness of new and existing debt securities in the form of credit ratings. Credit ratings are opinions about the future, therefore an element of uncertainty is always expected in the rating process. Literature suggests that the information asymmetry and the vagueness of firm assets (such as those of banks) further heighten the uncertainty in the credit rating process. This uncertainty leads to two important consequences. First, since CRAs remain conservative in their rating decisions, they are more likely to assign lower ratings when faced with high information asymmetry and uncertainty about the true credit risk of a debt issue. Similarly, if CRAs differ with respect to the level of respective conservatism, the information asymmetry and uncertainty about the true financial risk might lead them to issue dissimilar ratings for the same bond. Therefore, we argue that if IFRS improved the quality of accounting information then their application should lower the uncertainty and information

[19] We calculate the \$91,000 amount as follows: 92.42*3.89*0.17*0.15 where 92.42 and 3.89 is the median face value and median maturity in years of bonds for non-IFRS sample, 0.17 is the decrease in probability of getting a split rating for IFRS sample firms, and 0.15 is the extra yield spread for split rated bond based on Mansi et al, (2003).

asymmetry faced by CRAs. Accordingly, then, the firms that report under IFRS should, on average, receive higher ratings and experience lower probability of rating disagreements.

We find support in favour of this hypothesis. In particular, we find that bonds issued by firms that report under IFRS receive about 0.38 of a notch better ratings compared to the bonds issued by firms that do not report under IFRS. Next, in line with the previous research, we also find that a large proportion, around 68%, of bonds included in our full sample are split rated. However, our results show a significant decrease in the probability and level of rating disagreements between Moody's and S&P for the bonds issued by firms that report under IFRS. We also report a lower level of lopsided ratings for our IFRS sample. We take these results as evidence that IFRS is superior to local GAAP. To control for the possibility that improvement in accounting quality may not be attributable to accounting standards but rather to the specific environment of a firm or a change in sample composition, we construct various sub-samples. The results of the sub-sample analysis are consistent with our findings for the full sample.

Table 3.1: Definition of variables

Variables (short names)	Variable description
Panel A. Variables included in our model to test H1	
S&P_Rating	*S&P_Rating* presents the S&P ratings issued to a bond. Following existing literature, We convert these letter ratings into ordinal numbers. Namely, we convert letter rating AAA to numerical rating 1, letter rating AA to 2, letter rating A to 3 and so on.
Int_Cov	*Int_Cov* is defined as (operating income after depreciation + interest expenses) / (interest expenses)
Ltd_Assets	*Ltd_Assets* is the long term debt to total asset ratio calculated as (total long term debt / total assets)
Td_Assets	*Td_Assets* is the total debt to asset ratio defined as (total debt / total assets)
OperInc_Rev	*OperInc_Rev* presents the ratio of operating income after depreciation to the total revenue.
Beta	*Beta* is the equity beta of a firm calculated using the market model.
SE	*SE* is the standard error calculated from the market model used to calculate equity beta.
TA	*TA* represents the total assets of a firm.
Panel B. Variables included in our model to test H2 and H3	
Split	*Split* is a binary variable which is equal to 0 when both Moody's and S&P assign the same rating (at notch level) to a new bond and 1 when Moody's and S&P assign different ratings.
Abs_Split	*Abs_Split* is an ordinal variable which is equal to 0 when both Moody's and S&P assign the same rating (at notch level) to a new bond, *Abs_Split* is equal to 1 when Moody's and S&P ratings differ by one notch, *Abs_Split* is equal to 2 when Moody's and S&P ratings differ by two notches and so on.
IFRS	*IFRS* is a dummy variable which is equal to 1 for firms reporting under IFRS and 0 otherwise.
Loans&Leases	*Loans&Leases* is defined as (the total of amount of money loaned to customers after deducting reserves for loan losses + Loans made by the banks in order to finance leases.) *100 / (Total assets)
Cash&Deposits	*Cash&Deposits* is defined as (The total money available for use in the normal operations + the value of money held by the bank or financial company on behalf of its customers) *100 / (Total assets)
FA	*FA* is defined as (Total value of property, plant & equipment net of accumulated depreciation) *100 / (Total assets)
Int	*Int* is defined as (Intangible assets i.e. assets not having a physical existence) *100 / (Total assets)
OA	*OA* is defined as (Other assets not delineated other than intangibles) / (Total assets)
CapTA	*CapTA* is calculated as (Total capital) *100 / total asset ratio.
TA	*TA* represents the total assets of a firm.
TA^2	TA^2 is the square of total assets as defined above.
S&P_Rating	*S&P_Rating* is the notch level rating assigned to a new bond by S&P.
Mat	*Mat* represents the log of the number of months from the issue date of a bond until date of final maturity.
FV	*FV* is the face value of bond.
N_Analysts	*N_Analysts* is equal to the number of analyst following a firm scaled by the market value of firm's equity.
Std_Forecast	*Std_Forecast* is the standard deviation of the latest EPS forecast available before a bond issued, divided by the year end stock price.
MB	*MB* is defined as the market value of total equity plus total assets less book value of total equity divided by total assets.

Table 3.2: Descriptive statistics

	Non-IFRS					IFRS				
Panel A	Rating level distribution									
	Mean	Median	Std.	Min.	Max.	Mean	Median	Std.	Min.	Max.
S&P_Rating [a]	3.93	4.00	1.31	1.00	7.50	3.64	4.00	1.47	1.00	9.00
N	383					405				
Panel B	Spit rating distribution									
	Moody's ≠ S&P (%)	Average absolute gap	Rating gap distribution			Moody's ≠ S&P (%)	Average absolute gap	Rating gap distribution		
			Gap=1	Gap=2	Gap=3			Gap=1	Gap=2	Gap=3
Split	76.50%	1.10	48.30%	24.80%	3.39%	60.99%	0.87	38.27%	20.01%	2.72%
N			383					405		
Panel C	Descriptive statistics: Accounting variables-Rating level analysis									
	Mean	Median	Std.	Min.	Max.	Mean	Median	Std.	Min.	Max.
Int_Cov	1.545	1.141	5.141	1.016	97.004	1.586	1.124	4.701	0.957	88.298
OperInc_Rev	0.105	0.090	0.079	-0.015	0.943	0.119	0.091	0.094	-0.168	0.844
Ltd_Assets	0.216	0.244	0.120	0.012	0.481	0.137	0.100	0.141	0.010	0.739
Td_Assets	0.468	0.472	0.169	0.151	0.870	0.423	0.427	0.191	0.010	0.856
Beta	0.959	0.996	0.303	0.034	1.758	0.912	1.034	0.352	-0.159	1.533
SE	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.002
N			353					382		
Panel D	Descriptive statistics: Accounting variables-Split rating analysis									
Mat (months)	50.40	46.68	11.28	30.00	85.05	46.08	49.32	9.72	21.6	71.16
FV ($ millions)	328.07	92.42	494.07	2.50	3186.00	532.19	159.00	913.11	1.88	6077.18
N_Analysts (numbers)	22.15	25	10.11	2.00	44.00	27.07	29	8.55	3.00	8.00
Std_Forecast	1.27	0.3	1.96	0.01	9.84	0.54	0.27	0.90	0.01	5.29
Loans&Leases	61.36	78.00	24.94	0.00	93.61	59.28	63.78	22.57	0.00	92.06
Cash&Deposits	34.65	35.88	17.90	0.18	74.44	33.01	34.85	12.05	0.18	54.87
FA	1.42	0.88	3.11	0.07	37.80	1.17	0.79	3.40	0.01	39.09

Table 3.2 (continued)

Int	0.43	0.07	1.11	0.00	10.20	0.91	0.39	2.10	0.00	20.45
OA	2.14	1.25	5.04	0.04	24.39	5.63	2.69	4.94	0.00	42.44
CapTa	20.57	19.20	15.68	4.17	91.65	26.09	20.03	13.23	5.06	95.32
MB	8.72	1.03	41.27	1	482.73	267.57	1.06	15.83	0.99	292.08
TA ($10 millions)	20997.03	17071.50	18263.05	102.15	97405.81	58473.83	36428.67	55509.78	5.76	23903.37
N			383					405		

[a] Average of Moody's and S&P ratings

Table 3.3: Ordered Probit Regression explaining Effect of IFRS on credit ratings

This table presents the results of the ordered probit regressions models that are used to determine whether bonds issued by firms reporting under IFRS receive higher credit ratings compared to bonds issued by firms reporting under other accounting standards. The dependent variable for the probit regression models is *S&P_Rating* . *S&P_Rating* presents letter level ratings assigned by S&P to a bond. *S&P_Rating* is an ordinal variable while S&P assigns letter ratings to bonds. We convert these letter ratings into numerical ratings following existing literature. Namely, we convert letter rating AAA to numerical rating 1, letter rating AA to 2, letter rating A to 3 and so on. The control variables, except for *Int_Cov*, are based on Blume et al. (1998). With respect to *Int_Cov*, Blume et al. (1998) divide the interest coverage ratio of an issuer into four categories based on whether the interest coverage ratio is less than 5, between 5 and 10, between 10 and 20 and 20 and 100. We do not use such categories. Our variable of interest is *IFRS* dummy which is set to 1 for bonds issued by firms reporting under IFRS and 0 otherwise. In all models we include region dummies to control for any difference in the legal and political system, enforcement of law, investors' protections and ownership structure across regions. Variable definitions are provided in Panel A of Table 3.1. The p-values appear in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Variables	Coefficients (p-values)
IFRS	-0.201**
	(-0.038)
Int_Cov	0.018**
	(0.032)
OperInc_Rev	-0.200
	(0.763)
Ltd_Assets	0.930*
	(0.077)
Td_Assets	-0.385
	(0.398)
Beta	0.610***
	(0.000)
SE	-310.905
	(0.173)
TA	-0.000***
	(0.000)
Region dummies	Yes
N	735
Rating boundaries	
AAA	<-0.579
AA	-0.579<>-0.458
A	-0.458 <>-0.158
BBB	-0.158<>0.703
BB	0.703<>1.836
B	1.836<>2.395
CCC	2.395<>3.095
CC	>3.095

Table 3.4: Kappa and other statistics of probability and level of rating disagreements

This table presents the results of various measures of rating disagreements between CRAs such as kappa statistics, correlation of ratings issued by Moody's and S&P, percentage split rated bonds and the average absolute rating gap distribution for non-IFRS and IFRS samples. The kappa statistics determines the level of inter-rater agreement on scale range of -1 to +1 (-1 refers to the least agreement while +1 means perfect agreement). Kappa statistics is superior to simple calculation of percentage of agreement between raters since it also takes into account the possibility of agreement between raters occurring by chance. For our analysis, we use both the kappa and weighted kappa. We use kappa statistics to gather evidence as to whether reporting under IFRS lowers the probability of rating disagreements whereas weighted kappa statistics reveals whether reporting under IFRS leads to lower level of rating disagreements.

	N	Observed agreements	Agreement by chance	Kappa (Un-wght.)	Kappa (wght.)	Corr. between ratings	Moody's ≠ S&P (%)	Average absolute gap	Rating gap distribution		
									Gap=1	Gap=2	Gap=3
Non-IFRS	383	23.50	16.31	0.086	0.363	0.66	76.50%	1.10	48.30%	24.80%	3.39%
IFRS	405	39.01	18.76	0.249	0.516	0.81	60.99%	0.87	38.27%	20.00%	2.72%

Kappa statistics	<0.00	Poor[38]
Kappa statistics	0.00-0.20	Slight
Kappa statistics	0.21-0.40	Fair
Kappa statistics	0.41-0.60	Moderate
Kappa statistics	0.61-0.80	Substantial
Kappa statistics	0.81-1.00	Almost Perfect

[38] The kappa statistics range and labels are based on Landis and Koch (1977)

Table 3.5: Probit Regression explaining probability of split rating

This table presents the results of the probit and ordered probit regressions that are used to determine whether reporting under IFRS leads to lower probability and level of rating disagreements between CRAs. The dependent variable for the probit regression models (Model 1 and Model 2) is *Split*. *Split* is a binary variable which is equal to 0 when both Moody's and S&P assign the same rating (at notch level) to a new bond and 1 when Moody's and S&P assign different ratings. Our variable of interest *IFRS* is binary variable which is set equal to 1 if the bonds issuing firm for bonds that are issued by firms that report under IFRS and 0 otherwise. The control variables are Morgan (2002). In Model 2 we add three other variables identified by Livingston et al. (2007), the existence of which also influences the occurrence of split ratings. Model 3 and Model 4 respectively are similar to Model 1 and Model 2 except that they are based on ordered probit regression model. The dependent variable for these models is *Abs_Split*. *Abs_Split* is an ordinal variable which is equal to 0 when both Moody's and S&P assign same rating to a new bond, *Abs_Split* is equal to 1 when Moody's and S&P rating differ by one notch, *Abs_Split* is equal to 2 when Moody's and S&P rating differ by two notches and so on. In all models we include region dummies to control for any difference in the legal and political system, enforcement of law, investors' protections and ownership structure across regions. Column 4 presents the expected change in probability of occurrence of split rating when a variable increases from its 25th percentile value to 75th percentile value while others remain at their median value. For *IFRS* dummy the percentage change represents the difference in probability of occurrence of split rating between firms that report under IFRS and those which do not. The detailed variable definitions are provided in Panel B of Table 3.1. The p-values appear in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Variables	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Changes in prob. of split rating	Model 3 Coefficients (p-values)	Model 4 Coefficients (p-values)
IFRS	-0.468***	-0.614*	-17.22%	-0.410***	-0.709***
	(0.001)	(0.017)		(0.000)	(0.001)
Loans&Leases	0.006*	0.008	1.75%	0.002	0.018***
	(0.076)	(0.159)		(0.368)	(0.000)
Cash&Deposits	-0.002	-0.009	-1.48%	0.000	-0.016**
	(0.754)	(0.305)		(0.913)	(0.027)
FA	-0.048*	-0.125**	-1.71%	-0.053**	-0.120***
	(0.071)	(0.014)		(0.023)	(0.006)
Int	0.199***	0.164*	3.75%	0.203***	0.117
	(0.000)	(0.052)		(0.000)	(0.107)
OA	-0.020*	-0.012	-6.04%	-0.028***	-0.012
	(0.067)	(0.363)		(0.003)	(0.298)
CapTA	-0.015**	-0.015	-4.78%	-0.006	-0.017*
	(0.014)	(0.160)		(0.197)	(0.052)
TA	0.000*	0.000**	-7.92%	0.000	0.000***
	(0.084)	(0.021)		(0.146)	(0.000)
TA^2	-0.000	-0.000	9.71%	-0.000	-0.000***
	(0.184)	(0.148)		(0.598)	(0.004)
S&P_Rating	0.378***	0.325***	10.72%	0.363***	0.364***
	(0.000)	(0.000)		(0.000)	(0.000)
Mat	-0.025	-0.039	-2.93%	-0.049	0.035
	(0.706)	(0.623)		(0.332)	(0.632)
FV	-0.000*	0.000	-2.36%	-0.000	0.000
	(0.095)	(0.605)		(0.192)	(0.407)
N_Analysts		1529.5**			2829.0***
		(0.018)			(0.000)
Std_Forecast		-0.027			-0.038
		(0.589)			(0.356)
MB		-0.001			-0.007
		(0.761)			(0.205)
Region Dummies	Yes	Yes		Yes	Yes
N	788	788		788	788

Table 3.5 (continued)

Rating disagreements boundaries	
No disagreement	<-0.623
Disagreement at 1 notch level	-0.623<>0.811
Disagreement at 2 notch levels	0.811<>2.266
Disagreement at 3 notch levels	2.266<>2.699
Disagreement at 4 or more notch levels	2.699<>3.272

Table 3.6: Pattern of Lopsided Rating Disagreements

The table presents the result of independent sample t-test that is used to compares the pattern of lopsided ratings for IFRS and non-IFRS sample. The pattern of lopsided ratings for each sample is determined by calculating the percentage of bonds with better Moody's ratings (notch level) and percentage of bonds with better S&P ratings (notch level). The difference between these percentages is defined as pattern of lopsided ratings. To calculate the percentage of bonds with better ratings by either rating agency, we first convert letter rating issued by Moody's and S&P into numerical ratings in line with the existing literature. For example, we convert letter rating AAA to numerical rating 1, letter rating AA+ to 2, letter rating AA to 3 and so on. *, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

	Non-IFRS Sample	IFRS Sample
Average Moody's Rating	3.57	3.27
Average S&P Rating	4.30	4.00
Difference in average Ratings	0.73***	0.73***
Percentage of bonds with better Moody's Rating	65%	55%
Percentage of bonds with better S&P Rating	12%	6%
Level of lopsided Rating	53%***	49%***
No. of observations	383	405

Table 3.7: Robustness for level of ratings

This table presents the of results of sub-samples (i.e., constant sample, matched sample and constant sample of mandatory adaptors of IFRS) used in this study to test the robustness of the findings of the main analysis. The dependent variable for the probit regression models is *S&P_Rating*. *S&P_Rating* presents S&P letter level ratings assigned to a bond. *S&P_Rating* is an ordinal variable while S&P assigns letter ratings to bonds. We convert these letter ratings into numerical ratings following existing literature. Namely, we convert letter rating AAA to numerical rating 1, letter rating AA to 2, letter rating A to 3 and so on. Model 1 presents the results of ordered probit model for the constant sample. We define our constant sample as the one consisting of bonds issued by only those firms that issued bonds under both non-IFRS and IFRS reporting standards over the sample period. Model 2 is based on the matched sample. The matched sample is constructed in such a way that, for each firm, it contains equal number of bonds issued under IFRS and non-IFRS sample. That is to say, that if a firm has issued, say, 8 bonds reporting under non-IFRS standards and 10 bonds under IFRS then the 2 bonds (with the shortest maturity) issued under IFRS are excluded from the IFRS sample. Model 3 presents the probit regression results for the constant sample of mandatory adopters of IFRS. The constant sample of mandatory adopters is similar to the constant sample but does not include the bonds issued by the voluntary adopters of IFRS in pre-IFRS period. The control variables, except for *Int_Cov*, are based on Blume et al. (1998). With respect to *Int_Cov*, Blume et al. (1998) divide the interest coverage ratio of an issuer into four categories based on whether the interest coverage ratio is less than 5, between 5 and 10, between 10 and 20 and 20 and 100. We do not use such categories. In all models we include region dummies to control for any difference in the legal and political system, enforcement of law, investors' protections and ownership structure across regions. The detailed variable definitions are provided in Panel B of Table 3.1. The p-values appear in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Variables	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Model 3 Coefficients (p-values)
IFRS	-0.398***	-0.497***	-1.313***
	(0.003)	(0.001)	(0.000)
Int_Cov	0.004	0.004	0.015
	(0.709)	(0.653)	(0.273)
OperInc_Rev	0.853	1.063	-1.135
	(0.294)	(0.329)	(0.280)
Ltd_Assets	3.568***	3.757***	8.666***
	(0.000)	(0.000)	(0.000)
Td_Assets	-1.110*	-1.418*	-2.325***
	(0.077)	(0.079)	(0.002)
TA	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.688)
Beta	0.188	0.316	0.104
	(0.464)	(0.324)	(0.740)
SE	-873.384**	-798.418*	-1088.79***
	(0.020)	(0.060)	(0.002)
Region dummies	Yes	Yes	Yes
N	430	300	294

Table 3.8: Probit and Ordered Probit Regression explaining probability and level of split rating

This table presents the results of sub-samples (i.e., constant sample, matched sample and constant sample of mandatory adaptors of IFRS) used in this study to test the robustness of the findings of the main analysis. Model 1 to Model 3 test the influence of IFRS on probability of rating disagreements between CRAs for the constant, matched and the constant sample of mandatory adopters of IFRS respectively. The dependent variables in these three models is *Split*. *Split* is a binary variable which is equal to 0 when both Moody's and S&P assign a same rating (at notch level) to a new bond and 1 when Moody's and S&P assign different ratings. Model 4 to Model 6 test the influence of IFRS on the level of rating disagreements between CRAs for the constant, matched and constant sample of mandatory adopters of IFRS respectively. The dependent variable for these models is *Abs_Split*. *Abs_Split* is an ordinal variable which is equal to 0 when both Moody's and S&P assign same rating to a new bond, *Abs_Split* is equal to 1 when Moody's and S&P rating differ by one notch, *Abs_Split* is equal to 2 when Moody's and S&P rating differ by two notches and so on. We define our constant sample as consisting of bond issued by only those firms that have issued bonds under both non-IFRS and IFRS reporting standards. The matched sample is constructed in such a way that, for each firm, it contains equal number of bonds issued under IFRS and non-IFRS sample. That is, if a firm has issued, say, 8 bonds reporting under non-IFRS standards and 10 bonds under IFRS then the 2 bonds (with the shortest maturity) issued under IFRS are excluded from IFRS sample. The constant sample of mandatory adopters is similar to the constant sample but does not include the bonds issued by the voluntary adopters of IFRS in pre-IFRS period. The control variables are based on Morgan (2002). In all models we include region dummies to control for any difference in the legal and political system, enforcement of law, investors' protections and ownership structure across regions. The detailed variable definitions are provided in Table 3.1. The p-values appear in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

	Model 1 Coefficients (p-values)	Model 2 Coefficients (p-values)	Model 3 Coefficients (p-values)	Model 4 Coefficients (p-values)	Model 5 Coefficients (p-values)	Model 6 Coefficients (p-values)
IFRS	-0.747***	-0.681***	-0.971**	0.533***	-0.387**	-0.315
	(0.000)	(0.002)	(0.021)	(0.000)	(0.022)	(0.192)
Loans&Leases	-0.007	-0.003	0.018**	-0.004	0.004	0.009*
	(0.198)	(0.670)	(0.045)	(0.348)	(0.487)	(0.075)
Cash&Deposits	0.032***	0.031***	0.008	0.027***	0.021***	0.009
	(0.001)	(0.006)	(0.541)	(0.000)	(0.009)	(0.286)
FA	-0.066**	-0.041	-0.140**	-0.054*	-0.085**	-0.077**
	(0.046)	(0.311)	(0.021)	(0.051)	(0.029)	(0.015)
Int	0.173**	0.136*	0.072	0.153***	0.203***	0.064
	(0.012)	(0.081)	(0.521)	(0.009)	(0.003)	(0.333)
OA	-0.008	0.009	-0.045*	0.003	0.020	-0.027
	(0.691)	(0.693)	(0.057)	(0.847)	(0.249)	(0.130)
CapTA	0.019**	0.018*	0.059***	0.029***	0.026***	0.051***
	(0.040)	(0.096)	(0.000)	(0.000)	(0.003)	(0.000)
TA	0.000***	0.000*	0.000	0.000***	0.000***	0.000***
	(0.003)	(0.091)	(0.000)	(0.000)	(0.006)	(0.000)
TA^2	-0.000*	0.000	-0.000***	-0.000***	-0.000	-0.000***
	(0.051)	(0.356)	(0.008)	(0.000)	(0.399)	(0.004)
S&P_Rating	0.405***	0.361***	0.371***	0.374***	0.357***	0.360***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mat	-0.168*	-0.194*	-0.062	-0.136*	-0.074	0.017
	(0.072)	(0.088)	(0.638)	(0.050)	(0.373)	(0.836)
FV	-0.000	-0.000*	-0.000	-0.000	-0.000*	-0.000
	(0.304)	(0.088)	(0.110)	(0.440)	(0.069)	(0.157)
N	463	316	310	463	316	310

Chapter 4

Empirical analysis of the effectiveness of Market Abuse Directive

4.1 Introduction

Financial markets play an important role in the economic development of a country. This is particularly true when these markets operate with integrity, provide a level playing field to all investors, and enjoy investors' confidence. Given the importance of financial markets to the prosperity of a country, regulators always remain watchful of the operations of financial markets and, if necessary, bring in new regulations to correct or eliminate practices that may be detrimental to the integrity of these markets. The introduction of Market Abuse Directive (MAD) 2003/6/EC in 2003 in Europe is one of the latest examples of such efforts. The purpose of this study is to examine whether the implementation of this directive has been effective and whether its implementation is associated with any adverse consequences.

The EC introduced MAD with the aim to improve the integrity of financial markets and enhance investors' confidence on them. In this respect, the EC indentifies various market abuse activities that harm the integrity of financial markets. These activities include the insider dealing and market manipulation activities that give misleading signals regarding the demand or supply of the financial instruments, or that cause the prices of financial instruments to an artificially higher or lower level. The EC considers deterrence of such activities essential to enhance the integrity of financial markets and investors' confidence on them. Apart from that, the commission also considers timely and fair dissemination of information to the investors essential for smooth functioning of financial markets. Accordingly, MAD contains provisions that are directed to deter market abuse activities and that ensure prompt and fair disclosure of information to the public. For instance, this directive requires issuers of financial instruments to inform the public about any price sensitive inside information promptly after such information comes to their knowledge (Article 6(1)). Further, this directive prohibits the practice of releasing information regarding the operations and results of a firm to a selected group of players (investors as well as analysts). The directive also requires member states to take the necessary steps to prohibit market manipulation activities.

Even though the provisions in MAD are quite comprehensive and are further augmented by requiring member states to take other steps that could be necessary to deter market manipulation activities, however, there are a number of reasons why the goals of this directive might not be achieved. First, even though issuers are required to immediately disclose all insider information to the public, the directive does allow issuers to withhold such information under the circumstance that the non-disclosure of such information would not mislead investors in their financial decisions. The lack of an objective criterion for disclosure raises concerns that issuers might use this provision to withhold inside information in order to avoid uncertainty and volatility of their stock price. Second, there are concerns about the definition of “inside information” used by the directive in the provision that aims to prohibit inside trading and the provision that calls for the immediate release of all inside information to the public. The European Security Market Expert Group (ESME) report points to the inconsistent interpretation and application of the definition of “inside information”. According to this report, managers are employing different strategies to avoid immediate disclosure of inside information, which they prefer to not be public knowledge.[1] Additionally, there are no guidelines that specify at what point a certain event should be regarded as mature enough to be considered price sensitive information.[2] This could lead to inconsistent disclosure behavior among firms. Third, although the prohibition on the disclosure of information to selective individuals is aimed to enhance the integrity of the financial markets, this restriction may cause a decline in the level and quality of information available to investors. For example, prior literature identifies analysts’ reports and opinions as one of the crucial source of new information for the investors (Griffen, 1976; Imhoff and Lobo, 1984; Asquith et al., 2005). Analysts’ opinions are generally based both on information that is publically available and as well as on the insider information (Moizer and Arnold, 1984; Chugh and Meador, 1984). MAD prohibits the private disclosure of price sensitive information to all parties including the analysts. Thus, the implementation of MAD is expected to lower the level of information available to the analysts. This, in turn, might lower the accuracy of their forecasts. The implementation of MAD might also fail to achieve its objectives simply because mangers may still continue to provide classified information to select groups of investors instead of making the information fully public. Therefore, whether MAD is effective and influences the financial information environment is an empirical question that has not yet been answered in the available literature, thus, we set out to answer that question.

To investigate whether MAD is achieving its stated goals and to observe whether its introduction has brought any change in the quality and quantity of financial information, we conduct an empirical analysis on a sample of firms that are listed on the Frankfurt stock exchange during 2001 to 2006. Since all firms listed on Frankfurt stock exchange were required to follow MAD at the same point in time, we ran into the problem of the non-existence of a sample of firms against which the results of our treatment sample firms could be compared. To

[1] ESME (2007) report. “Market abuse EU legal framework and its implementation by member states: a first evaluation.” Pp. 5. Available at http://ec.europa.eu/internal_market/securities/docs/esme/mad_070706_en.pdf

[2] ESME (2007) report. “Market abuse EU legal framework and its implementation by member states: a first evaluation.” Pp. 5. Available at http://ec.europa.eu/internal_market/securities/docs/esme/mad_070706_en.pdf

counter this issue, following other studies that faced the same problem (e.g. Landsman et al., 2012; Daske et al., 2008), we include a sample of firms listed on NYSE to serve as the benchmark since these firms are not subject to MAD during the same time period. Based on our univariate and multivariate tests, we find evidence of the effectiveness of MAD. Specifically we find that, in comparison with pre-MAD years, the stock return volatility declines in post-MAD years. We interpret this result as a decrease in market manipulation activities. This interpretation is based on studies, for instance Agarwal and Wu (2004) and Jiang et al. (2005), that report a positive association between market manipulation activities and the level of stock return volatility. Further, based on Beaver (1968), we also interpret a decline in the level of stock return volatility as evidence that MAD lowers the gap between investors' existing information and the information contained in earnings announcements. We also find that the stock prices in the post-MAD period remain closer to their real prices (prices subsequent to the earnings announcements) during the specified time period (up to 60 days prior to the earnings announcement date). We interpret this as evidence that, pursuant to MAD, on average, managers convey information to the market on a timelier basis. We also find evidence of higher accuracy and lower dispersion of analysts' forecasts associated with MAD. While both accuracy and dispersion of analysts' forecasts are indicative of improved information quality, we interpret the decline in forecast dispersion as a signal of the uniformity of information available to all analysts. Finally, we report a decline in the average number of analysts following a firm, which, as argued by Hutton (2003) and Bushee et al. (2003), might be a signal of the decline in selective disclosures of private information to analysts. Our results are statistically significant after controlling for various firm specific characteristics. We test the robustness of our findings in several ways. First, we moved the implementation date of MAD to various artificial dates and redid all the analysis. This approach has been used in Christensen et al. (2011). The notion behind this approach is that if a particular event, in our case introduction of MAD, causes a change in the chosen proxies, then the results of the analysis that is based on the actual date of occurrence of the event should be stronger than the results of the analysis that are based on the artificial date of occurrence of the event under consideration. Second, we apply the full set of multivariate analysis on various sub-samples. These sub-samples include German firms only, the constant sample of German firms and the matched sample of US and German firms. Apart from that, we also include additional control variables in our multivariate analysis, namely market-to-book value (proxy for conservatism), volatility of earnings, and ratio of interest expenses to the total assets, that could potentially influence our dependent variables. The results of all robustness tests are consistent with the our main tests.

We focus on firms working under German setting to gather evidence as to whether MAD is achieving its objective because the successful working of regulations not only depends upon the thoroughness and comprehensiveness of regulations, but also upon the strength of rule of law in regimes in which regulations operate. In other words, a well carved regulation may fail to attain its objectives in weak rule of law regimes. Since the objective of this study is to examine the quality of MAD, it is important that we carry out our analysis on country that has a strong rule of law so as to minimize the possibility that a weakness in rule of law is wrongly interpreted as failure of MAD. Therefore, we base our analysis on a sample of firm listed on Frankfurt Stock Exchange, Germany. Germany ranks among the countries with the strongest and stable rule of law regimes.

Our study is valuable for at least two reasons: First, even after more than 6 years after the implementation of MAD, there is only a limited amount of evidence available regarding the outcomes of MAD. Therefore, the results of our study are relevant for market authorities and regulators who have been discussing the effectiveness of MAD and are pondering whether or not to amend MAD. Second, this study is an addition to the existing literature that examines the effectiveness of securities regulations. Up to now, a significant portion of evidence about the effectiveness of such regulations was based on U.S security regulations. However, evidence from the U.S setting may not hold for other countries. This is because the research on the outcomes of such regulations suggests that the effectiveness of security regulations varies across countries and depends upon the quality of a country's institutions, bureaucracy, and commitment toward the implementation of these regulations (e.g. Djankov et al., 2003). Therefore, our study contributes to security market regulation literature by focusing on the German market. The German market is not only one of the biggest markets in the world but also has some special features that distinguish it from most of other major financial markets (such as U.S and U.K) around the world. These features include presence of a bi-tiered board structure, a higher dependence on firms relating to financial institutions for financing, and other features of a network-oriented system.

The remainder of this study is organized as follows: The next section consists of a review of literature, and describes our motivation of this study. Section 3 provides an overview of the data, and Section 4 describes the methodology used. Section 5 presents the results, and Section 6 presents the summary and conclusion of our findings.

4.2 Literature review

To date, there is little empirical evidence available regarding the effects of MAD. However, another security market regulation, Regulation Fair Disclosure (Reg. FD)[3], which is in many respects similar to MAD, has been the subject of several studies. The evidence available on the effects of Reg. FD indicates that the quantity of information available to the market after instituting Reg. FD has improved. For example, Helfin et al. (2003) documents an increase in the earnings related to voluntary disclosures in the post Reg. FD period. The results in Bailey et al. (2003) suggest that firms commit themselves to a higher level of voluntary disclosures; however,

[3] Regulation FD, which became effective in the U.S. October 23rd, 2000, brought with it voluntary disclosure practices of public listed firms subject to the requirements of the SEC. The core requirement of this regulation is that a firm with a publicly listed security cannot provide inside information to a third party unless such information is simultaneously released to the public.

the increase in the voluntary disclosures is limited to those related to current quarter earnings. Consistent with the results of these studies, Straser (2002) reports an increase in quantity, although not in quality, of disclosures after Reg. FD; while Gomes et al. (2007) document an increase in the complexity of information as a result of implementing Reg. FD. While the existing evidence is quite conclusive regarding the effects of Reg. FD on the quantity of information, the evidence regarding the quality of information is mixed. Heflin et al. (2003) report an increase in the quality of information, measured in terms of stock return volatility and cumulative abnormal returns but do not find any significant change in the accuracy and dispersion of analysts' forecasts. Although, Bailey et al. (2003) find a decrease in stock return volatility, however they associate it with the decimalization of stock trading rather than with Reg. FD. Shane et al. (2001) also do not find any significant changes in the accuracy and dispersion of analysts' forecasts in the post Reg. FD period. A few studies, for example Bailey et al. (2003), Agrawal et al. (2006) and Mohanram and Sunder (2006), however report negative effects from Reg. FD on the analysts' forecast accuracy and dispersion.

The limited empirical evidence available on MAD is based on Monteiro et al. (2007) and Prevoo and Weel (2010). Monteiro et al. (2007) analyzes the trading announcements made by FTSE 350 and take-over announcements made by UK firms from 2000 to 2005. The trading announcement analysis provides evidence of less informed trading before such announcements, which indicates a cleaner market. However, the decline in informed trading is not significant in the analysis based on the announcements of future takeovers. Prevoo and Weel (2010) is based on the firms listed on the Amsterdam Stock Exchange and examines the effects MAD has on the information value of press releases issued by the firms, the level of insider-trading, leakage of information, and trading volume. The paper documents a) a decline in insider activities (only for a small, capitalized firm), and b) no conclusive evidence with respect to changes in the information value of firm press releases. In comparison to Prevoo and Weel (2010), we focus on the absolute cumulative abnormal return and stock return volatility around the annual earnings announcement and analysts' reports. The annual earnings announcements are considered to be the single most important event that helps investors evaluate a firm's performance (Heflin et al., 2003), while the analysts are considered to be one of the most sophisticated users of the acquired information.

4.3 Methodology

We use five measures (dependent variables), namely, stock return volatility, absolute cumulative abnormal return, accuracy of analyst forecast, dispersion of analyst forecast and analyst following to examine the effectiveness of MAD. We classify the these dependent variables into two groups, evidence from stock prices (stock return volatility, absolute cumulative abnormal return), and evidence from analysts' reports (accuracy of analyst forecast, dispersion of analyst forecast and analyst following). These variables have been widely used in literature similar to our study.

MAD became operational for all German firms at one point of time. From a methodological stand point, this means that our sample lacked a controlled group. To counter this issue we follow Landsman et al. (2012) and Daske et al. (2008) and include NYSE listed firms as the control sample. The inclusion of these firms tests whether any potential change for five measure used in this study is greater than that for the control sample firms.

4.3.1 Evidence from stock prices

Stock return volatility (SRV). We use stock return volatility as the proxy of the level of market manipulation activities. The choice of this proxy is based on Ausubel (1990), Allen and Gale (1992) and Benabou and Laroque (1992). These authors argue that the market manipulators and holders of insiders prefer volatility stock markets since dealings in such markets offer them more profitable trading opportunities compared to dealing in less volatile markets. Accordingly, these maker manipulators and holders of inside information release inside information in such a way that would increase the volatility of stock markets. Consistent with this theoretical perspective, Meulbroek (1992) find evidence of higher inside trading during the times of higher market volatility and thus further suggest the preference of insiders for volatile stock markets. On the other hand, by comparing the level of stock market volatility of more than 100 countries, Du and Wei (2004) conclude that the countries with more prevalent insider trading indeed have more volatile markets. In addition to its role as a proxy for market manipulation activates, the stock return volatility also serves a measure of the level of information content of the earnings announcements. The notion behind this form of measurement, based on Beaver (1968), is that if announcements of earnings reveal new information, which is not already known to investors, then investors will react to this new information which will lead to stock price movement. The level of investors' reactions and the resulting movement in stock prices would be proportional to the gap between the information content of earnings announcements and the level of information already possessed by investors. A larger information gap at the time of an earnings announcement would result in higher stock price movement. In the context of this study, if, in compliance of provisions of MAD, inside information is released to the market on a timelier basis, then the amount of new information contained in earnings announcements would be lower. This would result in lower stock price movement and volatility around earnings announcements.

We measured stock return volatility over three different windows, (-1, 0), (-1, +1), and (-2, +2), where day 0 is the earnings announcement day. Existing studies suggest that adjustments in stock prices resulting from earnings announcements start even before an earnings announcement and continue up to a few hours post-announcement (Patell and Wolfson, 1984). This means that the (-1, 0) window might be enough for our study. However, since earnings announcements can occur at any hour of the day, there is a possibility that some earnings announcements will be made near the closing trading hours, or even after trading hours. Therefore, to account for any reaction not captured by the smaller windows, we extend our analysis and include event windows up to (-2, +2) days.

Following Helfin et al. (2003), stock return volatility is defined as the sum of the squared market model, with prediction errors over the estimation window. More specifically, the stock return volatility for a particular estimation window is equal to:

$$SRV_{i,t} = \sum_{T=x_1}^{+x_2} \left(R_{i,t} - E\left[R_{i,t}\right]\right)^2$$

Where $R_{i,t}$ is the stock return for firm i for the day t in the estimation period, and $E\left[R_{i,t}\right]$ is the expected return for the same day while x_1 and x_2 define length of the window. We calculate $SRV_{i,t}$ for each firm for each sample year. The expected returns are based on the standard market model and are calculated using an estimation period of one year, ending on the first day of the last quarter before the year end.

Absolute cumulative abnormal returns (ACAR) is the absolute gap between stock prices on any particular day (before the earnings report date), and stock prices on the report day, represents the level of information that markets possess on that particular day. The lower absolute difference stands for more information held by financial markets. After MAD, the difference between post-announcement stock prices and stock prices at any given time before the earnings announcement should be lower. This is because if inside information is released to the public as it becomes known to the issuer, the market will get an opportunity to continuously update stock prices rather than be forced to make one big adjustment at the time of an earnings announcement in order to incorporate previously unknown information. However, as discussed in the previous section, if firms exploit provisions of MAD in order to withhold insider information or if, to the other extreme, firms start to inundate market with the irrelevant information then the *ACAR* in the post-MAD years may not be significantly different from the *ACAR* in the pre-MAD years.

In this study we define this difference as the absolute value of the cumulative abnormal return from a particular day before the earnings report day to the day following the earnings report day, and we measure it as:

$$ACAR_{i,t} = \left| \prod_{t=-x}^{+1} (1 + AR_{i,t}) - 1 \right|$$

$AR_{i,t}$ is the abnormal return for firm i on day t. x refers to a day relative to earnings announcement day. We calculate *ACAR* for each of the 60 days preceding the earnings announcement day. The lower *ACAR* for any day x before the earnings announcement day in the post-MAD period would provide evidence that relevant information is quickly reaching the market and vice versa. We use following regression equations to examine the effect of MAD on the stock price based proxies:

$$SRV_{it} = \beta_0 + \beta_1 MAD_{it} + \beta_2 Post_{it} + \beta_3 MAD{*}Post_{it} + \beta_4 RetVar_{it} + \beta_5 Car_{it} + \beta_6 NegCar_{it} + \beta_7 Loss_{it} + \beta_8 Pro_{it} + \beta_9 Size_{it} + \beta_{10} Industy\ dummies + \varepsilon \quad (1)$$

$$ACAR_{it} = \beta_0 + \beta_1 MAD_{it} + \beta_2 Post_{it} + \beta_3 MAD{*}Post_{it} + \beta_4 RetVar_{it} + \beta_6 Car_{it} + \beta_5 NegCar_{it} + \beta_7 Loss_{it} + \beta_8 Pro_{it} + \beta_9 Size_{it} + \beta_{10} Industy\ dummies + \varepsilon \quad (2)$$

SRV_{it} and $ACAR_{it}$ are the stock return volatility and the absolute cumulative abnormal return as defined above. *SRV* is summed over the (-1, 0), (-1, +1), and (-2, +2) estimation windows while *ACAR* is computed over (-5, +1), (-20, +1), and (-30, +1) windows. For all variables *i* and *t* refer to the firm and year respectively. *MAD* is an indicator variable which is equal to 1 for firms that belong to MAD adopting country, i.e., Germany, and 0 for firms that belong to the non-MAD adopting country, i.e., the US. *Post* is equal to 1 for all the fiscal years that end after October 2004 and 0 for the fiscal years that end before October 2004. The interaction between *MAD* and *Post, MAD*Post,* is our variable of interest. This interaction term effectively measures the difference-in-differences in our chosen proxies for the treatment sample firms relative to the control sample firms. With respect to the control variables, *RetVar* is the standard deviation of abnormal returns of each firm during the last quarter before the year-end. Beaver (1968) finds that firms with higher deviation in the abnormal returns prior to earnings announcements experience more erratic stock price movements during earnings announcements. *Car* is the proxy of the level of information available for a firm. *Car* is calculated as the cumulative abnormal returns of a firm over the last quarter before the year end. The inclusion of *Car* is based on Heflin et al. (2003) who report that the level of information available for a firm significantly influences the stock return volatility and the absolute cumulative abnormal returns of a firm. *NegCar* captures the sign of cumulative abnormal returns of a firm over the last quarter before the year-end. *NegCar* is set equal to 1 for firms that have negative cumulative abnormal returns in the last quarter before the year-end, and 0 for firms with positive stock returns. Christie (1982) posits that stock return volatility is expected to be higher for firms with negative stock returns in the period before earnings announcements. *Loss* and *NegSpec* control for the effect of negative earnings and the amount of special items reported in earnings, respectively. *Loss* is set equal to 1 for firms reporting negative earnings, and 0 otherwise. *NegSpec* is set equals to 0 for firms with positive special items reported in income statements. For firms with negative special items, *NegSpec* is the absolute value of special items scaled by the total assets of a firm.[4] The rationale behind the inclusion of indicator variable *loss* is based on findings in the literature that managers

[4] This is based on Heflin et al. (2003) who finds it informational to construct a variable representing the existence of special items in a firm's income statement.

manipulate earnings to avoid reporting a loss. The practice of earnings management make it difficult to forecast the earnings of a firm. *NegSpec*, is included because the impact of special items is always hard to predict because of their nature and infrequency. Therefore, firms that report loss or special items in financial statements are likely to experience stock return volatility. *Pro* is based on Penman (1996) and represents the growth potential of a firm. *Pro* is computed as the earnings/price ratio of a firm at the end of each year. Prior research (e.g. Collin and Kothari, 1989) posits that market reaction on earnings announcements is much larger for firms with a high growth potential. *Size* is the market value of the equity of a firm at the end of a fiscal year and is includes a control for the effect of firm size on the dependent variables. The detailed description and definitions of dependent and control variables is presented in Panel A and Panel B of Table 4.1.

4.3.2 Evidence from analysts' reports

From the perspective of an analyst's forecast, we focus on the differences in analysts' forecast accuracy, analysts' forecast dispersion, and the analysts' following before and after MAD. The accuracy of analyst forecasts has been a well-accepted way to measure the quantity and quality of information that is available to financial markets for a firm (e.g. Lang and Lundholm, 1996; Barron et al., 1998; Dichev, 1999); whereas the dispersion of analysts' forecasts and the analysts' following provide reliable information about the extent to which firms release private information to analysts (e.g. Botosan et al., 2004; Hutton, 2003).

Analysts' forecast accuracy. Analysts are considered to be one of the most affected groups of market participation since the implementation of MAD. This is because, in general, analysts form their opinions by taking into account both public as well as private information gained through their corporate contacts (Moizer and Arnold, 1984; Chugh and Meador, 1984). As discussed above, MAD not only calls for the immediate release of all material information but also requires that this information be released through public channels. These requirements can have both positive and negative effects on analysts' forecast accuracy. Analyst forecast accuracy may improve because the prohibition on selective disclosure of information means that, consistent with the management relation hypotheses (Lim, 1998; Kothari, 2001), analysts would no longer need to issue a positive opinion about a firm in order to get insider information from firm managers. Therefore, analysts are more likely to produce unbiased and much more accurate forecasts when they are less dependent on managers to gather the information required to make their forecast (Bailey et al., 2003). Analyst forecast accuracy may decline as a result of MAD if firms decide not to share any private information even with those analysts who previously had access to inside information. Managers may decide to avoid the requirements of MAD which necessitate that the issuer must immediately publically disclose inside information if such information has been disclosed to any third party. Similarly, more conservative mangers may, in order to avoid unintentional disobedience of MAD, even decide not to provide more detailed versions of financial information which they are required to provide to the public in the form of financial statements. This could, in general, lower the amount of information available to the analysts' making forecasts. Consequently forecast accuracy could decline after MAD.

Analysts forecast dispersion. The dispersion of analysts' forecasts is a measure of the level of consensus among different analysts. Several studies (e.g. Botosan et al., 2004) find an inverse relation between the precision of private information and analysts' forecast consensus. Based on a theoretical model, Barron et al. (1998) show that analyst forecast dispersion is a function of the ratio of public vs. private information used to make forecasts. Their model illustrates a fall in forecast dispersion as the use of private information declines in analysts' forecasting process. Lang and Lundholm (1996) also document that the dispersion of analysts' forecasts depends upon the information gap among analysts as opposed to a difference in interpretation of common information. Thus, to the extent that MAD restricts the provision of private information and requires the immediate release of material information; the level of information gap among different analysts is expected to become smaller which should result in an increase in consensus among analysts.

Following existing studies (e.g. Ashbaugh and Pincus, 2001), we define analyst forecast error as the absolute difference between the latest (before the EPS report date) analyst consensus (median) EPS forecast and the actual EPS of a firm divided by year-end stock prices. Based on this definition, we calculated analysts forecast error as:

$$Forecast\_error_{i,t} = \left| \frac{ConForecast_{i,t} - Act\_EPS_{i,t}}{P_{i,t}} \right|$$

According to the above equation, a lower value of forecast error corresponds to better information quality. We define analysts' forecast dispersion as the standard deviation of analysts' forecasts divided by year-end stock prices, which we calculated as:

$$Forecast\_Dispersion_{i,t} = \frac{Std\_Forecast_{i,t}}{p_{i,t}}$$

Analysts' followings. We use the number of analysts following a firm as another proxy for the level of private information available to analysts. Hutton (2003) finds that analyst followings is positively associated with the scale of private dissemination of firm information to analysts. Bushee et al. (2003) also supports this finding by showing a higher level of analyst following for firms that provide closed-conference calls. On one hand, the introduction of MAD is expected to increase the quantity of publically available information, while on the other hand, the implementation of MAD is likely to make private information more costly or difficult to obtain. Therefore, analysts who used to have an information advantage (due to their access to private information) would lose this advantage. Losing this information advantage may force analysts to move away from those firms and focus on fewer firms so as to market themselves based on their ability to make more accurate forecasts. We define analysts following as the number of analysts' forecasts contained in the latest consensus forecast prior to the earnings announcements as appearing in I/B/E/S.

We use following regression equations to examine the effect of implementation of MAD on our analysts' report based proxies:

$$\begin{aligned} Forecast\_Error_{it} = {} & \beta_0 + \beta_1 MAD_{it} + \beta_2 Post_{it} + \beta_3 MAD{*}Post_{it} + \beta_4 Size_{it} \\ & + \beta_5 ES_{it} + \beta_6 Std(ROE)_{it} + \beta_7 RetEarCor_{it} \\ & + \beta_8 Analysts\_Following_{it} + \beta_9 IFRS_{it} \\ & + \beta_{10} Ind\_dummies + \varepsilon \end{aligned} \tag{3}$$

$$\begin{aligned} Forecast\_Dispersion_{it} = {} & \beta_0 + \beta_1 MAD_{it} + \beta_2 Post_{it} + \beta_3 MAD{*}Post_{it} + \beta_4 Size_{it} \\ & + \beta_5 ES_{it} + \beta_6 Std(ROE)_{it} + \beta_7 RetEarCor_{it} \\ & + \beta_8 Analysts\_Following_{it} + \beta_9 IFRS_{it} \\ & + \beta_{10} Ind\_dummies + \varepsilon \end{aligned} \tag{4}$$

$$\begin{aligned} Analysts\_Following_{it} = {} & \beta_0 + \beta_1 MAD_{it} + \beta_2 Post_{it} + \beta_3 MAD{*}Post_{it} + \beta_4 Size_{it} \\ & + \beta_5 ES_{it} + \beta_6 Std(ROE)_{it} + \beta_7 RetEarCor_{it} \\ & + \beta_8 IFRS_{it} + \beta_{10} Ind\_dummies + \varepsilon \end{aligned} \tag{5}$$

$Forecast\_Error_{it}$, $Forecast\_Dispersion_{it}$, *and* $Analysts\_Following_{it}$ are the absolute value of analysts' forecast error, analysts' forecast dispersion and number of analysts following a firm. *MAD*, *Post*, and *MAD*Post* have the same meaning and interpretation as described for our stock price based proxies. The rest of the regressors are the variables identified in the previous research that affect the dependent variables of the regression equation (3), (4), and (5). *Size* is the market value of a firm's equity at the end of a fiscal year. Lang and Lundholm (1996) find firm size to be positively (negatively) associated with the accuracy (dispersion) of analysts' forecasts and the analyst following. The next two variables, *ES* and *Std(ROE)* capture the shock in a firm's earnings. *ES* is defined as the absolute difference between the current and previous year's earnings per share scaled by share prices at the end of the previous year, while *Std(ROE)* is the standard deviation of the return on equity of a firm calculated over the preceding five years. The inclusion of these variables is based on the grounds that the analysts' forecasts are likely to be more accurate and less dispersed for firms with stable earnings over time. *RetEarCor* is the correlation between the returns and earnings of each firm. King (1990) argues that the higher the return earnings correlation the better the forecasts of future earnings. *Analysts_Following* represents the number of analysts' forecasts contained in the latest consensus forecast prior to the earnings announcements as reported in I/B/E/S. Lang and Lundholm (1996) find a higher (lower) analysts' forecast accuracy (dispersion) for firms that have higher number of analysts following.

IFRS is an indicator variable which is 1 for firms that report under IFRS or US GAAP and zero for firms that do not. It is important to control for the type of accounting standards used by the sample firms since Ashbaugh and Pincus (2001) show that the quality of analysts' forecasts is influenced by the quality of accounting standards.

4.4 Data

The data for this study consists of all the public firms that are listed on the Frankfurt Stock exchange and have their financial year ending on the 31st of December. Our sample period starts in 2001 and ends in 2006. The sample period of 2001 to 2003 covers the pre-MAD adoption period while 2004 to 2006 cover the post-MAD period. We do not extend our sample beyond 2006 mainly because of a new set of regulations (the Transparency Directive) implemented on the 1st of January 2007; therefore, extending our sample period beyond 2006 might confound our results. Another reason we restrict our sample to 2006 is to ensure that our analysis is not affected by the consequences of the economic crisis on the financial market. We start by retrieving data for our treatment sample for the entire time period of our analysis. We then construct a sample on a yearly basis and exclude firms for which required financial and non-financial information is not available. In this way, for each of the six years included in our sample, we obtain a sample of treatment firms with all the required information available. We follow the same steps for our control sample firms.

We use three different databases to retrieve the necessary data .We retrieve the analysts' forecast and dispersion from the Institutional Brokers' Estimate System database (I/B/E/S). We gather stock price data from DataStream, while the required accounting data is obtained from Thomson One Banker. The earnings announcement dates are also taken from Thomson One Banker. We randomly checked these announcements with Factiva for their accuracy. We then combine the data retrieved from different databases using I/B/E/S tickers and ISIN numbers. After deleting the years with missing information, our final sample consists of 6095 firms observed with 1347 different firms (including the control sample) for our tests related to stock price analysis. For the tests on the analysts' forecast and standard deviation, the sample is based on 5,078 firm year observations from 1,223 distinct sample firms. The differences found between the two samples are due to the lack of available required data from I/B/E/S for some smaller firms. Table 4.2, Panel A presents the breakdown of our sample by industry. Our sample is dominated by (approximately 25% of the total sample) the finance/real estate industry (SIC 60-69), followed by the construction industry (SIC 15-17, 32, 52). The food/tobacco industry (SIC 1, 20, 21, 54) has the least representation with less than 2% of the firm-year observations. Panel B presents the number of firm-year observations for each of the years included in our sample. About 43% of our sample consists of observations from 2003 and 2004. The same number of firms can be found in both the pre-MAD and post-MAD years (for example, 2001 had 118 firm-year observations. while its corresponding post-MAD year 2006 had 112 firm-year observations).

4.4.1 Descriptive statistics

Table 4.3 presents descriptive statistics of the treatment and control sample firms. According to the statistics reported in Panel A for treatment sample firms, the mean *SRVs* are smaller in the post-MAD period compared to those in the pre-MAD period. Namely, the mean *SRVs* for the three event windows used in this analysis are 0.0014, 0.0024, and 0.0068 in the post-MAD period and 0.0025, 0.0041, and 0.0109 during the pre-MAD period. The mean *ACARs* over the three windows during the post-MAD period (0.0486, 0.0829, 0.1080) are also lower than the respective *ACARs* during the pre-MAD period (0.0630, 0.1182, 0.1372). Similarly, in comparison with the pre-MAD sample, the mean error of the analysts' forecasts *Forecast_Error* (0.075 vs. 0.045), the dispersion of the analysts' forecasts *Forecast_Dispersion* (0.026 vs. 0.016), and the average number of analysts following a firm, *Analysts_Following* (11.52 vs. 9.39) also declined during the post-MAD period. In terms of the control variables, the pre and post-MAD samples are significantly different from each other with respect to *NegCar* (0.466 vs. 0.416)*, Car* (0.180 vs. 0.131)*, Loss* (0.401 vs. 0.246)*, Pro* (0.311 vs. -0.029)*, NegSpec* (0.040 vs. 0.027), *ES* (0.304 vs. 0.122), *Std(ROE)* (31.059vs 27.577), and *IFRS* (0.738 vs. 0.936). However, the sample firms are quite similar to each other in terms of *Size* (4.961 vs. 4.893), *RetVar* (0.040 vs. 0.038), *RetEarCor* (0.275 vs. 0.303), and *RegQuality* (0.1563 vs. 1.474).

Panel B compares the descriptive statistics for the control sample firms. Just as we observed for the treatment sample firms, relative to the pre-MAD period, the control sample firms also experience a decline in the *SRV* (0.0007, 0.0009, 0.0026 vs. 0.0009, 0.0013, 0.0038), *ACAR* (0.0348, 0.0622, 0.0767 vs. 0.0409, 0.0721, 0.0908), *Forecast_Error* (0.004, 0.010), and *Forecast_Dispersion* (0.002, 0.003) in the post-MAD period, while there was a slight increase in *Analysts_Following* (9.20, 8.75). In terms of the control variables, the pre and post-MAD samples are similar with respect to *Size* (7.431 vs. 7.827), *RetVar* (0.023 vs. 0.024), *RetEarCor* (0.117 vs. 0.093), *IFRS* (1.0 vs. 1.0), and *RegQuality* (1.543 vs. 1.594).These samples differ significantly from each other with respect to *NegCar* (0.359 vs. 0.485), *Car* (0.119 vs. 0.078), *Loss* (0.174 vs. 0.101), *Pro* (0.007 vs. 0.041), *NegSpec* (0.246 vs. 0.127), *ES* (0.082 vs. 0.039), and *Std*(*ROE*) (26.773 vs. 40.763).

Next, we compare the characteristics of the treatment and the control group of a firm in the post-MAD period. According to these statistics, the control group firms are significantly larger than the treatment group in terms of *Size* (4.893, 7.827). The firms from the control set have a significantly lower level of deviation in abnormal returns (*Retvar* 0.038, 0.024), absolute value of cumulative abnormal returns (*Car* 0.131, 0.078), and earnings surprises (*ES* 0.122, 0.039). Similarly, the control group contains fewer firms that reported negative earnings (*Loss* 0.246, 0.101). The control group also appears to operate under a slightly better regulatory environment (*RegQual* 1.474, 1.594), contain a higher proportion of firms that report under a high quality accounting standard (IAS/US GAAP IFRS 0.936, 1.000) and have better growth potential (*Pro* -0.029, 0.041). However, the treatment group contains a smaller proportion of firms for which cumulative abnormal returns were negative over the last quarter before the end of a particular year (*NegCar* 0.416, 0.485). Treatment group also has a significantly lower standard deviation of earnings (*Std(ROE)* 27.577, 40.763) and a higher return earnings correlation (*RetEarCor* 0.303, 0.093). Finally, the control group contained a higher amount of special items in their financial statements (*NegSpec* 0.027, 0.127).

Taken together, the descriptive statistics reveal two important facts. First they show that the treatment and control sample firms differ significantly in terms of firm characteristics which suggests the need to control for the differences in these firm characteristics. Second these statistics show that both sample firms experienced a change in chosen proxies during the pre and post-MAD period and therefore justify our choice of the use of difference in the differences analysis.

4.5 Results

4.5.1 Univariate evidence from stock prices and analysts' reports

In this sub section, we present the results of our univariate analysis for the five measures used in this study. We apply a difference in differences approach in an effort to account for the possible changes in the levels of proxies used in our analysis that might not be related to MAD but that might relate to the general improvement in the financial information environment during the time period covered by our analysis. For this purpose, firstly we compute the average difference between each measure's pre and post-MAD value for our treatment sample. Secondly, we compute the average difference for the each measure's over the same time period for our control sample. Finally, we compare the differences between the results of our treatment and control sample firms. In order to be included in this analysis, we require each firm to have the necessary data available in both the pre-MAD and respective post-MAD time period. This means that if the data for 2004 (the post-MAD period) is available for a firm, then this firm can only be included in the analysis if the data for 2003 (corresponding pre-MAD period) is also available for the same firm.

Table 4.4 (from Panel A to Panel H) presents the result of this univariate analysis. The results of the analysis, based on both the stock return based measures and analysts' forecasts, in general, provide evidence of successful functioning MAD. For example, over the three windows used in this analysis, i.e., (-1,0), (-1,+1), and (-2,+2), *SRVs* for the treatment sample firms declined from 0.0025, 0.0041, and 0.0109 in the pre-MAD period to 0.0014, 0.0024, and 0.0068 in the post-MAD period. During the same time period, our control firms also experienced a decline in *SRV* of 0.0002, 0.0004, and 0.0012, respectively, for the same three event windows. However, the difference in differences analysis, based on the independent sample t-test, shows that the decline in the *SRV* for the treatment sample firms is significantly higher compared to the decline in the control sample firms. With respect to the absolute cumulative abnormal returns (*ACAR),* the results for (-5, +1), (-20, +1), and (-30, +1) windows show that, compared to the pre-MAD years, the *ACAR* declined by 0.0144, 0.0353, and 0.0292 for treatment sample firms and by 0.0061, 0.0099, and by 0.0141 for the control sample firms in the post-MAD years. The difference in differences analysis once again reveals a significantly higher decline in *ACAR* for the treatment sample firms compared to the control sample firms.[5] Figure 4.1, Panel A graphically presents the *ACAR* for our treatment sample firms over a period of 60 trading days before the earnings report day to 1 trading day after the reporting day. In Panel B of Figure 4.1 we plot the scaled *ACAR*. The scaled *ACAR* presents the level of *ACAR* on any particular trading *day x* before the reporting date, relative to the *ACAR* on *day 60* before the reporting date. In both Panel A and Panel B, the lines representing the *ACAR* and the scaled *ACAR* in the post-MAD period are plotted below the lines representing the *ACAR* and the scaled *ACAR* in the pre-MAD period. This means that, relative to the pre-MAD period, stock prices in the post-MAD period remain closer to their post-announcement prices in the time period leading up to the announcement date.

In terms of the evidence from the analysts' reports and analyst following, the accuracy of analyst forecast improves by 0.030 in the post-MAD period for our treatment sample firms; this improvement is higher than that experienced by our control sample (0.006) firms in the same time period. The difference (0.024) in the respective improvement in the accuracy of forecast accuracy between treatment and control sample firms is also statistically significant. Both treatment and control sample firms experienced a decline in analyst forecast dispersion. Importantly, this decline is significantly higher (by 0.009) for treatment sample firms compared to the control sample firms. The average number of analysts following a firm also declined significantly for treatment sample firms from 11.52 in the pre-MAD years to 9.39 in the post-MAD years. Over the same years, the average number of analysts following increased slightly from 8.75 per firm in pre-MAD years to 9.20 per firm in the post-MAD years for our control sample firms. The difference in differences analysis shows that the average number of analysts following for our treatment sample firms declined by 2.58 compared to the control sample firms.

The above results, in general, provide evidence that the implementation of MAD achieves its stated goals. However, these results should be interpreted with caution since this difference in differences analysis does not control for correlated factors that potentially influence the outcome of our chosen proxies.

4.5.2 Multivariate evidence from stock price information

Stock return volatility. Table 4.5 in Panel A reports the results of estimating equation (1) over (-1, 0), (-1, +1) and (-2, +2) windows. The coefficients on the variable of interest, *MAD*Post,* are -0.001, -0.001 and -0.003 respectively for (-1, 0), (-1, +1) and (-2, +2) windows. The coefficients on the variable of interest, *MAD*Post,* are -0.001, -0.001, and -0.003 respectively for (-1, 0), (-1, +1), and (-2, +2) windows. These coefficients differ from zero at $p<0.01$ level and

[5] For brevity we only present the results of (-5, +1), (-20, +1), and (-30, +1) windows. However, the unreported results of the other windows largely lead to analogous conclusions.

indicate a statistically significant decrease in *SRV* for the treatment sample firms after implementation of MAD. As previously stated, according to the construction, a negative coefficient on *MAD*Post* indicates that this decline is net off any potential decline in *SRV* that occurred for the control sample firms during the same time period. The coefficients on the control variables are generally consistent over the three windows and are in line with those predicted in the literature. For instance, the coefficients on *RetVar, Car*, and *Loss* are positive and indicate that the firms that have greater variation in abnormal returns, have higher level of absolute cumulative abnormal returns before earnings announcements, or report losses experience higher stock return volatility around the earnings announcements dates. *Size* and *Pro* are negative and show that the bigger firms and the firms that have higher price to earnings ratios experience lower stock return volatility around the earnings announcement date. In panel B, we add the variable *RegQuality* to control for the change in the level of regulation quality over the sample period.[6] The coefficient on *RegQuality* is negative and significant and reveals that the level of stock return volatility decreases as the quality of regulations improves. The inclusion of *RegQuality* leads to a decline in the coefficients on *MAD*Post* for all three event windows, but the coefficients are negative and statistically different from zero. Therefore, controlling for *RegQuality* does not change the finding that introduction of MAD leads to a decline in *SRV*.

Absolute cumulative abnormal returns. Next, we estimate the regression equation (2) which examines whether firms release inside information on a more timely basis after implementation of MAD. The regression results for three *ACAR* windows (-5, +1), (-20, +1), and (-30, +1) are presented in panel C of the Table 4.5. For all three windows the coefficient on *MAD*Post* are negative (-0.008, -0.011, and -0.020) and significantly different from zero at $p<0.01$. These results are close to the results reported in the difference in differences analysis and indicate that the absolute difference between the pre-announcement and post-announcement prices became smaller after implementation of MAD. Importantly, the decrease in the level of difference between the pre and post-announcement prices for the treatment sample firms is higher relative to the control sample firms. The majority of the control variables have the expected coefficient signs. Panel D shows that the inclusion of variable *RegQuality* to control for the change in the level of regulation quality makes our results stronger.

Overall, the stock prices based proxies show a significant decline in the *SRV* and *ACAR* for the treatment sample firms after the implementation of MAD. Based on prior literature, we interpret in these proxies as evidence that implementation of MAD lowers the market manipulation activities (lower *SRV*) and makes inside information available to the market on a more timely basis (lower *ACAR*).

4.5.3 Multivariate evidence from analysts' reports

[6] The variable *RegQuality* is based on Kaufman et al. (2009). This variable does not specifically relate to the strength of the securities regulations in a country. Rather, it reveals the ability of the government to formulate and implement sound policies and regulations (Christensen et al., 2011).

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Analysts' forecast error. Table 4.6., Panel A presents the results of the regression equation (3) with the absolute value of the forecast error as the dependent variable. Our variable of interest, *MAD*Post*, is negative (-0.177) and significant ($p<0.01$) and thus indicates that the analysts' forecast accuracy improves after the implementation of MAD. With respect to the control variables, the negative coefficient on *Size* suggests that financial analysts are able to make more accurate earnings forecasts for larger firms. The coefficients on *RetEarCor* and *Analysts_Following* are expectedly negative but not significant. The positive coefficients on *ES* and *Std(ROE)*, are consistent with the notion that the accuracy of analysts' forecast declines when firms experience higher earnings surprises or when the volatility of return on equity increases. The *IFRS* dummy has an unexpected positive sign but it is not significantly different from zero. The inclusion of variable *RegQuality* slightly changes the coefficients on *MAD*Post* but, qualitatively, our results remain the same.

Analyst forecast dispersion. The results of regression equation (4), with the analyst forecast dispersion as a dependent variable, are presented in the panel B of Table 4.6. The coefficient on *MAD*Post* is negative (-0.029) and significant at $p<0.01$ and thus indicates a decline in the analysts' forecast dispersion after MAD. The decline in the level of analysts' forecast dispersion for treatment sample firms is higher than any decline in the dispersion of analysts' forecasts happening for the control sample firms during the same time period. As discussed in the earlier section, the decline in the forecast dispersion not only indicates a richer information environment but, as Barron et al. (2005) argue, also indicates a decline in private information. The control variables, in general, have the expected coefficient signs and, for instance, show a lower analysts' forecast dispersion for bigger firms *(Size)* and for the firms that have higher analysts' following *(Analysts_Following)*. Furthermore, the coefficients on control variables show that firms that have higher earnings surprises *(ES)* experience a higher analysts' forecast dispersion. Coefficient on *RetEarCor* and *IFRS* have unexpected signs whereas the coefficient on *Std(ROE)* is not significantly different from zero. Consistent with the finding for the analysts' forecast error based analysis, the inclusion of *RegQuality* does not materially change our analysts' forecast dispersion results.

Analyst following. Panel C presents the results of the analysis with the number of analysts following a firm as the dependent variable. For this analysis, the coefficient of *MAD*Post* is negative (-2.494) and significant ($p<0.01$), which indicates a decline in the number of analysts following a firm in the time period subsequent to the implementation of MAD. Regarding the control variables, the positive coefficient on *Size* and *IFRS* show that larger firms and firms that report under high quality standards have greater analysts' following. The negative coefficient on *Std(ROE)* is consistent with the notion that firms with less stable earnings are followed by fewer analysts. The negative coefficient on *RetEar(Cor)* is contrary to the view that analysts' prefer to follow those firms that have a higher return-earnings correlation.

Taken together, the results based on stock prices evidence and on analysts' reports show that the implementation of MAD is associated with a decline in market manipulation activities (lower *SRV*), the immediate of disclosure of inside information *(*lower *ACAR)*, an improved quality and quantity of information (lower *Forecast_Accuracy* and *Forecast_Dispersion*), and a decline in provision of selective disclosures *(*lower *Forecast_Dispersion* and *Analysts_Following)*.

4.6 Robustness tests

First of all, we perform an analysis to test whether our previous results are, indeed, attributable to the implementation of MAD. For this purpose, we superficially move the implementation date of MAD for each year included in our sample and re-run our analysis. If our previously reported findings are a consequence of the implementation of MAD then our results should be strongest for the analysis done based on the true implementation date of MAD and should become weaker when we use superficial implementation dates. The outcomes of this analysis are reported in Table 4.7. For evidence based on the analysis of stock prices, the significance of the coefficient on *MAD*Post*, as expected, weakens as we move the superficial implementation date of MAD to earlier years (2002 and 2003) than the actual implementation year of MAD (2004). For example, for window (0, +1) of the stock return volatility analysis, the significance of coefficient on *MAD*Post* changes from t = -2.949 for the analysis that is based on the actual implementation year (2004) to t=-0.261 for the analysis that is based on superficial implementation year (2003). The significance of *MAD*Post* continues to rise (from t= -2.949 to t= -5.906) as we move the superficial date of implementation to later years (2005 and 2006). The rise in the significance of the coefficient on MAD after year 2004 shows that MAD became more effective with the passage of time. This is consistent with Ernsberger et al. (2010), who report that the implementation of a regulation in German settings requires about two years to show its full effects. With regard to the analysis based on analysts' forecast accuracy and analysts' following, the significance of *MAD*Post* peaks at the true implementation date of MAD. The significance of *MAD*Post* falls as we move away from the true implementation date. This trend is not as visible in the analysts' forecast dispersion regression, the coefficient on *MAD*Post* falls after the actual date of implementation. Overall, this analysis indicates that the findings reported in our main analysis can reasonably to attributed to the implementation of MAD.

We also vary the composition of our sample firms to test the robustness of our results. The results of these robustness tests are available in Table 4.8-4.10. First, we run the full set of regression analysis based on the sample of German firms only. Second, to alleviate potential concerns that any changes in our chosen proxies might be driven by changes in sample composition, we restrict this sample to only those German firms that were present in both pre and post-MAD years. Third, we also used a sample of US and German firms matched based on size (market value), industry (based on the Campbell, 1996), and year. The construction procedure of this sample is as follows: for each year (for example, 2001) we pick up, one by one, each firm *i* from our treatment sample and try to find a control sample firm (from 2001) from the same industry that has the closest market value to that of treatment sample firm i. We repeat this process for the entire set of firms included in our treatment sample. If a match is found we include both the treatment and control sample firms in our final sample. After a control sample firm has been matched with a treatment sample firm, that (control sample) firm is removed from the list of candidate (control sample) firms that could potentially be matched with a treatment sample firm. Finally, we also include in our analysis several other variables that could potentially influence our dependent variables. Specifically, we include market-to-book value (a proxy for conservatism), volatility of earnings, and ratio of interest expenses to the total assets in our regression analysis for SRV and $ACAR$. The results of these robustness tests are virtually identical to those of our main analysis.

4.7 Conclusion

The purpose of the enactment of MAD directive is to augment the integrity of security markets and enhance public trust in regard to these markets. For this purpose, MAD contains provisions that are aimed to reduce market manipulation activities, require prompt disclosure of inside information and restrict selective disclosures. Though regulators are optimistic about the success of MAD, and anecdotal evidence also suggests so, there is very limited empirical evidence available to support this optimism. Based on extant literature, we use stock prices based proxies (stock return volatility and absolute cumulative abnormal returns) to examine the market manipulation activities and prompt disclosure of information to the security market. Also based on the literature we draw on analysts' forecast based proxies (analysts' forecast error, analysts' forecast dispersion and analysts' following) to observe the disclosure of inside information. The analysts' forecast based proxies also provide evidence about the quality of information disclosed by firms.

Based on our analysis of the firms listed on the Frankfurt Stock Exchange, we find evidence of a successful functioning MAD. In particular our results indicate a decrease in the level of stock price volatility around earnings announcements days, and a decrease in the level of absolute cumulative abnormal return measured over (-60, +1) days window in post-MAD years. The decrease in stock return volatility indicates that level of market manipulation lowers after implementation of MAD. A decrease in the absolute cumulative abnormal returns indicates that firms feed market with new information earlier in post-MAD years compared to the pre-MAD years. The results also reveal a decrease in the analysts' forecast error, analysts' forecast dispersion and analysts' following after implementation of MAD. The decline in analysts' forecast reveals a richer level of information available to the market after implementation of MAD. The decline in analysts' forecast and analysts' following indicate a decline in the level of private information provided by firms to the analysts. Altogether, our results provide positive news for regulators in Europe that their policy has been effective. These results remain robust when the analysis is based on German firms only sample, the constant sample of German firms and the matched sample of German and U.S firms. The robust tests where we move the enforcement date of MAD to several superficial dates provide us reasonable assurance that the results reported in this study are attributable to the implementation of MAD.

Table 4.1: Definition of variables

Variables (short names)	Variable description
Panel A. Definition and description of dependent variables.	
SRV	*SRV* stands for the stock return volatility which is defined as squared market model prediction errors summed over the (-1, 0), (-1, +1) and (-2, +2) estimation windows.
ACAR	*ACAR* stand for the absolute cumulative abnormal return. *ACAR* is calculated as the absolute gap between the stock prices on any particular day before earnings report and the stock prices on the earnings report date.
Forecast_Error	*Forecast_Error* is the absolute difference between the analysts' consensus (median) forecast of EPS of a firm and the actual EPS. This value is scaled by the year end stock prices. The analysts' forecast information is taken from I/B/E/S
Forecast_Dispersion	*Forecast_Dispersion* is standard deviation of individual analysts' EPS forecast of a firm scaled by year end prices. The individual analysts' forecast dispersion is taken from I/B/E/S
Analysts_Following	*Analysts_Following* represents the number of analysts' forecasts contained in the latest consensus forecast prior to the earnings announcements. This figure is taken from I/B/E/S.
Panel B. Definition and description of the test and control variables used in stock prices based analysis.	
MAD	*MAD* identifies whether a firm belongs to MAD adopting country (i.e., Germany) or not.
Post	*Post* is our test variable which is equal to 1 for all firm years (both for treatment and control sample firms) that end after October 2004 and 0 otherwise.
*MAD*Post*	*MAD*Post* is the interaction term between *MAD* and *Post*.
RetVar	*RetVar* is the standard deviation of a firm's abnormal returns over the market model estimation period. Following Heflin et al. (2003) for each firm the *RetVar* of a post-MAD year (e.g. 2001) are equal to the corresponding pre-MAD year (e.g. 2006).
NegCar	*NegCar* is a dummy variable which is equal to 1 for a firm when the cumulative abnormal returns over the last quarter before end of particular year are negative.
Car	*Car* is the absolute value of cumulative abnormal returns during the last quarter before the end of financial year
Loss	*Loss* is a dummy variable which is equal to 1 for firms reporting negative earnings in a year and 0 otherwise.
Pro	*Pro* is the price to earnings ratio of a firm
NegSpec	*NegSpec* is the absolute value of special items included in financial statements scaled by total assets
Size	*Size* is the total market value of a firm at the end of a year
Panel C. Definition and description of the test and control variables used in analysts' forecast based analysis.	
MAD	*MAD* identifies whether a firm belongs to MAD adopting country (i.e., Germany) or not.
Post	*Post* is our test variable which is equal to 1 for all firm years (both for treatment and control sample firms) that end after October 2004 and 0 otherwise.
*MAD*Post*	*MAD*Post* is the interaction term between *MAD* and *Post*.
Size	*Size* is the total market value of a firm at the end of a year

Table 4.1 (continued)

ES	*ES*, earnings surprise is calculated as the absolute difference between the current and previous years' earnings per share scaled by share price at the end of previous year.
Std(ROE)	*Std(ROE)* is the standard deviation of return on equity computed over period of five years.
RetEarCor	*RetEarCor* is the correlation between earnings and annual returns computed over a period of five year.
Analysts_Following	*Analysts_Following* represents the number of analysts' forecasts contained in the latest consensus forecast prior to the earnings announcements. This figure is taken also taken from I/B/E/S.

Table 4.2: Breakdown of sample in industries and years

	Treatment Sample		Control Sample	
	No. of firm-year observations	No. of firms	No. of firm-year observations	No. of firms
Panel A. Industry breakdown				
Finance/real estate industry (SIC 60-69)	250	84	1,241	233
Consumer durables industry (SIC 25, 30, 36-37, 50, 55, 57)	213	60	440	86
Basic industry (SIC 10, 12, 14, 24, 26, 28, 33)	149	37	487	93
Food/tobacco industry (SIC 1, 20, 21, 54)	26	8	179	41
Construction industry (SIC 15-17, 32, 52)	93	35	159	35
Capital goods industry (SIC 34-35, 38)	203	57	420	80
Transportation industry (SIC 40-42, 44, 45, 47)	19	5	108	20
Utilities industry (SIC 46, 48, 49)	76	19	567	100
Textile/trade industry (SIC 22-23, 31, 51, 53, 56, 59)	113	42	116	40
Service industry (SIC 72-73, 75, 80, 82, 89)	267	77	359	66
Leisure industry	71	24	150	35
Total	1480	448	4,615	899
Panel B. Yearly breakdown				
	No. of firm-year observations	Percentage	No. of firm-year observations	Percentage
Year 2001	224	15.13	702	15.21
Year 2002	172	11.62	760	16.47
Year 2003	305	20.61	807	17.49
Year 2004	345	23.31	812	17.59
Year 2005	210	14.19	794	17.20
Year 2006	224	15.13	740	16.03
Total	1480	100	4,615	100

Table 4.3: Descriptive statistics for variables used in regression analysis

	Panel A								Panel B							
	Treatment sample Pre-MAD				Treatment Sample Post-MAD				Benchmark Sample Pre-MAD				Benchmark Sample Post-MAD			
	N	Mean	Median	Std. Dev	N	Mean	Median	Std. Dev	N	Mean	Median	Std. Dev	N	Mean	Median	Std. Dev
Stock prices eveidence- Dependent variables																
SRV(-1, 0)	701	0.0025	0.000	0.008	779	0.0014	0.000	0.006	2269	0.0009	0.000	0.002	2346	0.0007	0.000	0.004
SRV(-1, +1)	701	0.0041	0.001	0.011	779	0.0024	0.001	0.007	2269	0.0013	0.001	0.005	2346	0.0009	0.000	0.004
SRV (-2, +2)	701	0.0109	0.004	0.025	779	0.0068	0.002	0.019	2269	0.0038	0.002	0.013	2346	0.0026	0.001	0.009
ACAR(-5, +1)	701	0.0630	0.045	0.070	779	0.0486	0.031	0.061	2269	0.0409	0.029	0.045	2346	0.0348	0.025	0.035
ACAR(-20, +1)	701	0.1182	0.075	0.135	779	0.0829	0.057	0.096	2269	0.0721	0.052	0.078	2346	0.0622	0.044	0.062
ACAR(-30, +1)	701	0.1372	0.097	0.157	779	0.1080	0.077	0.121	2269	0.0908	0.063	0.096	2346	0.0767	0.056	0.075
Stock prices eveidence-Dependents variables																
Forecaset_Error	471	0.075	0.018	1.366	654	0.045	0.007	0.277	2441	0.010	0.002	0.083	1533	0.004	0.002	0.010
Forecast_Dispersion	357	0.026	0.012	0.117	458	0.016	0.005	0.039	2198	0.003	0.001	0.009	1395	0.002	0.001	0.003
Analysts_Following	471	11.52	4.000	10.918	654	9.39	4.000	8.856	2443	8.75	7.000	6.793	1533	9.20	7.000	6.572
Stock prices eveidence- Control variables																
Retvar	701	0.040	0.035	0.020	779	0.038	0.036	0.133	2269	0.023	0.020	0.013	2346	0.024	0.020	0.016
NegCar	701	0.466	0.000	0.499	779	0.416	0.000	0.493	2269	0.359	0.000	0.480	2346	0.485	0.000	0.500
Car	701	0.180	0.127	0.169	779	0.131	0.093	0.137	2269	0.119	0.081	0.135	2346	0.078	0.056	0.079
Loss	701	0.401	0.000	0.490	779	0.246	0.000	0.431	2269	0.174	0.000	0.379	2346	0.101	0.000	0.301
Pro	701	0.311	0.030	1.559	779	-0.029	0.050	0.404	2269	0.007	0.050	0.602	2346	0.041	0.050	0.090
NegSpec	701	0.040	0.000	0.196	779	0.027	0.000	0.156	2269	0.246	0.000	0.429	2346	0.127	0.000	0.330
Size	701	4.961	4.560	2.527	779	4.893	4.370	2.550	2269	7.431	7.390	1.844	2346	7.827	7.800	1.632
Analysts' following- Control variables																
Size	471	5.399	5.174	2.533	654	5.644	5.388	2.386	1759	7.647	7.552	1.681	2217	7.854	7.797	1.528
ES	471	0.304	0.060	0.712	654	0.122	0.037	0.415	1759	0.082	0.021	0.248	2217	0.039	0.016	0.080
Std(ROE)	471	31.059	10.757	87.810	654	27.577	12.288	61.949	1759	26.773	7.282	241.421	2217	40.763	7.459	368.201
RetEarCor	471	0.275	0.390	0.621	654	0.303	0.366	0.422	1759	0.117	0.139	0.445	2217	0.093	0.114	0.415
IFRS	451	0.738	1.000	0.440	654	0.936	1.000	0.246	1759	1.000	1.000	0.000	2217	1.000	1.000	0.000
RegQuality	471	1.563	1.560	0.021	654	1.474	1.470	0.037	1759	1.543	1.530	0.040	2217	1.594	1.590	0.021

Table 4.4: Univariate analysis, based on difference in differences analysis, to examine the effect of implementation of MAD on stock price and analysts' forecast based proxies

	N	Pre-MAD period	Post-MAD period	Difference	p-value
Panel A. *SRV* (-1, 0)					
Treatment Sample	1398	0.0025	0.0014	0.0011***	0.007
Control Sample	4456	0.0009	0.0007	0.0002**	0.047
Difference in differences				0.0009***	0.002
Panel B. *SRV* (-1, -1)					
Treatment Sample	1398	0.0041	0.0024	0.0017***	0.000
Control Sample	4456	0.0013	0.0009	0.0004***	0.002
Difference in differences				0.0013***	0.000
Panel C. *SRV* (-2, +2)					
Treatment Sample	1398	0.0109	0.0068	0.0041***	0.000
Control Sample	4456	0.0038	0.0026	0.0012***	0.000
Difference in differences				0.0029***	0.000
Panel D. *ACAR* (-5, +1)					
Treatment Sample	1398	0.0630	0.0486	0.0144***	0.000
Control Sample	4456	0.0409	0.0348	0.0061***	0.000
Difference in differences				0.0083**	0.012
Panel E. *ACAR* (-20, +1)					
Treatment Sample	1398	0.1182	0.0829	0.0353***	0.000
Control Sample	4456	0.0721	0.0622	0.0099***	0.000
Difference in differences				0.0254***	0.000
Panel F. *ACAR* (-30, +1)					
Treatment Sample	1398	0.1372	0.1080	0.0292***	0.000
Control Sample	4456	0.0908	0.0767	0.0141***	0.000
Difference in differences				0.0151***	0.000
Panel G. *Forecast_Error*					
Treatment Sample	720	0.075	0.045	0.030**	0.038
Control Sample	3144	0.010	0.004	0.006**	0.012
Difference in differences				0.024***	0.007
Panel H. *Forecast_Dispersion*					
Treatment Sample	510	0.026	0.016	0.010*	0.086
Control Sample	2716	0.003	0.002	0.001***	0.000
Difference in differences				0.009***	0.000
Panel I. *Analysts_following*					
Treatment Sample	720	11.52	9.39	2.13***	0.000
Control Sample	3144	8.75	9.20	-0.45***	0.000
Difference in differences				2.58***	0.000

Table 4.5: Regression model explaining the Effect of MAD on stock prices based proxies

This table presents the results of the regression analysis used to determine effect of implementation of MAD on the movement of stock prices around earnings announcements. Panel reflect the effect MAD on the stock return volatility (*SRV*) over the three different time windows i.e., (0,+1), (-1,+1) and (-2,+2). In panel B, we include *RegQuality* to control for the level of enforcement of regulation over of sample period. Panel C present the result of the regression analysis relating to the effect of MAD on the absolute cumulative abnormal returns (*ACAR*) calculated over 3 different time horizons i.e., from the day following the earnings announcement to the 5, 20 and 30 days before the earnings announcements. In Model 7-9. Panel D presents the results of the analysis where we include *RegQuality* to control for the level of enforcement of regulation over of sample period. Variable definitions are provided in Table 4.1. The p-values appear in the parentheses and are based on robust standard errors adjusted for firm clustering. *significant at 10% level, **significant at 5% level, ***significant at 1% level.

	Panel A *SRV*			Panel B *SRV*			Panel C *ACAR*			Panel D *ACAR*		
	Coefficients (p-values) (0, +1)	Coefficients (p-values) (-1, +1)	Coefficients (p-values) (-2, +2)	Coefficients (p-values) (0, +1)	Coefficients (p-values) (-1, +1)	Coefficients (p-values) (-2, +2)	Coefficients (p-values) (-5, +1)	Coefficients (p-values) (-20, +1)	Coefficients (p-values) (-30, +1)	Coefficients (p-values) (-5, +1)	Coefficients (p-values) (-20, +1)	Coefficients (p-values) (-30, +1)
MAD	-0.001***	-0.002***	-0.004***	-0.001***	-0.002***	-0.004***	-0.010***	-0.015***	-0.018***	-0.016***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.001)	(0.003)	(0.000)	(0.063)
Post	-0.000	-0.000	-0.000*	0.000*	0.000	0.000	-0.003***	-0.007***	-0.003*	-0.008***	-0.002	-0.016***
	(0.794)	(0.321)	(0.080)	(0.097)	(0.145)	(0.476)	(0.003)	(0.005)	(0.080)	(0.001)	(0.222)	(0.000)
*MAD*Post*	-0.001***	-0.001***	-0.003**	-0.002***	-0.002***	-0.005***	-0.008**	-0.011	-0.020***	-0.005	-0.013***	0.019**
	(0.003)	(0.003)	(0.015)	(0.000)	(0.000)	(0.000)	(0.026)	(0.153)	(0.001)	(0.501)	(0.003)	(0.047)
RetVar	0.001	0.003**	0.006*	0.002*	0.003**	0.006*	0.021	0.056	0.040	0.036	0.022	0.047
	(0.115)	(0.016)	(0.084)	(0.073)	(0.010)	(0.064)	(0.314)	(0.314)	(0.214)	(0.266)	(0.282)	(0.395)
NegCar	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.002*	0.001	0.001	0.000	-0.002*	0.000
	(0.137)	(0.183)	(0.307)	(0.166)	(0.221)	(0.354)	(0.065)	(0.680)	(0.752)	(0.845)	(0.077)	(0.830)
Car	0.002***	0.003***	0.007***	0.002***	0.003***	0.007***	0.028***	0.081***	0.070***	0.071***	0.0282***	0.083***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Loss	0.000**	0.001***	0.003***	0.000**	0.001***	0.003***	0.011***	0.024***	0.023***	0.022***	0.011***	0.023***
	(0.018)	(0.001)	(0.000)	(0.016)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pro	-0.000	-0.000	-0.002**	-0.000	-0.000	-0.002**	-0.005***	-0.014**	-0.006*	-0.006*	-0.005***	-0.014**
	(0.425)	(0.162)	(0.011)	(0.424)	(0.163)	(0.011)	(0.000)	(0.031)	(0.068)	(0.069)	(0.000)	(0.031)
NegSpec	-0.000	0.001	0.000	-0.000	0.000	0.000	-0.001	0.001	-0.001	-0.001	-0.001	0.001
	(0.500)	(0.665)	(0.659)	(0.423)	(0.715)	(0.695)	(0.498)	(0.851)	(0.755)	(0.818)	(0.469)	(0.747)
Size	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.003***	-0.006***	-0.006***	-0.006***	-0.003***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RegQuality				-0.006***	-0.008***	-0.015***				0.114***	-0.037**	0.225***
				(0.000)	(0.000)	(0.002)				(0.000)	(0.040)	(0.000)
Constant	0.003***	0.005***	0.0133***	0.012***	0.017***	0.037***	0.080***	0.161***	0.137***	-0.040	0.1378***	-0.189***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.437)	(0.000)	(0.002)
Ind dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.5 (continued)

Adj. R^2	3.89%	6.40%	8.08%	4.05%	5.85%	8.18%	9.76%	11.72%	11.78%	11.96%	9.82%	12.20%
N	6095	6095	6095	6095	6095	6095	6095	6095	6095	6095	6095	6095

Table 4.6: Regression model explaining Effect of MAD on analysts' reports based proxies

This table presents the results of the regression analysis used to determine effect of implementation of MAD the quality of analysts' forecasts and analysts' following. Panel A reflects the effect of MAD on the accuracy of analysts' forecasts. Panel B presents the result of the regression analysis examining the effect of MAD on the dispersion of analysts forecast dispersion. Panel C examines the effect of MAD on the average number of analysts following a firm. Variable definitions are provided in Table 4.1. The p-values appear in the parentheses and are based on robust standard errors adjusted for firm clustering. *significant at 10% level, **significant at 5% level, ***significant at 1% level.

	Panel A		Panel B		Panel C	
	Forecast_Error		*Forecast_Dispersion*		*Analysts_Following*	
	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)
MAD	-0.187***	-0.184***	-0.037***	-0.037***	-8.941***	-8.993***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post	0.009	0.003	0.000	-0.000	-0.581***	-0.442***
	(0.205)	(0.698)	(0.850)	(0.936)	(0.000)	(0.001)
*MAD*Post*	-0.177***	-0.159***	-0.029***	-0.028***	-2.494***	-2.873***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Size	-0.014**	-0.014**	-0.001*	-0.001*	3.083***	3.084***
	(0.039)	(0.038)	(0.067)	(0.066)	(0.000)	(0.000)
ES	0.326*	0.327*	0.025***	0.025***	1.049***	1.039***
	(0.059)	(0.059)	(0.000)	(0.000)	(0.000)	(0.000)
Std(ROE)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.463)	(0.463)	(0.530)	(0.530)	(0.937)	(0.939)
RetEarCor	-0.006	-0.005	0.004*	0.004*	-0.515	-0.520**
	(0.708)	(0.720)	(0.051)	(0.051)	(0.046)	(0.044)
Analysts_Following	--0.000	0.000	-0.000	-0.000		
	(0.998)	(0.988)	(0.126)	(0.127)		
IFRS	0.072	0.073	0.014*	0.014*	3.617***	3.608***
	(0.181)	(0.178)	(0.064)	(0.064)	(0.000)	(0.000)
RegQuality		0.130		0.002		-2.721*
		(0.140)		(0.746)		(0.055)
Constant	0.201***	-.0010	0.038***	0.035***	-4.877***	-0.606
	(0.002)	(0.995)	(0.000)	(0.003)	(0.000)	(0.807)
Ind dummy	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	10.31%	10.31%	14.14%	14.14%	59.32%	59.32%
N	5078	5078	4392	4392	5078	5078

Table 4.7: Robustness test

This table presents the results of our analysis where we superficially move the implementation date of MAD, one by one, over year from 2002 to 2006 and re-run the analysis. For example, first we assume that MAD is implemented in year 2002. Accordingly, we set MAD equal to 1 for each financial year 2002 to 2006 and 0 for year 2001. Similarly we repeat this procedure for year 2003, 2004, 2005 and 2006. We do not start from year 2001 because in that case MAD would be equal to 1 over entire sample period of our analysis. For brevity, we do not report results of the control variables.

Panel A	*SRV* (0, +1)		*SRV* (-1, +1)		*SRV* (-2, +2)	
	Coefficients	t-stat	Coefficients	t-stat	Coefficients	t-stat
2002	0.001	3.794	0.001	1.971	0.003	2.363
2003	-0.000	-0.261	-0.000	-0.533	-0.002	-0.967
MAD	-0.001	-2.949	-0.001	-2.966	-0.003	-2.447
2005	-0.001	-4.865	-0.002	-4.478	-0.004	-4.545
2006	-0.001	-5.906	-0.002	-5.031	-0.004	-4.405
Panel B	*ACAR* (-5, +1)		*ACAR* (-20, +1)		*ACAR* (-30, +1)	
	Coefficients	t-stat	Coefficients	t-stat	Coefficients	t-stat
2002	0.005	1.266	0.001	0.136	0.029	2.996
2003	-0.006	-1.407	-0.013	-1.879	0.003	0.428
MAD	-0.008	-2.226	-0.020	-3.182	-0.011	-1.429
2005	-0.017	-5.159	-0.024	-4.015	-0.025	-3.397
2006	-0.015	-4.774	-0.020	-3.166	-0.034	-4.708
Panel C	*Forecast_ Accuracy*		*Forecast_ Dispersion*		*Analysts'_ Following*	
	Coefficients	t-stat	Coefficients	t-stat	Coefficients	t-stat
2002	0.078	2.889	0.004	0.784	-2.242	-3.781
2003	-0.257	-2.692	-0.040	-4.014	-2.891	-6.512
MAD	-0.177	-3.237	-0.029	-3.832	-2.494	-6.578
2005	-0.120	-3.133	-0.027	-4.632	-1.929	-5.314
2006	-0.057	-2.734	-0.019	-4.630	-1.827	-4.759

Table 4.8: Robustness tests
(Stock return volatility)

This table presents the results of the effects of MAD on the stock return volatility for various. For each of the sample we present the results of stock return volatility calculated over (0, +1), (-1, +1) and (-2, +2) days windows. Panel A presents the results of the analysis which is based on a sample of all German firms for which required data is available for the year 2001-2007. Panel B presents the results of our constant sample firms i.e., the firms that are present in the pre-MAD and corresponding post-MAD year. Panel C presents the results of our analysis based on the matched sample of US and German firms. Variable definitions are provided in Table 4.1. The p-values appear in the parentheses and are based on robust standard errors adjusted for firm clustering. *significant at 10% level, **significant at 5% level, ***significant at 1% level.

		Panel A *SRV*			Panel B *SRV*			Panel C *SRV*	
	Coefficients (p-values) (0, +1)	Coefficients (p-values) (-1, +1)	Coefficients (p-values) (-2, +2)	Coefficients (p-values) (-0, +1)	Coefficients (p-values) (-1, +1)	Coefficients (p-values) (-2, +2)	Coefficients (p-values) (0, +1)	Coefficients (p-values) (-1, +1)	Coefficients (p-values) (-2, +2)
*MAD*Post*							-0.001***	-0.002***	-0.003***
							(0.006)	(0.002)	(0.006)
MAD							-0.001***	-0.002***	-0.004***
							(0.000)	(0.000)	(0.000)
Post	-0.001**	-0.001**	-0.001	-0.001***	-0.002***	-0.003***	0.000	0.000	-0.000
	(0.027)	(0.020)	(0.125)	(0.001)	(0.001)	(0.003)	(0.639)	(0.633)	(0.610)
RetVar	-0.000	0.001	0.000	-0.000	0.000	-0.001	0.001	0.002*	0.004
	(0.741)	(0.483)	(0.910)	(0.644)	(0.803)	(0.752)	(0.476)	(0.098)	(0.298)
NegCar	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.000	-0.000	-0.001
	(0.485)	(0.762)	(0.696)	(0.450)	(0.288)	(0.255)	(0.106)	(0.105)	(0.172)
Car	0.001	0.002*	0.003	0.003	0.004**	0.005	0.002*	0.003**	0.006**
	(0.157)	(0.095)	(0.277)	(0.100)	(0.036)	(0.176)	(0.064)	(0.012)	(0.015)
Loss	0.001*	0.001***	0.003***	0.001	0.002**	0.004***	0.000	0.001**	0.002***
	(0.069)	(0.009)	(0.008)	(0.101)	(0.027)	(0.008)	(0.266)	(0.049)	(0.003)
Pro	-0.000	-0.000	-0.001***	-0.000	-0.000	-0.002***	-0.000	-0.000	-0.001*
	(0.191)	(0.167)	(0.000)	(0.102)	(0.228)	(0.000)	(0.745)	(0.440)	(0.065)
NegSpec	0.000	0.000	0.002	-0.000	-0.000	-0.000	-0.000	7.51e-06	.000
	(0.576)	(0.680)	(0.280)	(0.381)	(0.429)	(0.854)	(0.830)	(0.975)	(0.919)

Table 4.8 (continued)

Size	-0.000**	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***
	(0.028)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.002***	0.003***	0.009***	0.003***	0.004***	0.012***	0.003***	0.005***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	2.89%	4.67%	6.83%	4.73%	6.95%	9.78%	3.48%	6.14%	7.50%
N	1888	1888	1888	1398	1398	1398	2894	2894	2894

Table 4.9: Robustness tests
(Absolute Cumulative Abnormal Return)

This table presents the results of the effects of MAD on the absolute cumulative abnormal return (*ACAR*) for various samples that we use in our robustness tests. For each of the sample we present the results of *ACAR* calculated over (-1, +5), (-1, +20) and (-1, +30) days windows. Panel A presents the results of the analysis which is based on a sample of German firms for which required data is available for the year 2001-2007. Panel B presents the results of our constant sample of German firms i.e., the firms that are present in the pre-MAD and corresponding post-MAD year. Panel C presents the results of the analysis based on the matched sample of US and German firms. Variable definitions are provided in Table 4.1. The p-values appear in the parentheses and are based on robust standard errors adjusted for firm clustering. *significant at 10% level, **significant at 5% level, ***significant at 1% level.

	Panel A *ACAR*			Panel B *ACAR*			Panel C *ACAR*		
	Coefficients (p-values) (-1, +5)	Coefficients (p-values) (-1, +20)	Coefficients (p-values) (-1, +30)	Coefficients (p-values) (-1, +5)	Coefficients (p-values) (-1, +20)	Coefficients (p-values) (-1, +30)	Coefficients (p-values) (-1, +5)	Coefficients (p-values) (-1, +20)	Coefficients (p-values) (-1, +30)
*MAD*Post*							-0.010*	-0.024***	-0.018**
							(0.052)	(0.001)	(0.042)
MAD							-0.010***	-0.017***	-0.016**
							(0.001)	(0.008)	(0.023)
Post	-0.010***	-0.020***	-0.013***	-0.014***	-0.026***	-0.023***	-0.005**	-0.002	-0.003
	(0.003)	(0.001)	(0.003)	(0.000)	(0.000)	(0.004)	(0.048)	(0.593)	(0.527)
RetVar	0.003	0.007	-0.005	-0.010	0.007	0.004	0.008	0.012	0.007
	(0.853)	(0.799)	(0.912)	(0.630)	(0.836)	(0.949)	(0.723)	(0.728)	(0.899)
NegCar	-0.001	0.001	0.003	-0.005*	-0.001	-0.004	-0.004**	-0.004	-0.005
	(0.646)	(0.867)	(0.667)	(0.091)	(0.842)	(0.598)	(0.030)	(0.292)	(0.265)
Car	0.003	0.042**	0.054**	-0.008	0.040*	0.037	0.010	0.050***	0.048**
	(0.800)	(0.021)	(0.018)	(0.573)	(0.055)	(0.165)	(0.362)	(0.002)	(0.011)
Loss	0.009**	0.026***	0.026***	0.013**	0.031***	0.032***	0.012***	0.024***	0.021***
	(0.042)	(0.000)	(0.001)	(0.010)	(0.000)	(0.003)	(0.000)	(0.000)	(0.005)
Pro	-0.002***	-0.000	-0.003	-0.002***	-0.000	-0.003	-0.003**	-0.004	-0.014
	(0.000)	(0.640)	(0.239)	(0.000)	(0.674)	(0.351)	(0.026)	(0.414)	(0.132)
NegSpec	0.001	0.016	0.012	-0.010	0.002	-0.001	0.001	-0.002	0.003
	(0.915)	(0.265)	(0.465)	(0.173)	(0.865)	(0.976)	(0.715)	(0.689)	(0.674)
Size	-0.002***	-0.004***	-0.005***	-0.003***	-0.005***	-0.006***	-0.003***	-0.007***	-0.008***
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4.9 (continued)

Constant	0.061***	0.010***	0.121***	0.080***	0.121***	0.146***	0.073***	0.126***	0.142***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ind dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	4.83%	7.20%	7.91%	7.28%	9.13%	7.91%	7.58%	9.24%	8.32%
N	1888	1888	1888	1398	1398	1398	2894	2894	2894

Table 4.10: Robustness tests
(Analysts forecast quality and analysts following)

This table presents the results of the effects of MAD on the quality of analysts' forecasts and analysts' following for various samples that we use in our robustness tests. The three different models in Panel A reflect the effect of MAD on the accuracy of analysts' forecasts based on a sample of German firms, constant sample of German firms i.e., the firms that are present in the pre-MAD and corresponding post-MAD year and the matched sample of US and German firms, respectively. Panel B and Panel C present similar results of the effect of MAD on the forecast dispersion and analysts following. Variable definitions are provided in Table 4.1. The p-values appear in the parentheses and are based on robust standard errors adjusted for firm clustering. *significant at 10% level, **significant at 5% level, ***significant at 1% level.

	Panel A *Forecast_Error*			Panel B *Forecast_Dispersion*			Panel C *Analysts_Following*		
	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)
MAD			-0.178***			-0.029***			-8.817***
			(0.006)			(0.001)			(0.000)
Post			0.019			-0.000			-0.671***
			(0.409)			(0.788)			(0.008)
*MAD*Post*	-0.139***	-0.031*	-0.172**	-0.010	-0.015	-0.019**	-3.096***	-3.095***	-2.802***
	(0.004)	(0.055)	(0.016)	(0.135)	(0.116)	(0.010)	(0.000)	(0.000)	(0.000)
Size	-0.032*	-0.008	-0.023**	-0.005	0.002	-0.001	3.213***	3.488***	3.005***
	(0.098)	(0.170)	(0.042)	(0.130)	(0.563)	(0.670)	(0.000)	(0.000)	(0.003)
ES	0.347	0.050***	0.352*	0.031***	0.019***	0.027***	1.269***	0.726***	0.673
	(0.119)	(0.000)	(0.087)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.751)
Std(ROE)	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.005***	-0.005***	0.001**
	(0.597)	(0.380)	(0.242)	(0.388)	(0.384)	(0.324)	(0.002)	(0.002)	(0.014)
RetEarCor	-0.017	0.006	-0.057	0.011*	0.005	0.005	-1.479***	-2.058***	-0.985***
	(0.743)	(0.706)	(0.121)	(0.087)	(0.383)	(0.145)	(0.000)	(0.003)	(0.000)
Analysts_Following	0.002	-0.001	0.000	0.000	-0.001	-0.000			
	(0.387)	(0.176)	(0.858)	(0.922)	(0.147)	(0.202)			
IFRS	0.081	0.010	0.058	-0.001***	0.012	0.007	0.399***	4.429***	3.909***
	(0.150)	(0.627)	(0.307)	(0.000)	(0.336)	(0.353)	(0.000)	(0.000)	(0.000)
Constant	0.242*	0.081*	0.245***	0.064***	-0.002	0.024***	-17.000***	-21.716***	-12.743***
	(0.075)	(0.077)	(0.003)	(0.003)	(0.939)	(0.007)	(0.000)	(0.000)	(0.000)
Ind dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 4.10 (continued)

Adj. R2	14.58%	8.44%	13.63%	12.65%	6.35%	13.87%	69.97%	71.47%	65.87%
N	1125	720	2032	799	510	1596	1125	720	2032

Figure 4.1: Panel A. description of the figure

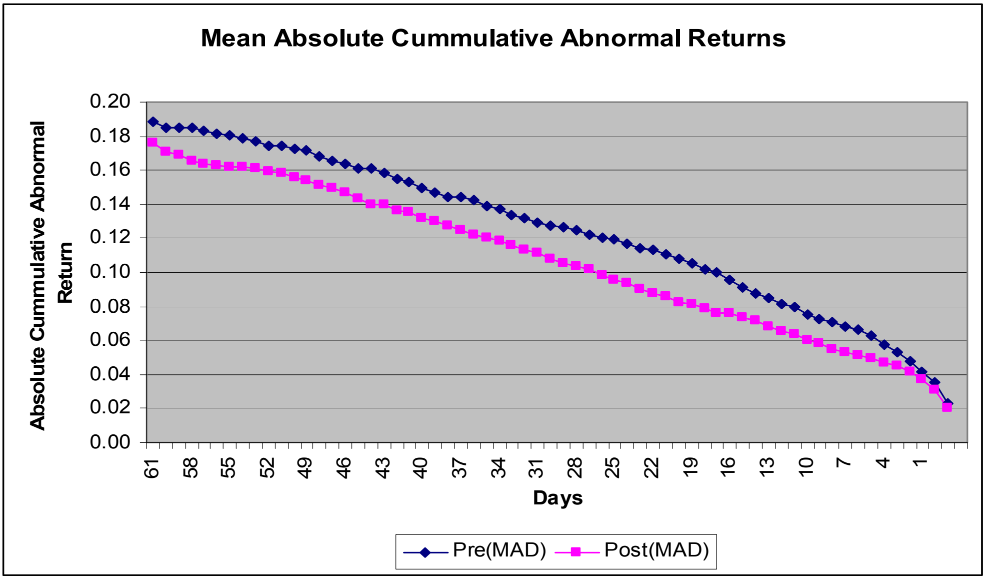
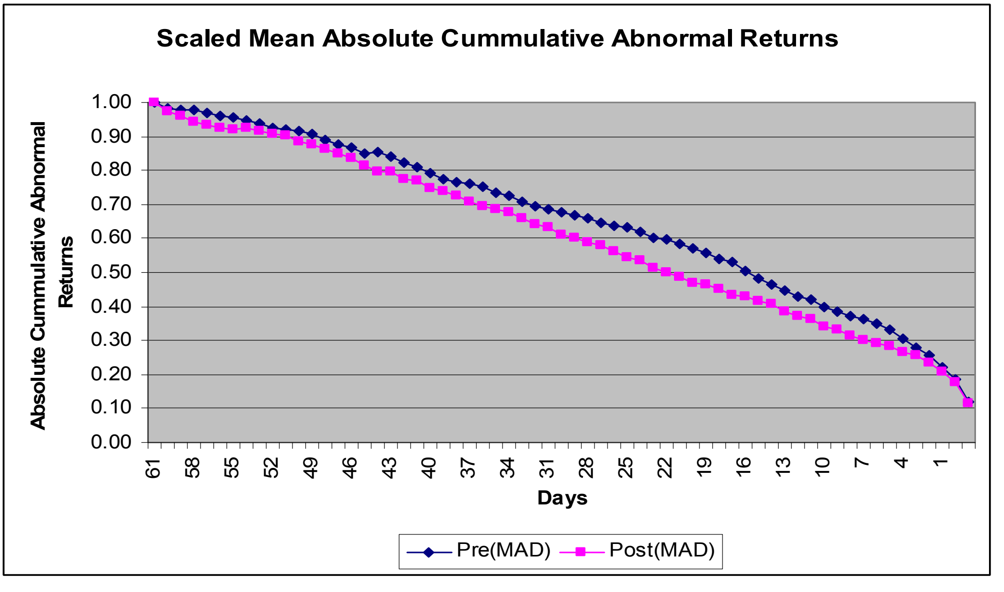


Figure 1 Panel B



Chapter 5

Summary and conclusion

5.1 Summary of main findings

This thesis studies the role of credit rating agencies (CRAs) in capital markets and the effects of two important regulatory decisions that are meant to improve the quality of information available to the capital markets and hence their integrity. In particular, this thesis examines a) the importance of CRAs to debt markets and the level of trust investors place on the credit ratings assigned by CRAs, b) whether the adoption of International Financial Reporting Standards (IFRS) has improves the quality of accounting information in the European Union (EU), and c) whether the implementation of Market Abuse Directive (MAD) has been successful in deterring market manipulation activities, reducing selective disclosure of private information, and improving the flow and quality of information to capital markets.

Credit ratings are the opinions of CRAs about the credit quality of various debt securities and are known to influence investors' choices as well as policymakers' regulatory decisions. Over the years, however, the CRAs have been subject to strong criticism related to their integrity, independence, and accuracy of information. CRAs became even more controversial because of their alleged negligence that led to the recent financial crisis. Chapter 2 shows that, amid these controversies, investors do not appear to rely on credit ratings as the sole evidence of a debt security's credit risk. Rather, they appear to carry an analysis of their own to form an opinion about the accuracy of those ratings. That is, the investors seem to distinguish whether or not credit ratings assigned by CRAs correspond to the ratings that are expected based on publically available information (expected ratings) and adjust the required yield accordingly. In particular, the results show that after controlling for all relevant factors, the investors require a higher yield for bonds that receive higher than expected ratings compared to similar bonds for which the credit ratings assigned by CRAs are equal to their expected ratings. The results also show that the difference between the ratings assigned by CRAs and expected ratings lowers the information content of credit ratings. This chapter also sheds light on the premium required by investors on split rated bonds. The results confirm the findings of previous studies that show that investors demand a premium, referred to as an opacity premium, on split rated bonds. However, as opposed to the previous studies, this chapter shows that part of the opacity premium fades away when the odds that actual ratings assigned to the split rated bonds might be higher than the expected ratings are accounted for. Finally, this chapter also shows that Moody's updates the ratings of bonds that receive higher than expected ratings much earlier when they bonds sell at higher than expected yield. No such evidence is found for S&P.

Chapter 3 examines whether the introduction of IFRS improves the quality of accounting information in EU. The move towards IFRS is a global trend and a large number of countries requires, or at least allows, firms to prepare their financial statements in accordance with IFRS. The scale of adoption of IFRS raises a natural question of whether or not the switch from local GAAP to IFRS is actually achieving the desired objectives. Many recent studies try to answer this question by focusing on equity markets while the evidence from the debt market largely remains ignored. Chapter 3 fills this gap in the literature by examining and comparing the quality of accounting information prepared under IFRS and other local GAAP used in the EU from the perspective of CRAs, an important information intermediary of the debt markets. The particular proxies for the quality of accounting information used in this chapter are the level of credit ratings assigned by the CRAs and the frequency and magnitude of rating disagreements between the CRAs. The review of existing literature reveal that both of these proxies reflect the level of information asymmetry and uncertainty that exists in the rating process which, in turn, depend on the quality of accounting information.

Based on the analysis of bonds issued by European financial firms during 1996-2008, the results in Chapter 3 reveal that bonds issued by firms reporting under IFRS receive better ratings and are less likely to be split rated compared to the bonds issued by a firm reporting under other accounting standards. The results in Chapter 3 also reveal a decline in the pattern of lopsided ratings after firms start to report under IFRS. These results remain robust to various sample compositions. All together the results in Chapter 3 show that reporting under IFRS improves the quality of accounting information as IFRS based financial reports seem to make it easier for the CRAs to value the assets of the issuer's firm and its financial risk.

Chapter 4 focuses on one of the important directives, MAD, promulgated in Europe with the purpose to enhance the integrity of the security markets. Although regulators are optimistic about the success of MAD (and anecdotal evidence also suggests so), there is very limited empirical evidence available to support this optimism. Chapter 4 concentrates on the three most important provisions of this directive that aim to a) deter the market manipulation activities, b) require prompt release of all inside information through public sources, and c) disallow private disclosure of material information to selected individuals such as security analysts. The results provide strong evidence of the success of these MAD provisions. In particular, the results in Chapter 4 show that the stock return volatility around the earnings announcement decreases after the implementation of MAD. The existing literature shows that a reduction in market manipulation activities and the prompt disclosure of private information lowers the volatility of stock prices. Further, results show that the stock prices in the post-MAD period remain closer to their real prices (prices subsequent to the earnings announcements) during the time period prior to earnings announcements. This finding indicates that firms feed market with new information earlier after enactment of MAD. With respect to the restriction on selective disclosures, Chapter 4 concentrates on the accuracy and dispersion of the analysts' forecasts as well as the analysts' following. Chapter 4 provides evidence that the accuracy of analysts' forecasts improves and the dispersion of analysts' forecasts declines in the post-MAD years. Chapter 4 further reports a decline in the average number of analysts following a firm. A review of analysts' reports literature shows that a restriction on the selective disclosure of information reduces analysts' dependence on firm management and thus reduces bias in their forecasts which in turn improves the accuracy of their forecasts. The same literature also reveals that a restriction of the provision of selective disclosures narrows the heterogeneity of information possessed by different analysts which leads to a reduction in the dispersion of analysts' forecasts. Finally, the literature on analysts' reports shows that analysts prefer to follow those firms that give them access to private information. A restriction of the provision of private information forces analysts to allocate their resources to a smaller number of firms in order to market themselves based on the accuracy of their forecasts. Based on these findings, the results in Chapter 4 provide evidence of a decline in the level of selective disclosures.

5.2 Suggestions for future research

This thesis consists of three studies that examine the importance of credit rating information for the debt market, whether the introduction of IFRS improves the quality of information, and whether the implementation of MAD achieves its objectives. The topics covered in this thesis pertain to the efforts made to improve the functionality of the security markets. The development of security markets is an ongoing process and needs continuous monitoring and introduction of new rules.

Chapter 2 examines the worth of credit rating information for the debt market. As discussed in this thesis, the CRAs came under strong criticism for their negligence that led to the recent financial crisis. This criticism led regulators around the world to ponder a framework that would allow for better monitoring of CRAs so as to make their rating methodology more transparent and hold them more accountable for any deliberate negligence. The Rating Accountability and Transparency Enhancement (RATE) and Regulation (EC) No 1060/2009 of the European Parliament are two major examples of such frameworks. In addition to the effects of these regulatory steps, CRAs themselves are also expected to be cautious of losing the value of their services. Together, these factors are likely to force CRAs to undertake actions to make rating criteria more transparent and understandable. Future research may investigate whether or not these actions enhance investors trust in the credit rating information.

Chapter 3 provides evidence that the implementation of IFRS improves the quality of accounting information in Europe. One of the important objectives of the International Accounting Standard Board (IASB) is to enhance the comparability of accounting information. However, the critics think that a simple adoption of IFRS might not make the accounting information comparable over different countries because of difference in level of enforcement of regulations in different countries. Further, although the current currently available evidence generally suggests that application of IFRS improves the quality of accounting information, the adoption of IFRS might lead countries to abolish their own accounting standard boards and, consequently, lower the competition among the accounting standard boards (Ball, 2006). This is ultimately expected to lower the quality of accounting standards in the long run. Future studies may examine whether the adoption of IFRS enhances the comparability of accounting information across different countries and their long term impact on the quality of accounting information.

Chapter 4 examines and provides evidence about the effects of MAD on market manipulation activities, flow of information to the security markets and provision of selective disclosures. Among other objectives, the implementation of MAD is aimed at creating a single market in financial services and to facilitate cross border cooperation within EU. Future research might investigate whether these objectives have been achieved.

Samenvatting (Summary in Dutch)

Dit proefschrift onderzoekt de rol van kredietbeoordelaars in kapitaalmarkten en de effecten van twee nieuw van kracht zijnde belangrijke regelgeving die bedoeld zijn om de kwaliteit te verbeteren van de beschikbare informatie voor kapitaalmarkten en als gevolg daarvan hun integriteit. Dit proefschrift onderzoekt in het bijzonder a) het belang van kredietbeoordelaars voor de schuldmarkten en de mate waarin investeerders de kredietbeoordelingen vertrouwen van kredietbeoordelaars, b) of de adoptie van de International Financial Reporting Standards (IFRS) de kwaliteit van de financiële informatie heeft verbeterd in de Europese Unie (EU), en c) of de implementatie van de Market Abuse Directive (MAD) succesvol is geweest in het afschrikken van mogelijke overtreders van marktmanipulatie, in het reduceren van ongelijke informatieverstrekking aan verschillende stakeholders, en het verbeteren van de informatiestroom en de kwaliteit van de informatie aan de kapitaalmarkten.

Kredietbeoordelingen zijn de meningen van kredietbeoordelaars over de kredietwaardigheid van verscheidene soorten schuldbewijzen en staan erom bekend dat ze de keuzes van investeerders beïnvloeden, alsook de nieuwe regelgeving die beleidsmakers ontwikkelen. Door de jaren heen hebben kredietbeoordelaars echter met stevige kritiek te maken over hun integriteit, onafhankelijkheid, en over de nauwkeurigheid van hun informatie. De rol en info van kredietbeoordelaars werd alleen maar controversiëler door hun vermeende nalatigheid welke leidde tot de huidige financiële crisis. Hoofdstuk 2 laat zien dat te midden van deze controversies, investeerders niet alleen lijken te steunen op kredietbeoordelingen als bewijs voor het kredietrisico van een schuldbewijs. In plaats daarvan lijken ze zelf een analyse uit te voeren om een oordeel te vormen over de nauwkeurigheid van de kredietbeoordelingen. Dat wil zeggen, beleggers lijken te kijken of kredietbeoordelingen van kredietbeoordelaars overeenkomen met de verwachte kredietbeoordelingen op basis van openbaar beschikbare informatie en passen hun vereiste rendement daarop aan. De resultaten van het onderzoek laten zien dat nadat alle relevante factoren beheerst zijn, investeerders een hoger vereist rendement verlangen voor obligaties die een hoger dan verwachte kredietbeoordeling krijgen in vergelijking met obligaties die een kredietbeoordeling krijgen die overeenkomt met hun eigen verwachtingen. De resultaten van het onderzoek laten ook zien dat het verschil tussen de kredietbeoordelingen van kredietbeoordelaars en de eigen verwachte beoordeling, de informatiewaarde vermindert van de kredietbeoordelingen. Dit hoofdstuk schept ook licht op de premie die investeerders verlangen bij het splitsen van obligaties. De resultaten bevestigen de bevindingen uit eerdere onderzoeken die laten zien dat beleggers een premie verlangen, een zogenaamde opaciteit premie, bij het splitsen van obligaties. Echter, in tegenstelling tot eerdere onderzoeken laat dit hoofdstuk zien dat een deel van de opaciteit premie verdwijnt wanneer de kans dat de kredietbeoordelingen van de kredietbeoordelaars voor de gesplitste obligaties hoger is dan de verwachte eigen beoordeling op basis van openbaar beschikbare informatie. Hoofdstuk 3 onderzoekt of de introductie van

IFRS de kwaliteit van de financiële informatie in de EU heeft verbeterd. De overgang naar IFRS is een wereldwijde trend en een groot aantal landen vereist, of staat toe, dat ondernemingen hun jaarrekeningen opstellen in overeenstemming met IFRS. De omvang van de overgang naar IFRS roept de vraag op of er niet overgegaan moet worden van nationale accountingstandaarden naar IFRS om de nagestreefde doelen te bereiken. Veel recente onderzoeken proberen deze vraag te beantwoorden door te focusen op de aandelenmarkten, terwijl de ontwikkelingen op de schuldmarkten grotendeels worden genegeerd. Hoofdstuk 3 vult deze kloof in de literatuur door de kwaliteit van financiële informatie te onderzoeken en vergelijken bij toepassing van IFRS en andere nationale accountingstandaarden in de EU vanuit het perspectief van de kredietbeoordelaars, een belangrijke groep informatieverstrekkers voor de schuldmarkten. De gebruikte proxies voor de kwaliteit van de financiële informatie in dit hoofdstuk, zijn de hoogte van de verstrekte kredietbeoordelingen door kredietbeoordelaars en de mate en omvang van de verschillen tussen kredietbeoordelingen van verschillende kredietbeoordelaars. Het literatuuronderzoek in de bestaande literatuur laat zien dat beide proxies de mate van informatie assymetrie en onzekerheid weerspiegelen die bestaat in het kredietbeoordelingsproces. Deze zijn op hun beurt weer afhankelijk van de kwaliteit van de financiële informatie.

Op basis van de analyse van obligaties die uitgegeven zijn door Europese financiële instellingen tussen 1996 en 2008, onthullen de resultaten in hoofdstuk 3 dat obligaties die zijn uitgegeven door instellingen die IFRS toepassen, betere kredietbeoordelingen krijgen dan die zijn uitgegeven door andere instellingen. De resultaten in hoofdstuk 3 onthullen ook een afname van het aantal scheve kredietbeoordelingen nadat ondernemingen IFRS toepassen. Deze resultaten blijven robuust bij verschillende sample composities. Samenvattend laten de resultaten in hoofdstuk 3 zien dat het toepassen van IFRS de kwaliteit van de financiële informatie verbeterd doordat het voor kredietbeoordelaars makkelijker wordt de waarde van de activa en de financiële risico's te beoordelen.

Hoofdstuk 4 richt zich op een van de belangrijkste richtlijnen, MAD, die is afgekondigd in Europa met als doel de integriteit van de effectenmarkten te vergroten. Alhoewel beleidsmakers positief zijn over het succes van MAD (en anekdotisch bewijs hetzelfde suggereert), is er weinig emperisch bewijs beschikbaar om dit optimisme te ondersteunen. Hoofdstuk 4 concentreert zich op de 3 meest belangrijke bepalingen van deze richtlijn die ernaar streven a) marktmanipulatie activiteiten af te schrikken, b) gelijk binnen het bedrijf beschikbare informatie naar buiten toe te communiceren via openbaar toegangkelijke informatiekanalen, en c) niet toe te staan dat materiële informatie wordt verstrekt aan specifieke individuen zoals analisten. De resultaten geven sterke aanwijzingen dat de MAD bepalingen succesvol zijn. De resultaten in hoofdstuk 4 laten onder meer zien dat de volatiliteit van aandelenrendementen rond winstaankondigingen afneemt na toepassing van MAD. De bestaande literatuur laat zien dat een vermindering van marktmanipulatie activiteiten en het gelijk naar buiten toe communiceren van intern beschikbare informatie, de volatiliteit vermindert van aandelenkoersen. De resultaten laten verder zien dat aandelenkoersen nadat MAD van kracht is, dichter in de buurt blijven van de werkelijke waarden (de waarden volgend op winstaankondigingen) gedurende de periode voorafgaand aan de winstaankondigingen. Deze resultaten wijzen erop dat ondernemingen sneller nieuwe informatie verstrekken aan markten nadat de MAD richtlijn van kracht is geworden. Ten aanzien van dat MAD niet toestaat dat materiële informatie wordt verstrekt aan specifieke individuen zoals analisten, richt hoofdstuk 4 zich op de nauwkeurigheid en de spreiding van de prognoses van analysten. Hoofdstuk 4 levert aanwijzingen dat de nauwkeurigheid van de prognoses van analysten verbeterd en de spreiding van de prognoses vermindert sinds MAD van kracht is. Hoofdstuk 4 laat verder een afname zien van het gemiddelde aantal analysten dat een onderneming volgt. Een literatuuronderzoek over rapporten van analysten laat zien dat een beperking in het verstrekken van informatie aan specifieke individuen, ertoe leidt dat analysten minder afhankelijk worden van managers. Dit leidt vervolgens tot minder subjectiviteit in prognoses hetgeen leidt tot nauwkeurigere prognoses. Tot slot laat het literatuuronderzoek over rapporten van analysten zien dat analysten er de voorkeur aan geven om ondernemingen te volgen waarvan ze meer informatie krijgen dan anderen. De beperking hiervan als gevolg van MAD, leidt ertoe dat analysten zich richten op een kleiner aantal ondernemingen om zich te onderscheiden op basis van de nauwkeurigheid van hun prognoses. Op basis van deze bevindingen geven de resultaten in hoofdstuk 4 aanwijzingen dat er een afname is in het verstrekken van informatie aan specifieke individuen zoals analysten.

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Biography

Khurram Shahzad (1973) is an assistant professor in the Accounting Department of the Faculty of Economics and Business Administration, Vrije University Amsterdam. He received his Masters in Philosophy (M.Phil.) in Business Research from the Rotterdam School of Management, Erasmus University in 2008. Earlier, he obtained his professional degree in accounting from Association of Chartered Certified of United Kingdom (ACCA) in 2001. After completing his ACCA, he started his career in a chartered accountant firm. He stayed there for more than three years and worked on several internal and external audits as well as consultancy assignments. Later, he joined COMSATS institute of information technology in Lahore, Pakistan to pursue a career in academia. In 2006, he moved to the Netherlands in pursuit of his Ph.D. and joined Erasmus Research Institute in Management (ERIM) as a Ph.D. candidate. His research interests are in the area of credit rating agencies with a particular focus on the issues that influence investors' trust on credit rating information and the factors that are pertinent to the accuracy of credit ratings. He has presented his work at several conferences, such as the Australasian Finance and Banking Conference and the European Accounting Association Congresses. During the course of his Ph.D., he taught several courses at the Rotterdam School of Management, Erasmus University, Rotterdam. He also supervised numerous graduate and undergraduate student theses.

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CREDIT RATING AGENCIES, FINANCIAL REGULATIONS AND THE CAPITAL MARKETS

This thesis studies the role of credit rating agencies (CRAs) in capital markets, and the effects of two important regulatory decisions that are taken to improve the quality of information available to the capital markets. In particular, this thesis examines a) the importance of credit ratings to the debt markets and the level of trust investors place on CRAs b) whether the adoption of International Financial Reporting Standards (IFRS) improves the quality of accounting information in European Union, and c) whether implementation of Market Abuse Directive (MAD) has been successful in deterring the market manipulation activities, improving the quality and flow of information to the capital markets, and reducing selective disclosure of private information. Chapter 2 of this thesis shows that the extent of investors' reliance on the credit ratings depends on whether or not these ratings correspond to the ratings that are expected based on publically available information. Chapter 3 demonstrates that the reporting under IFRS is associated with higher credit ratings and a lower probability and level of rating disagreements between CRAs. The results in Chapter 4 reveal a decrease in the level of market manipulation activities and the provision of selective disclosures subsequent to the implementation of MAD. Chapter 4 also provides evidence of more timely and accurate information flowing to the security markets after implementation of MAD. Overall the findings in this thesis show that the participants in the capital markets prefer credit ratings that have strong association with the publically available information and that financial regulations introduced during the last decade enhanced the quantity and quality of information available to the capital markets.

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