Credit Rating Impact on Information Environment
A study on the informational impact of credit ratings in financial markets using equity analysts’ performance as proxy.

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Abstract

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Title: Credit Rating Impact on Information Environment – A study on the informational impact of credit ratings in financial markets using equity analysts’ performance as proxy.

Introduction: The credit rating agencies provide risk assessment for a massive amount of financial assets around the world. These risk assessments are in turn used by numerous different market participants. The general idea behind this industry is that the credit ratings provide additional information or alternatively increase the quality of information in financial markets. Recent studies (most of which is written after the financial crisis of 2008) argue that there are several issues in the rating processes leading to failure to provide accurate ratings. Other studies still claim that credit rating agencies still provide useful information or alternatively increase the quality of information by sorting and ranking public knowledge of assets. We see the need for an investigating study examining the informational benefits of credit rating in the information environment of markets.

Research Approach: How does the issuing of credit ratings impact the information environment in financial markets?

Purpose: The study aims to contribute to the understanding of the current and historical effects that credit ratings have, and have had, on the information quality of markets and hence the efficiency of markets.

Method: Our study takes a deductive research approach where the methodology is one of a quantitative and explanatory character. To analyze the effects on market information we use the BKLS model (Barron, Kim, Lim & Stevens, 1998), which uses equity analysts’ performance as proxy for the information environment. These data are then used in a long-term time-series study looking for long-term changes in analysts’ performance with yearly observations. Furthermore we test the instant market effects on stock prices from the issuing of a credit rating in a secondary short-term time-series study with daily observations.

Conclusions: We find that the issuing of a credit rating in fact decreases the amount/quality of information available in financial markets (both public and private information). We contribute these effects to conflicts of interest in the rating processes and agency problems in the relationship between issuer and credit rating agency. Several practical examples of this are found such as ratings shopping, solicitation of ratings issuing, agencies offering consultant services and the lack of regulatory measures taken by regulators such as ESMA and SEC. We propose several ways of developing the research in this field; most importantly we want to see future studies on the differences between solicited/unsolicited issuing of ratings.
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Chapter 1: Introduction

In this first chapter we introduce the background of our study by briefly explaining the credit rating industry and the criticism that has been directed at credit rating agencies in recent years. We then move on to discussing the research problem and the need for this type of study with basis in recent theoretical work in the field of information environment and credit rating industry. Finally, we produce our research approach and the theoretical and practical contributions that we hope to make.

1.1 Background

The credit rating agency (henceforth; CRA) issues publicly available ratings, ranking the default risk of a wide variety of assets (bonds, default swaps, firms, municipalities, countries, etc.). The industry is largely dominated by three major actors; Moody’s, Standard & Poor’s and Fitch Ratings making up 95 percent of the ratings market. Where Moody’s and S&P are undoubtedly the larger agencies (SEC, 2012). The rating being issued provides information about the risk level of assets to market participants such as credit issuers (e.g. commercial banks), investors and equity analysts. The credit issuers are logically interested in the assets’ ability to pay back debt. However, when discussing the investor’s and equity analyst’s use of credit ratings one would refer to its assessment of overall risk level in the asset. This means that CRAs have a bigger role to play than just providing information to creditors about the ability of assets to pay back debt. Hence, CRAs are tasked to provide market information that implicates all parties in a financial market. The question that needs to be put is; how accurate is this information?

In mid-2008 the financial market in the United States started to collapse. The period that followed has been called the greatest financial crisis in global modern history. Several different factors have been discussed globally as to what caused the crisis - the CRAs activities are among them (Lewis, 2010). In short, the rating industry kept investment grade ratings (i.e. highest range of ratings) on several highly criticized assets in the financial markets up until days before the collapse - when these assets suddenly went from being AAA (highest) rated to junk bond (lowest) status (e.g. FHLMC’s (Freddie Mac) preferred stock). The ratings issued during this period have been said to provide little or no information of value (Lippert, 2010) - and still market participants all over the globe traded on this information.
The industry is under minimal supervision and the regulation concerning their rating processes can be described as very lenient in aspects such as transparency and consistency (Rousseau, 2006; Griffin & Tang, 2012). Taking into account the immense effect that credit ratings have on the financial markets and the systematic risk of society (Abad & Robles, 2014) the industry's self-regulatory characteristics could be considered irresponsible. In the wake of the massive failure of CRAs during the period of the financial crisis the informational aspects of the credit rating warrants extensive research and discussion. Does the credit rating provide additional information or increase information quality to the market? This is where we find motivation for our study and where we hope to contribute with empirical input.

1.2 Research Problem

An efficient market rests on the idea that information reaches out to the “many” and is widely available. The financial market should reflect a market place where the prices are a representation of all available information – with emphasis on ‘should’. The efficient market hypothesis created by Eugene Fama (1970) states that a financial market can have three different forms; weak form, where market prices reflects all fundamental information, semi- strong form, where the market reflects all available public information and strong form where all available information including both public and private, are at the hands of the investors and the entire market. This is interesting to note because of the underlying assumptions of the efficient market hypothesis stating that a single investor, in a strong form market, would not be able to beat the overall market over a long period of time, since all information is available to the entire market and to all market participants. This because one market participant does not possess more information than the next. However the hypothesis of the strong efficient market has withstood a certain amount of critique since its implementation in the 1970s. It can be argued that it is possible to beat the market over time, as shown in investors such as Warren Buffet’s extraordinary return on his investments (Loomis, 2012), implying that one can continuously get a return from private information and that the market in fact does not reflect all possible information.

Other than the example of Buffet, there are several anomalies regarding the efficient market hypothesis that contradicts Fama’s (1970) original theory of a strong market (Naseer & Tariq, 2015) and suggests that the market is more likely of the semi-strong or weak form. One of the more famous anomalies is the January effect, which exhibits how there is an extraordinary increase in stock prices in January. This increase can be contributed mostly to investors selling
stocks in December for tax purposes and repurchasing the stocks in January (Haugen & Jorion, 1996). Furthermore, there are anomalies connected to the calendar such as, Monday return and “around holidays return” (Naseer & Tariq, 2015), that display effects similar to the January effect. Moreover we have the paradigm of *behavioral finance* that describes how psychology is a part of investor decisions such as overconfidence, herding behavior and over/under reactions, which contradicts the efficient market theory of rational decisions across the market (Naseer & Tariq, 2015; Shiller, 1995; Ramiah, Xu & Moosa, 2015).

Considering the empirical evidence and the number of anomalies contradicting the efficient market hypothesis it is important to examine how information functions in financial markets as well as who is providing the information. One of the many providers, or handlers, of information in the market are the CRAs. They act as *information intermediaries* handling what we can call raw data from the firm with the prospect of turning it into more easily obtainable information for the market participants. Estrella (2000) describes the CRA as an intermediary working to decrease the information asymmetry between the rating issuer and its stakeholders. In other words, this means that the CRA’s purpose is to increase the amount of information or quality of information available in the market.

There have been numerous studies regarding credit ratings and their role as information intermediaries in the market (Brennan, Hein, & Poon, 2009; Coval, Jurek, & Stafford, 2009; Crouhy, Jarrow, & Turnbull, 2008). Prior to the financial crisis of 2007 the CRA’s rating were regarded to fulfill their purpose as information intermediaries (Oderda, Dacorogna, & Ljung, 2003), assuring investors that the rating issued reflected the actual default risk of the financial product, company or country. In short, they were perceived to increase the quality of information in the market (Rhee, 2015). However, in the aftermath of the financial crisis it was revealed that they had a more villainous role in the downfall of the financial system (Wojtowicz, 2014). Specifically, the CRAs used their reputation to issue good ratings to sub-par financial products, thus encouraging trusting investors to invest in financial products with biased credit ratings (Wojtowicz, 2014).

The Securities and Exchange Commission (SEC) reported the following statement from an email conversation with a credit rating analyst in 2007 exemplifying the total disregard for their market function at the time;
The CRAs in this period can be said to have created false information to some extent and thereby decreasing the quality of information in the market. Bolton, Freixas and Shapiro (2012) observe a phenomenon where multiple CRAs on a market decrease the efficiency of information. The study showcases how an issuer pins two CRAs against each other in order to receive a better rating. A duopoly of CRAs would therefore have a diminishing effect on efficiency. Demitras and Cornaggia (2013) discuss a further problem with credit ratings. Their study focuses on how companies use earnings management in order to manipulate the credit rating received by CRAs. By deferring cost to a later period and rushing income statements a company would be able to receive a better credit rating, which in turn creates a comparative advantage for the firm (Demitras & Cornaggia, 2013). Demitras and Cornaggia’s (2013) results point toward certain stickiness in the credit rating. The initial credit rating tends to stick to the firm even though the company, in the period after the initial credit rating, will produce a result burdened by the earlier accruals (Demitras and Cornaggia, 2013).

A question to be asked is how the CRAs actually contribute to information in the market place. Both the study by Bolton et al (2012) and Demitras and Cornaggia (2013) raise questions regarding the integrity of CRAs and the effect they have on information. A study produced by Rhee (2015) discusses why CRAs even exist. CRAs, as mentioned, was one of the villains in the financial crisis where they used their reputation to inflate the ratings of stocks, and famously also of sub-par bonds (eg sub-prime-loan crisis). Despite the recent criticism Rhee (2015) believes that the credit rating agencies have a role to play in the market place. He points toward the immense cost that would be inquired by analysts and investors if they had to do due diligence on every single investment that they have a stake in. The CRAs are able to apply a standardized model for rating the firm’s default risk in a more effective way. Rhee (2015) continues to discuss how although CRAs deliver a vital ingredient in the information environment of the market, they do not actually create any new information but rather sort already existing information into a credit rating (Rhee, 2015). This information produces a default risk report and is then used by investors and by equity analysts to produce their earnings forecasts etc. This further suggests that CRAs in fact has a role to play in keeping the market efficient, providing to the stakeholders a judgment on a large number of hard to access parameters from each issuer. Thus enabling stakeholders such as equity analysts to focus their
attention towards the gathering of other information. Duarte, Han, Harford and Young (2008) confirm that CRAs and credit ratings in fact work as information distributors and that firms having been issued a credit rating have more information disseminating to the public than that of a firm without a credit rating.

Mei and Subramanyam (2008) then find, in their study, a strong relationship between equity analyst coverage and CRA coverage. Credit rating issuing and the increased CRA coverage correlates negatively with the following of equity analysts. This indicates that the analyst in fact does rely on CRA data in his/her forecasting. Their findings (Mei & Subramanyam, 2008) possibly also suggests that the credit rating works as a substitute in some ways to the analyst’s own credit risk rating. This could mean that the proportions of public and private information on the market are distorted. To elaborate on this, it is possible that the information available to the public actors is unchanged or increased with further CRA coverage while the proportion of private information available to the analyst’s decreases relative to the public. Furthermore, Lui, Markov and Tamayo (2012) find the equity analyst’s own risk ratings to be more powerful than that of the CRA, further criticizing the reliability of the credit rating. If then the credit rating, in the way that Bolton et al (2012) and Demitras and Cornaggia (2013) proclaims, contains bias, the analysts data and forecasting relying on credit ratings would also be contaminated. The structure of this relationship and the quality of CRA reports would thereby determine the overall information quality of the market - both public and private information. These studies and others such as (Griffin & Tang, 2012; Lynch, 2009) contain specific findings that would incriminate the credit rating as a provider of information. Still, CRA reports are an integral part of the market and society today (Bolton, Freixas & Shapiro, 2012) and still serves a purpose (Rhee, 2015). Further, Robert S. Hansen (2015) provides additional evidence to the efficiency benefits of functioning information intermediaries on the market. His study suggests that intermediaries possess the resources to decrease information asymmetries as well as providing additional information. Him suggesting that new information could be delivered to markets with the initial analyst coverage of firms somewhat contradicts Rhee’s (2015) claim that CRAs merely sort and rank information. The contrasting paradigms of critique against and the proclaimed necessity of CRAs and credit ratings lead us to a question of whether the credit rating of a firm actually provides additional information to the market. Although earlier studies has merely called for minor reformations to address the faults of CRAs and the field actually seems to be in consensus surrounding the necessity of CRAs, the effectiveness of the agencies and the rating as an information provider stands to be tested. This research approach is in
accordance to what Schipper called for in her article from 1991 and still we cannot find substantial research in the area of credit ratings as an input to the information environment of markets (Schipper, 1991).

Furthermore, according to the assumption of the semi-strong form of EMH, the market consists of public information that’s available to everyone, while it also contains market participants gathering its own private information (Naseer & Tariq, 2015). These actors would in our case be the equity analysts. Thus, the private information is only available to them and creates a valuable product for analysts to market. To better understand the informational effects of the credit rating of a firm one would have to test the outcome of public and private information. The general assumption that CRAs increase public information might also indicate that it decreases private information or diminishes the share of private information relative the total information in the market. Mei and Subramanyam (2008) find that there are fewer analysts covering firms with better credit rating coverage. This would lead us to believe that the two are in fact substitutes. The question that arises is if equity analysts then shifts focus (coverage) to other firms with less CRA coverage to increase their private information? Or to at least keep the current ratio of private information relative total information held by equity analysts? If this is the case, and the private information stays the same, the total information available on the market would be assumed to increase following the issuing of a credit rating.

Previous tests on information environment have been conducted using multiple models some of which uses analysts’ earnings forecast as proxy (Sheng & Thevenot, 2012). Barron, Kim, Lim and Stevens (1998) proposed the use of the BKLS model, named after and created by Barron, Kim, Lim and Stevens, to test effects on the informational environment in markets. The authors suggest that the effect of accounting information and events within the accounting regulatory space on the information environment can be empirically tested using analysts’ forecasting accuracy and dispersion. Later studies based on this idea have studied a range of events, meta regulation and the effect of market structures (Sheng & Thevenot, 2012; von Koch, Nilsson & Jönsson, 2015; Kim & Shi, 2012). Yet to be tested in this manner is the effect of credit rating issuing and whether it provides additional private and public information, and in general increases the market information quality. The contrasting hypothesis would be that, in accordance with Rhee (2015), they do not provide any new information but rather sort the already existing information. If the latter hypothesis is accepted then questions arise as to whether the information in place is altered in respect to the relative share of private and public
information. Should the public information increase relative to the private information, as discussed earlier, this would still be an indication of credit ratings in fact creating more effective markets according to the effective market hypothesis (EMH) (Naseer & Tariq, 2015).

Furthermore, the effects of initial analyst coverage of a firm can be analyzed in other ways than examining the changes in public and private information. Li and You (2015) studies the effects of initial coverage and termination of coverage from equity analysts and their role as information intermediaries (as compared to our studies stance of analyzing credit rating analysts as information intermediaries). Their study provides no evidence of analysts providing any reducing effects on information asymmetry in the information environment. However, they find that the coverage of a firm introduces investor recognition effects on the firm and thereby increases the firm value, as well as finding that termination of coverage has a negative effect on firm value. Demiroglu and Ryngaert (2010) further finds evidence that the equity analyst coverage of a firm provides an investor reaction to market trade. The stock becomes more liquid as well as returns abnormally positive returns upon the announcement of coverage (Demiroglu & Ryngaert, 2010). With these findings on initial equity analyst coverage we motivate a similar examination of initial credit rating analyst coverage of a firm. Hence, in addition to analyzing the more long-term effects on information environment and public/private available information, an analysis of the direct market effects on initial coverage is warranted to more fully grasp the value of CRAs.

To summarize, there has been several studies criticizing the effectiveness of CRAs performance, pinpointing bias in their reports and hazardous behavior that can in fact damage the market participants (Bolton et al, 2012; Demitras and Cornaggia, 2013; Rhee, 2015; Lynch, 2009). These studies are more frequent after the collapse of the financial markets in 2008-2009 where CRAs played a suggested villainous role in misleading investors (Griffin & Tang, 2012). Setting aside the behavior of the credit rating analysts, previous studies all seem to accept the CRAs as an integral part of today’s financial markets with respect to their positive contribution to information environment (Rhee, 2015; Hansen, 2015). What remains to be seen is whether this effect, that the CRAs present, actually increases market information, or whether it merely shifts the balance of power between private and public information. With the help of the BKLS model (Barron, Kim, Lim and Stevens, 1998) we will, in this study, examine the effect to determine the role of CRAs in information environment of markets or alternatively specify its contribution to market efficiency by using equity analyst performance as proxy. In addition to
this, the study will also examine the instant market effects on initial credit rating analyst coverage, in a similar fashion to that of how equity analysts previously have been studied (Li & You, 2015; Demiroglu & Ryngaert, 2010).

This leads us to our somewhat dual research approach;

*How does the issuing of credit ratings affect the public and private information available in markets? And how does the initial credit rating affect market stock prices?*

**1.3 Contribution**

The following study provides additional insight in the relationship between the credit rating issuing and the information environment. Previous, similar studies in the field of information intermediaries have focused on the equity analyst as a provider of information (Hansen, 2015; Li & You, 2015). Specifically, the sell-side equity analyst has been the main focus in these studies (Li & You, 2015). Hansen (2015) calls for the need for similar research being done on other information intermediaries on the market, such as credit rating analysts. Since the financial crisis of 2008-2009 the CRAs market function has been under pressure and regulatory actions has been developed in some instances (ESMA, 2013; SEC, 2010). In further researching the credit rating function and increasing public knowledge of credit rating potential and limitations we decrease the systematic risk in society (Abad & Robles, 2014). Since bad ratings as well as badly understood ratings increase the systematic risk (Abad & Robles, 2014), with evidence in the sub-prime-loan crisis of 2008, further understanding of the rating process and its consequences is vital for the further efficient development of the industry.

Furthermore, giving the market participants increased insight in the informational benefits of the credit rating will potentially provide better precision in market activities such as earnings forecasting and investing. This in turn will lead to more efficient markets, where asset pricing is more precise. Other practical contributions that our study hope to make pertains to the regulatory aspect of the industry, where our results can give decision makers further information about the processes of credit rating. These practical contributions to market participants and decision makers in the regulatory space of credit rating industry aim to aid in the progress of improving the information environment and making financial markets more efficient.
1.4 Disposition

- **Theoretical Method**: In chapter two we describe the theoretical approach to our study and the research methodology we undertake.

- **Theoretical Framework**: The third chapter covers the framework of studies and theories that make up the basis of our study's hypotheses and analysis.

- **Empirical Method**: The fourth chapter describes the methodological course of our study covering the practical methods and data management.

- **Results**: The fifth chapter presents the empirical results of our hypotheses testing and robustness test.

- **Analysis and Discussion**: In chapter six we analyze the empirical results and discuss our findings with basis in the studies of our theoretical framework.

- **Conclusion**: The seventh chapter presents the conclusions from our research and the theoretical and practical implications of our study.

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**Chapter 2: Theoretical Method**

In this chapter we explain the methodology behind the study. Initially, the theoretical approaches and assumptions that constitute the basis for our study are explained after which the research methodology is covered. Finally, a walkthrough of the data collection and the incorporation of theories are made.

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### 2.1 Theoretical outset

The following study will rely on neoclassical economic theories such as the **efficient market hypothesis** (EMH) and **agency theory** as well as the more recent field of **information**
environment to explain the different elements of our results. The efficiency of the market, famously discussed in Fama’s (1970) study will act as a basis for the study’s underlying assumption of information as a parameter of market efficiency. EMH and its relation to information environment contain the main motivation of studying the factors of information production in the market and their effect on market efficiency. Furthermore, Jensen and Meckling’s (1976) development of the field of agency theory and information asymmetry is the second theoretical pillar of the study. It provides an understanding of our studied market participants, most importantly the CRAs, and enables the analysis of their relationship with issuer firms, equity analysts and investors. Finally, the information environment in the market becomes central for our study and demands a thorough analysis of existing theoretical framework within the field, which is closely related to the EMH. This review will include theories connected to the factors of information quality as well as the separation of private and public information. Studies of known factor and providers of information will be briefly analyzed in order to fully explore the focal factor, which is the credit rating, as a potential provider of market information. The categorization of public and private information will enable the study and analysis of more specific effects of the credit rating issuing. The BKLS model (Barron et al, 1998) will allow the effect on private/public information and its share of the total information to be analyzed - rather than just the question of “more or less” (or unchanged) available total information. In the empirical method the study will present a brief introduction to the model of BKLS (Barron et al, 1998) its parameters and definitions as well as the actual application in our study and its potential contribution to our results. In summary, the theories that carries this study is based on research made in the aftermath of the efficient market hypothesis (Fama, 1970), a short range of studies on agency theory as well as research on information environment.

Furthermore, studies on the relationship between the CRA, the credit rating and the equity analyst’s performance will need further introduction. The research that can be found on the subject today relates mostly to either 1) analyst behaviour and attention to credit rating as a part of his/her routine, 2) to the general effect on stock price predictions following a credit rating issuing or 3) the general effect of biased credit ratings. The former contributes more to the behavioral, or psychological, approach to understanding the equity analyst and not focusing entirely on the credit rating (Lui et al, 2012; Mei & Subramanyam, 2008). The credit rating effect on stock prices focus on market movement and investor behavior. These studies often contain a high degree of behavioral finance and attention to investor/CRA relationships.
(Poornima, Umesh & Reddy, 2015). The last portion of studies that we come across, is in the field of public finance, which tries to explain the possible outcomes of biased credit ratings and the societal costs of certain traits within the field of credit rating issuing (Goel & Thakor, 2015; Ferguson, Barrese & Levy, 1998). Few previous studies focus on the informational aspect of the credit rating effect and its actual contribution to the efficiency parameters of the market: private and public information and information quality. Here is where we found the purpose of this study. The above theories and the discussed studies will be reviewed in the theoretical framework of this study after which a discussion of the linkage between CRAs and information environment will be conducted.

One must also, before going any further, realize that there are several different efficiency parameters of the market, and the opinions on which is the best possible measure is widely disputed and the debate often also contains a political aspect. With this study, we do not assume that information quality and the way in which we proxy the level of efficiency (equity analysts performance) in the market is the correct, or best, one. We do however proclaim, in accordance with Sheng and Thevenot, (2012), that the efficiency of the market can be measured in information quality and hence the equity analyst’s forecast accuracy and dispersion.

2.2 Research Approach
The main practical goal of the study is to determine the effects in analyst forecast accuracy as function of credit rating issuing. The theoretical background of our research approach leaves us to believe that there is a certain type of correlation between our two variables; credit rating issuing and equity analysts accuracy. Expecting this certain correlation, or lack of correlation, gives the study a deductive character. Meaning, we are aiming to test our hypothesis based on pre-existing theories concerning our proposed correlation. Since we are not trying to explore an area of the field in an exploratory study or construct any new theories in this particular study, the inductive research strategy will not be applied. The inductive strategy can give other researchers the chance to explore the actual relationships of equity analysts and the credit rating, and from there construct a hypothesis or theory. Our study however has the purpose of testing whether our relationship has a proposed character or not, making us inclined to apply a deductive strategy. This choice of approach based on the discussed parameters is in accordance to Bryman and Bell’s (2005) recommendations on research methodology.
The empirical result of the study is meant to generalize the current effect of the credit rating issuing. This, together with the deductive research approach, will demand a quantitative data analysis since our data needs to contain several observations that are quantifiable and the study needs the be able to draw general conclusions of the results. Using a qualitative research method would diminish the possibility to draw general conclusions regarding the CRAs and their effect on information and the data would be more difficult to quantify (Bryman & Bell, 2005). We see possibilities in the qualitative research approach, since it would enable a deeper and richer understanding of the importance or the perceived importance of the credit rating issuing. For example, interviewing analysts regarding how they perceive CRAs and the issued ratings could enhance the understanding of CRAs’ and credit ratings’ impact on analysts’ everyday work and perceived performance.

The combination of deductive and quantitative research method affects our choice of epistemological approach. This study will have a positivistic research approach due to it being a deductive and quantitative study, both being connected to the view of positivism. The positivistic approach demand an objective point of view, where the researchers own opinion does not affect the results (Bryman & Bell, 2005). Furthermore, our theoretical framework, which is largely based on the famous theoretical work of Fama (1970), Jensen (1978) and Jensen and Meckling (1976), demand that we apply the same positivistic and opportunistic view of the market participants that they have applied.

2.3 Research Methodology

The main goal of our deductive study is hence to analyze the effects of credit rating issuing in an information environment. Mainly, and more precisely, we will test the effects of credit rating issuing on equity analysts’ forecast accuracy and dispersion. This will, first and foremost, require data on credit rating issuing and on forecast accuracy and forecast dispersion. Our main research focus and goal of the study infers some statistical boundaries on us. To be able to generalize our results in any way, the statistical tests need a certain amount of sample observations in order to extrapolate the results to a general population. One, two, or indeed 20 companies would not allow us to generalize the results of our study and the conclusion of our research could only be regarded as an untested hypothesis. Therefore, a larger amount of observations needs to be made. A quantitative research methodology is according to Bryman and Bell (2005) associated with larger quantities of data and suits its purposes well. Our
deductive approach to our problem also plays a role in the choosing of a quantitative study. Having a predetermined hypothesis that according to our problem discussion needs to be tested and analyzed exhibits the characteristics of a deductive strategy (Bryman and Bell, 2005), as mentioned earlier.

The problem discussion set the parameters of the research approach (Jacobsen, 2002). Discussing an explanatory problem will dictate the approach towards a quantitative study, while the descriptive problem discussions more often lead to a qualitative approach (Jacobsen, 2002). In our study, we discuss a problem of uncertainty in the relationship of credit rating issuing and the market information as well as its effect on market movement. The problem exhibits a certain degree of uncertainty in the characteristics of a specific relationship, which requires testing to be clarified. Therefore, our problem discussion is of a clarifying or explanatory character and our research will therefore also have a quantitative approach.

However, if a qualitative approach were to be used as strategy researchers could take advantage of its exploratory properties. The results of such studies could describe in detail the relationship between the equity analyst, the analyst’s forecasting and the use of a credit rating. Moreover, it could lead to the development of new hypotheses of the relationship describing new parameters in the CRA/equity analyst interaction. These types demand a descriptive problem discussion and an exploratory approach, which most often benefits from the qualitative research strategy (Jacobsen, 2002). Furthermore, a qualitative study often entails elements where researchers bias is an issue (Jacobsen, 2002). Examples of this are where the researchers should try to pick an objectively chosen sample of observations but fails, or where researchers own preferences and opinions cloud the data collecting in interviews or surveys.

Our study, however, uses a predetermined explanatory problem as motivation for the research, we set out to generalize the results and we aim to stay clear of researchers bias in the sampling and in the collecting of data.

2.4 Collection of Studies and Theories

In order to produce a study with relevant information, studies on our subject have to be reviewed and used. By using the university's search engine OneSearch we have managed to sufficiently gather and develop our theories. We used search words such as: Financial crisis, Information Environment, Credit ratings, CDO, Initial Credit Rating, Equity Analyst Performance, Credit
Rating Effect on Information, Efficient Market Hypothesis, EMH Anomalies, Agency Theory Review, Credit Rating Agencies and Herding Behavior, most of which were used in different combinations in order to generate results that are applicable to our research. The studies generated helped us create a wide understanding of factors that affect the market, market information and other impacts of CRAs. Neoclassical economic theories produced by Fama (1970) and Jensen (1978) lay the groundwork for our thesis.

The neoclassical theory, which the study mainly stands upon, is the efficient market hypothesis, EMH, which was created by Fama (1970) and later further reviewed by Jensen (1978). The EMH, though criticized in practical application, is widely accepted as a theory and has been tested in several different markets in order to be validated. Many of the studies gathered from OneSearch are based on the assumptions of the EMH. Therefore it is important to understand the implications of the EMH.

The theories and articles used in our study are mostly gathered from scientific studies that are Peer reviewed which indicates a high level of reliability and validity since they are reviewed by scientist in the same field as the study concerns. Most of the studies are published in the esteemed Journal of finance or equivalent to it regarding the field it pertains to. Therefore we feel confident in basing our hypothesis and analysis on information provided in the studies gathered. There is however a working paper used in our study. Estrella’s (2000) working paper is issued by the Bank for International Settlements (BIS), and is used to discuss CRAs. We find Estrella’s (2000) article to be relevant to our problem discussion as well as valid regarding it being archived at the Bank for International Settlements.

To maintain an objective point of view in accordance to our positivistic outset, it is important to understand the implications we face with the studies used. Some studies might focus their attention towards the Anglo-Saxon countries and therefore suggests conclusions that cannot be applied to every company in our sample. We need to understand that our results may see different effects depending on, for instance, which country a company is based. The main theory, EMH, for example was conducted on Anglo-Saxon countries, but has been tested on several other markets to validate its results. Controlling for all such effects will demand resources not available to the study at present time.
Chapter 3: Theoretical Framework

In this chapter we thoroughly examine the theoretical framework from which we draw the base of our hypotheses as well as support our findings. We start out by explaining the classical underlying economic theories to our study and move on to discuss more recent studies on information environment, credit rating issuing and equity analyst performance. The chapter ends with the formulating of our hypotheses.

3.1 The Efficient Market Hypothesis and Information Environment

Our study relies on the neoclassical economic theories developed by Fama in 1970 and later on by Jensen and Meckling (1976) and Jensen (1978). These theories suggest that an investor as well as an equity analyst makes rational decisions based on all available information on the market. The rationality of the market participant is an assumed characteristic and a necessity for the efficient market hypothesis (Fama, 1970) to be accepted. The EMH and its neoclassical assumptions of the rational market participants have been widely criticized in studies of its anomalies. Some of which contrastingly points to the irrationality of the market participants in the over- and under reactions to market information (Thaler, 1992). More specifically, phenomenon’s such as the January effect and Monday returns (Naseer & Tariq, 2015) as well as the paradigm of behavioral finance (Shiller, 1995) all contradicts the explanatory grade of the EMH. Although massive criticism towards the EMH, it is still regarded as useful in theoretical work and research. Elton, Gruber, Brown and Goetzmann (2014) explain the usefulness of models such as EMH even though proven wrong (or not completely true) by practical evidence. The authors compare it, in an example, to a physicist’s experimentation of movement in a frictionless environment. Just as the physicist shuts out the surrounding world to test his one parameter of movement, the economist does not always take into account anomalies, such as the ones mentioned earlier, when formulating and testing his/her hypotheses (Elton et al, 2014). Even though it may not be a complete description of the actual market mechanics, the EMH and Eugene Fama’s work has contributed to how we define an efficient market. In this study, the anomalies of the EMH will be discarded in some sense and the theory (EMH) will be used to try and explain efficiency and the information environment of the market.

In the theories surrounding the EMH, efficiency is largely dependent on what we call information environment. Since, information is a major determinant of how efficient an
investment decision will be, it therefore determines the degree of efficiency in markets. An efficient market is defined as one where price levels reflect all available information (Fama, 1970) and the price is an estimate of the true value of an asset, without any bias. Thus, for the price levels to be unbiased and “true”, the underlying information needs to be both unbiased and accessible to the investor. In summary, the characteristics of the information made available to the market participants, henceforth; information environment is central to the efficiency of the market.

Other definitions of information environment have been constructed in later research. Wang Zhou and Chen (2011) write about information environment as a product of market efficiency: “market efficiency describes the degree to which available information is swiftly and accurately translated into stock prices” (p. 164). A few years later Clinton, White and Woidtke (2014) refers to information environment, with a somewhat broader definition, as the complete relationship between stock prices and available information.

Beyer, Cohen, Lys and Walther (2010) claim accounting information and the corporate information environment is key to understanding the decision making in capital markets. As a primary provider of information to the market they name corporate accounting and reporting. This is an area that is becoming increasingly regulated and controlled by national and international regulation (so called meta regulation, e.g. IFRS) in order to secure effective markets. However, Beyer et al (2010) point towards the information intermediaries, such as analysts and CRAs, as other important providers of information. These market participants act under relatively minimal regulation compared to firms. Beyer et al (2010) take securities analysts as an example of an intermediary and try to explain the function of the analyst in the information environment of the market. In their article they call for further research in the area of information environment and the interaction between the participants of the market and the information intermediaries (Beyer et al, 2010). Lee (2012) elaborates on the relationship between information providers and market participants; stating that even when information is considered available it might not provide any additional insight to the market participant if not properly constructed (Lee, 2012). His study focuses on the readability of reports, but could be translated into other parameters of available information. These ideas turn the scope towards the providers of information, the information intermediaries and how they operate to effectively provide market participants with additional insight, in the form of unbiased and readable information.
In summary; the relatively recent arrival of the concept of information environment in markets calls for researchers in the field to study the relationships between participants in the market with respect to the exchange of information. Moreover, current studies assume that these relationships directly affect the efficiency of the market, motivating its further research.

3.2 Agency Theory
When talking about information environment and the relationships between market participants the theory of agency needs to be incorporated in the discussion. Through the contract theory studies in the 60s and 70s, agency theory was developed as a branch of studies (Eisenhardt, 1989). Jensen and Meckling’s (1976) study further develops theories about information asymmetries that emerge between agent and principal - which is the base pillar of agency theory. Researchers within the field view information as a purchasable commodity in accordance to how we have previously discussed it. The two main categorizations of problems in the trade of information between agent and principal is the issue of (1) moral hazard and (2) adverse selection. Moral hazard commonly refers to the agent taking advantage of information given as a result of a contract being constructed. To elaborate, if the agent uses information given after the contract has been signed to benefit himself at the expense of the principal this situation is characterized by what’s known as moral hazard. Jensen and Meckling (1976) use the form manager and the owner as a typical example of a hazardous relationship. The second information asymmetry; adverse selection refers to pre-contract information being used by one part to take advantage of the other, who is lacking the same information (Eisenhardt, 1989). This can be explained with the example of an agent who deliberately withholds vital information from the principal prior to signing a contract (Jensen & Meckling, 1976). What these two information asymmetries rely on is the positivistic and opportunistic nature of humans (Eisenhardt, 1989). This view of human nature is commonly applied in economic theory and something that demands being addressed in the study of information intermediaries and their relationships with other market participants.

3.3 Credit Rating Issuing
The CRAs are one of the major information intermediaries active in the market place. By sorting existing information into a single variable, they are able to create a rating system, which indicates the default risk, and enable market participants to compare investments based on a single variable (Rhee, 2015; Demirtas & Cornaggia, 2013). At the same time as CRAs issuing
of a rating benefit the market participants it is more often than not commissioned by the company, country or bond being rated (Lynch, 2009). Further, the main source of revenue from CRAs are created from rating bonds, companies, countries etc., creating a conflict of interest since they are hired to act as information intermediaries in what could be described as a principal-agent relationship (Bolton et al, 2012). Lynch (2009) discusses this conflict further in his study where he discusses the implications of CRAs reputation on the regulatory framework, which they are surrounded by. He points toward the problem with CRAs using a self-regulatory approach, where only the risk of failure will keep them unbiased and in check. Lynch (2009) means that the conflict of interest impairs the CRAs ability to stay unbiased in their ratings.

The studies by Bolton et al (2012) and Lynch (2009) touches the subject of information asymmetry, were as there is skewness in the information available between the market participants and the financial object they are invested in. The CRAs are supposed to be information intermediaries as mentioned earlier, but might be biased towards the issuers of debt, which could impair their ability to fulfill their purpose. This asymmetrical information is described by Lynch (2009) where he exhibits how it is an immense cost for market participants to do due diligence on their investments and therefore rely on CRAs rating to make rational decisions, at the same time as the incentives of the CRAs are aligned with their clients who pay for the issuing of a rating. This creates asymmetrical information, where CRAs know more about the rating than the market participant, who put their trust in that the CRAs act legitimate (Lynch, 2009). Lynch (2009) continues to discuss the changing format of credit ratings, where it used to be market participants who ordered the CRAs to create a rating for an investment, whereas now the issuer of a bond or stock are the ones paying to be rated. Lynch (2009) describes it as the CRAs being “captured” by the issuers (the clients).

Capture theory is contributed to George Stigler’s (1971) work ‘The Theory of Economic Regulation’ and it states how a regulating agency might be controlled by the industry it is set out to regulate, thus being “captured”. Lynch (2009) showcase how CRAs income is 80-90 percent contributed to issuers paying to be rated, which indicates that the CRA industry is captured by the issuers. Furthermore, Rousseau (2006) describes the credit rating industry as highly concentrated, where few agencies control the market. He point towards how there are three major agencies who control a substantial part of the market at the same time as there are regulations put in place prohibiting new actors from entering and becoming legitimate agencies. Rousseau (2006) discusses how it is in the best interest of the CRAs to maintain the status quo
and thus restrain others from entering the market and increasing competition. He discusses the same problem as Lynch (2009) regarding the conflict of interest the CRAs is faced with, but describes the problem in relation to the agent-principal theory. Rousseau (2006) finds three agent-principal problems; firstly, as discussed earlier, CRAs obtain most of their revenue from the issuers that are rated, thus they might be inclined to inflate the ratings in order to maintain their business. Secondly, the CRAs offer consulting services to the issuer, and the rating provided by the CRAs might be influenced by whether they buy these services or not. The issuer might buy the services out of fear of being negatively rated or in hope of receiving a higher rating. Thirdly, in order for CRAs to provide an issuer with a rating, they are allowed access to non-public information to conduct their analysis, which enables them to produce information content that is not readily available to investors. Rousseau (2006) then argues that this has both positive and negative effects on the information in the marketplace, since it creates more publicly available information at the same time as it opens up for speculation regarding the ratings thus increasing the volatility in the market. Lynch (2009) and Rousseau’s (2006) studies exhibit agent-principal problems regarding the CRAs and in particular a moral hazard issue, where CRAs are in a position to use their market position to dictate the ratings according to their interest rather than them reflecting the default risk.

CRAs might seem to provide more societal problems than benefits, but there are studies proclaiming the importance of having an information intermediary sorting the public information into easily understood ratings. Rhee (2015) argues the cost benefit of CRAs. The two main arguments for the importance of CRAs are (1) that they do in fact reduce the information asymmetry on the market and (2) reduce the cost of regulation. Rhee (2015) point toward the “lemon” problem attributed to Akerlof (1970) where as borrowers know more about the financial situation than the lender. Akerlof (1970) explain how this create a problem; a lender cannot tell which borrower is a “good” borrower and which one is a “lemon”, bad borrower. Therefore the “good” borrowers will face a premium that covers the risk of a “lemon”, since the lender cannot separate the “good” from the “lemons”. This increased premium will drive out the “good” borrowers and only “lemon” borrowers will remain in the market place. Rhee (2015) explains how CRAs alleviate this problem by acting as a seal of quality, thus enabling lenders to apply premiums according to the inherent risk of the borrower. Rhee (2015) argues against this reason, since he point out how there is no clear cut evidence towards the implications of not having CRAs, they are simply a more cost efficient way for investors to handle the “lemon” problem. Another argument presented regarding CRAs role in
the marketplace is the reduced cost of regulation, were as CRAs reduce the net cost of regulation by alleviating investors and regulators from creating an infrastructure that would be able to analyze bond investments (Rhee, 2015). The argument for the reduced regulatory cost has a substantial basis, and is regarded as a valid reason for the existence of CRAs (Rhee, 2015). Rhee (2015), however, has an alternative argument for the existence of CRAs. He argues that they provide a consistent informational pedagogy that spans the entire credit market, thus acting as a sorter of information. He argues for the fact that the CRAs can scale their business in a much larger way than any single market participant. This economy of scale enables CRAs to reduce costs for the market participants by sorting and formatting a large amount of information into a variable that is easily understood (Rhee, 2015). The above sections reflect theories and studies that explain the environment in which CRAs are active. In order to create a full picture of CRAs, empirical studies have to be examined.

Demirtas and Cornaggia (2013) study discusses the credit rating with the perspective of the firm being issued a rating, i.e. the issuer. The basis for the study is regarding whether US industry firms use accruals in order to boost their accounted earnings when a rating is being issued and whether there is a stickiness to the rating, making it beneficial for the firm to use accruals even though the long term effect of the accruals will lead to diminished earnings after the initial rating, making it an even sum game in the end. Demirtas and Cornaggia (2013) showcase how the debt market in the US is by far the most commonly used financial market of firms. Thus, the rating is of utmost importance for US firms in order to be competitive. Demirtas and Cornaggia (2013) mean that CRAs are reluctant to revise their initial rating, since they value stability and accuracy in their ratings - leading to said stickiness in ratings - and the motive for issuers to manipulate earnings. These are the cornerstones of the study, where they want to empirically review if managers manipulate earnings with accruals in order to reduce the cost of debt financing. Their findings strongly suggest issuers use abnormal accruals to inflate their earnings in the period leading up to the initial credit rating. The conclusion to their study shows how accruals enable firms to improve their rating substantially (Demirtas & Cornaggia, 2013). They also present two possible explanations to why it is possible for firms to use accruals to inflate their rating. Firstly CRAs are misled by the abnormally high accruals and find it to be superior and sustainable or secondly that CRAs recognize the accruals but rely on issuers reported numbers. In summary, Demirtas and Cornaggia (2013) suggest that managers of the issuer firm manipulate accounted earnings (using accruals) in the period before the initial credit
rating in order to exploit the stickiness of ratings. With stickiness, referring to the unwillingness of the CRAs to recognize inaccurate initial assessments and change their ratings.

Bolton et al (2012) study discusses credit ratings and CRAs through an efficiency and competition point of view. They create a model to study the difference between CRA monopoly and duopoly on rating accuracy, as well as the inflation of ratings by the CRAs when there are more trusting investors in the market. The model has seven key building blocks, which describes the different factors affecting the CRAs: 1. Issuer Payment for ratings 2. Issuer shopping for ratings 3. CRA credit models may vary in precision 4. CRAs can make “adjustments” to their credit risk model outputs 5. Reputation concerns for CRAs 6. Barriers to entry in the credit rating industry 7. Sophisticated and “trusting” investor clienteles (Bolton et al, 2012). By incorporating these factors in the model, the authors are able to demonstrate under what situations CRAs are more likely to inflate ratings, what impact it might have on efficiency of the market and what impact regulatory proposals might have (Bolton et al, 2012).

The most important result from the study is that a duopoly rating industry is less efficient than a monopoly industry. This is explained by the authors in regards to 2. Shopping for ratings, where an issuer is able to take advantage of the investors by only buying the best rating. A problem that the author presents is that a rating is only published when the issuer wants it to be published. If the issuer is not satisfied with the rating, they are able to take their business to another CRA and thus choose the best rating out of the two (Bolton et al, 2012). Therefore, the investor might not make investment decisions based on the most accurate rating, rather on the rating which the issuer wants to portray to the public (Bolton et al, 2012). Another result from the study is that CRAs are more likely to inflate ratings when there is a high degree of “trusting” investors or when the reputational damage of being inaccurate is low. This is aligned with factor 7. Sophisticated and “trusting” investor clienteles. Bolton et al (2012) explains that a “trusting” investor is an investor who uses the rating at face value instead of as a part of the due diligence. By face value the authors mean the default risk rating that the CRA has presented in absolute terms. A “trusting” investor is for example; a pension fund manager, according to the authors, whose ex-post return might only affect their own compensation marginally. They are usually also restricted in that they can only invest in highly rated investment products (Bolton et al, 2012). The time periods characterized by a high degree of trusting investor are often associated with periods of extraordinary economic growth. During these “boom” periods the reputational damage of being inaccurate is reduced, thus enabling CRAs to inflate ratings with less downside reputational risk to their business (Bolton et al, 2012). The final major result from their study
is that CRAs inflate ratings with issuers who are repeat customers or with whom they expect future large issuing (Bolton et al, 2012). In summary, the study by Bolton et al (2012) gives further evidence of CRAs aligning their incentives with the issuers. Issuers can “shop for ratings”, forcing CRAs to account for issuers demands when creating a rating. The study also shows how CRAs are more likely to inflate ratings when there is a high degree of trusting investors on the market, as well as inflating ratings for repeat customers (Bolton et al, 2012).

Griffin and Tang (2012) discuss CRAs ratings in regard to Collateralized Debt Obligations, CDOs, which is a financial product where different types of debt are combined into a financial product and sold to investors. In their study they compare the ratings issued by CRAs of CDOs with the ratings created by CRAs standardized model, which is created by using the inputs and outputs of CRAs and applying it to 916 CDOs issued between 1997 and 2007. Griffin and Tang (2012) exhibit several interesting results. The data used find that only 1,3% of AAA rated CDOs who closed between 1997 and 2007 met CRAs reported AAA default probability, whilst the rest did not (Griffin & Tang, 2012). Moreover, their results show how 92,4% of AAA rated CDOs only met the AA default standard. Furthermore, the authors find that CRAs had adjusted their model resulting in several CDOs receiving an AAA rating, but could not find explanations in likely variables, such as manager experiences or credit enhancements. This adjustment amounts to a 12,1% difference between the CDOs rated AAA by the authors CRA model and the CDOs who received AAA ratings by the CRAs. Griffin and Tang (2012) further discuss the cost implications of having CDOs downgraded to reflect the actual default risk. In their concluding remarks, Griffin and Tang (2012) discuss how their result exhibit how a quantitative approach is sufficient in calculating default risk, and thus proclaim how the qualitative measures that CRAs have taken to improve their rating models are the wrong approach. The authors would rather see an increase in transparency and for the CRAs to open up their black box. In summary, Griffin and Tang (2012) show how CRAs consistently inflated CDOs rating during the years 1997-2007, as well as adjusting their model to issue AAA ratings to more CDOs than their quantitative and standardized model originally allowed. Their study also discusses the cost implications of having the CDOs correctly rated. Griffin and Tang (2012) concludes that CRAs are not to blame their model, but rather focus on being transparent and open in order to remedy the issues facing their business model.

In summary, CRAs have moral hazard issues regarding their business as discussed by Rousseau (2006). By having an issuer pay model, the CRAs are put in a conflict of interest which might
lead to inflated ratings, showcased in studies by Demitras and Cornaggia (2013), Bolton et al (2012), and Griffin and Tang (2012). Lynch (2009) describes CRAs as being captured (Stigler, 1971) by the issuers thus resulting in CRAs having to align their incentives with the issuers in order to maintain revenue. At the same time as evidence point toward CRAs causing more trouble than they're worth, Rhee (2015) gives a different point of view, explaining how CRA help reduce regulation cost as well as helping market participants by sorting information into a variable that is easily understood. Rhee (2015) also discusses CRAs as a remedy for the “lemon” problem first discussed by Akerlof (1970).

3.4 CRAs and Regulation

In the U.S in order to become a CRA the company has to be a Nationally Recognized Statistical Rating Organization, NRSRO for short, designated by the U.S Securities and Exchange Commission, SEC (Rousseau, 2006). Being “nationally recognized” in the U.S is one of the main criteria in order to become a NRSRO (Rousseau, 2006). A problem is that too much weight is put on the criteria resulting in a catch-22 problem whereas in order to be “nationally recognized” the organization has to be a NRSRO, and in order to become a NRSRO the organization has to be “nationally recognized” (Rousseau, 2006). This, in combination with the lack of transparency and formality in the recognition process of NRSROs, create barriers to entry for organizations aiming to become CRAs and favors existing CRAs already recognized as NRSROs (Rousseau, 2006). Another factor in the regulation environment that is important to note, is that CRAs express opinions regarding the default risk (Lynch, 2009). In the U.S, this is protected under the first amendment, which enables the CRAs to not take responsibility when their models produce faulty ratings, claiming that they only expressed an opinion (Lynch, 2009). The implication of an opinion-based rating creates certain issues. As Bolton et al (2012) point out, CRAs are able to modify their models, and thus each rating is not based on the same metrics. Regulating for opinions is a difficult task. The SEC implemented the Dodd-Frank act, where more focus is being put on monitoring the performance and correctness of the ratings (SEC, 2014). The Dodd-Frank act is an initial step towards a more regulated industry for CRAs, where conflict of interest issues are reduced. Similar regulation has been put forward by the European commission where focus lie in disclosure policies for CRAs, aiming to reduce the conflict of interest (European Commission, 2016).

3.5 Equity Analysts

When measuring the information in markets the equity analysts’ performance, either accuracy or dispersion, can be used as a proxy (Barron et al, 1998; Sheng & Thevenot, 2012). The equity
analyst gathers, what Barron et al. (1998) calls, common information (also denoted public information) which is turned into forecasts. The commonly discussed forecast is the earnings forecast of firms. With common information, Barron et al. (1998) refers to all public information as well as the focal analyst’s private information. This infers that the analysts have more information than the public when forecasting equity and future earnings. Barron et al. (1998) define analyst accuracy as the mean error of earnings forecasts. Dispersion is measured as the spread of earnings forecasts between analysts, which also represents the consensus of analysts on an equity (Barron et al., 1998).

The idea of using analyst performance as proxy is based on the efficient market hypothesis (Fama, 1970) where equity should be accurately priced, dependent on the information available. This means that the price of equity should be reflecting the true value of the equity. This is achieved by having all information on the equity in question (Fama, 1970). The underlying assumption here is that equity analyst’s accuracy in forecast earnings is a good measurement of the level of information available.

3.6 Initial Coverage

Analyst’s initial coverage of a firm could have instant impacts on the information environment, directly adding value for firms and investors alike. Branson, Guffey and Pagach (1998) examined the market effects of equity analysts initiating coverage of a firm. Depending on firm size and previous coverage, they find a significant market reaction. Their study focuses on price level movement and does not analyze the informational benefits or effects on market efficiency (Branson et al., 1998). In a later study Li and You (2015) further provide evidence of equity analyst coverage providing an investor recognition effect and an addition to firm value. Although these studies and others on the subject of initial coverage (Demiroglu & Ryngaert, 2010) focuses on the market value or return on investments when analyzing the effects of analyst coverage it is relevant to take into account the instant market reactions when analyzing information intermediaries and their effect on information environment. Hansen (2015) provides support to using these studies in identifying the impacts on efficient markets and information environment. His study of existing theories evaluates the influence of initial analyst coverage on market efficiency with respect to a decrease in information asymmetry between firm and investor as well as the possibility of new information being constructed in the rating. Further he includes two other sources of value adding from initiating coverage: expected improved firm governance and increased trading volumes in the stock leading to increased
liquidity (Hansen, 2015). These suggested results of an initial rating or initial coverage of equity analysts also become central when discussing the credit rating issuing. The assumption that needs to be made is that CRAs act as an information intermediary in the same way equity analyst’s function, which is supported by Mei and Subramanyam (2008). In accordance to Hansen’s (2015) study we would then assume that an initial credit rating on a firm would decrease the information asymmetry in the firm-investor relationship and that the rating has the possibility to deliver new information. This information could be constituted by former private information or public information previously neglected by market participants (Hansen, 2015).

Interestingly enough, Li and You (2015) finds contrasting evidence in their study stating that initial coverage of equity analysts in fact does not contribute to the decrease of information asymmetries in practice. Their study pertains to the behavioral finance paradigms of investor reactions and solely finds the evidence of increased market value of a covered stock, contributed to the “investor recognition”, which we mentioned earlier. What these time-series studies have in common, and what is also interesting in our study, is that they study instant reactions and find market reactions on initial coverage to be very swift. It therefore motivates an analysis on a brief period of time during the release of a rating. In summary, studies on initial coverage detect instant market reactions and value-adding elements of the ratings (Demiroglu & Ryngaert, 2010; Hansen, 2015; Li & You, 2015). These elements have the possibility of increasing information quality and adding to the efficiency of markets from the information environment perspective.

3.7 Private and Public Information

The efficient market hypothesis demands that all publicly held information is reflected in the stock prices (Fama, 1970), meaning that no investor can earn long term excess returns on purely public information. To elaborate, the investor can earn excess returns only if he/she capitalizes on new public information before stock prices have adjusted to their true value. However, the true value is achieved relatively fast in an efficient market (Clinton et al, 2014; Lee, 2012) taking away the possibility of long term excess returns. Publicly held information is made up by, but not limited to, firm reports such as earnings announcements, stock-splits and other types of information that is easily and accessible without cost to the general market participant (Fama, 1970). This leaves us with the possibility to earn excess returns on privately held information only. Privately held information is contrastingly the opposite of the easily and costless accessible information and in general held by active market monitors or insiders, such as the market analysts (Rhee, 2015). The equity analyst would then possess more information than
the average investor with access only to public information. Hence the analyst possesses the ability to generate a return higher than that of the average investor. This makes out the basis for equity analyst firms’ source of income. To elaborate on the basic business idea of equity analyst firms, the sell-side analyst capitalizes on his/her superior information by selling it to the investor. The cost of resources that it would take for the average investor to gain the same amount of information as the powerful analyst firm is higher than that of buying the information from that firm. This equilibrium makes the market of private information pareto superior and effective.

In conclusion, to enhance the information environment of the entire market, and not just a select group of market participants, the total amount of information or indeed the quality of information needs to increase. It would not be enough if the amount/quality of private information increased while public information decreased in the same ratio, or vice versa. Mei and Subramanyam’s (2008) study indicated that a substitution effect could be found between certain elements of public information and private information, more specifically CRA reports and equity analyst’s coverage, which highlights the need to examine changes in information environment with respect to both categories.

### 3.8 Credit Rating Impact on Analyst Performance

Previously we discussed how equity analysts use available common information in their forecasting work (Barron et al, 1998). In accordance to the efficient market (Fama, 1970) and information environment theories (Wang et al, 2011; Clinton et al, 2014) the performance of the equity analyst is largely dependent on available common information. Hence, factors of information should affect equity analyst performance such as earnings forecast accuracy as well as the mean dispersion of forecasts. One of these information factors, or providers of information, could be the credit rating according to the studies examined in our research.

The purpose of the CRA and the credit rating process is to counter information asymmetries between the rating issuer and the issuer’s stakeholders (Lynch, 2009). This idea of a CRA contribution to market information environment constitutes the basis of our research. Rhee (2015) further builds on the positive effect of CRAs in an information environment, although he slightly adjusts the precise effect of the rating. To elaborate, he suggests that CRAs primary function is sorting and ranking information. To interpret his conclusions this would mean that the credit rating does not in fact bring new information to the market but rather makes it easier
to access and more easily readable. By making information readable to more market participants it actually has an effect on the market efficiency and pricing of equity (Lee, 2012). Thus, the CRA would, even with Rhee’s (2015) interpretation mean that the equity analyst performance would improve and thereby improving on the information environment. In conclusion, the basic idea of the CRA function suggests that the credit rating increases market information and analyst performance.

In contrast to this idea there has been a number of studies criticizing the CRAs market function, some of which we discussed earlier in this chapter. Lynch (2009) and Bolton et al (2012) concludes that even though the CRA’s main goal is to counter information asymmetry or provide information, the process in which this is done contains issues regarding the withholding of information and transparency. Some important examples of issues found in the credit rating process are the principal-agent problems arising between the CRA and the paying issuer (Lynch, 2009; Bolton et al, 2012), the issuer’s choosing of a “best rating” where there is a CRA duopoly (Bolton et al, 2012), issuer’s earnings management and the resulting manipulation of the credit rating (Demitras & Cornaggia, 2013) and the reputational concerns of a competing CRA (Bolton et al, 2012). These situations together with other issues with the credit rating issuing can be considered theoretical evidence of the CRAs providing less information to the market or rather decreasing information asymmetries at less than their optimal capacity.

Griffin and Tang (2012) show how issuers for a long period have been overrated by CRAs to a very high degree. In their study they found that almost 99 percent of the AAA rated issuers were in fact not qualified for that high of a rating at all. This resulted, among other thing, in the wrongful crediting of these issuers by lenders for ten years. Furthermore, Bolton et al (2012) concludes in their study how the credit rating issuing can trick investors into accepting the rating at what they call face value. The authors of the study mean that this makes investors inclined to skipping due diligence on an investment (Bolton et al, 2012). This would also pertain to lenders skipping due diligence on issuers, in favor of relying on the credit rating and setting inaccurate and biased interest rates. These two examples of CRA performance and consequences are both exhibiting issues leading to diminishing information, worse information quality or the increase in information asymmetries. In contrast to the issues previously discussed, these two problems actually seems to results in a worse information environment. If this is the case and the information environment is in fact worsened this would affect the equity analyst performance (Clinton et al, 2014), as it is dependent on underlying information.
In conclusion to these theories, the credit rating issuing is meant to bring increased information quality and resulting in a better information environment. Improving on the information would lead to a more efficient pricing of market assets and among them; equity. In turn the equity analysts would increase forecasting accuracy and decrease the level of dispersion in forecasts as a result of the credit rating increasing information quality. The credit rating process however includes some issues in the provision of information - leading one to doubt the actual contribution of the CRAs. Based on this doubt, the central hypotheses in this study will be testing these assumptions and are formulated as;

H1: The issuing of a credit rating correlates positively with equity analysts’ forecasting accuracy.

H2: The issuing of a credit rating correlates negatively with equity analysts’ forecasting dispersion.

Using the same approach that Barron et al (1998) uses in their study we can achieve a higher exactness in our results by further developing these hypotheses. According to Barron et al (1998) and their BKLS model it is possible to mathematically determine the more exact informational effect of changes in equity analyst performance. The effect of an increase in analyst performance can be separated into public and private information. In accordance to the EMH and studies on information environment, the total amount of information or the total quality of information needs to increase in order to create a more efficient market. However the categorization of public and private information gives a more detailed picture of the credit rating as an information intermediary. Rhee (2015) claims the CRA sorts and ranks information rather than delivers new information. This would contradict the hypothesis of an increase in total market information and rather gives some support for a shift in the ratio between the two categories. The following hypotheses are formulated to capture and explain the effect of the credit rating on the information environment (where private and public information is tested separately):

H3: The initial credit rating issuing is positively correlated with public information.

H4: The initial credit rating issuing is positively correlated with private information.
Finally, our last hypothesis is based on studies on direct and instant impact of rating issuing. These studies (Branson et al, 1998; Demiroglu & Ryngaert, 2010; Li & You, 2015) show how markets behave in certain ways as a result of rating issuing. These studies focus mainly on the results of the face value of the rating (high or low, good or bad) and the consequences on the market. However, in analyzing the effects of credit rating issuing on the information environment the face value of the ratings is less relevant. All remaining the same, the observed instant effect of a rating or the lack thereof could be a vital part in explaining the market function of credit ratings. For example, a reaction to the issuing of a credit rating shown in price levels would tell us more about how the credit rating is absorbed by the market participants. Controlling for the face value of the rating, the coverage in itself could lead to increased price levels as a result of investor recognition (Li & You, 2015). The issuing of a new credit rating could then, in the way that Li and You (2015) suggest with equity analysts and investor recognition, mean an increase in firm value and hence add to investor value. This would then further support the importance of the CRA as an information intermediary from an investor’s point of view.

H5: The initial issuing of a credit rating increases market stock prices.
Chapter 4: Empirical Method

Under empirical method we describe the practical methodology behind the study and the testing of hypotheses. First, we introduce the design of our study, which is somewhat parted into a primary and secondary study for the testing of our different hypotheses. Then we continue explaining in detail the operationalization of data and variables and the statistical testing. The chapter aims to give the reader a comprehensive understanding of our chosen methods for testing the credit rating impact on the informational aspects of markets.

4.1 Research Design

The researcher in a quantitative and explanatory study is recommended the options of conducting either a cross-sectional study or a time-series analysis. The choice rests on the other parameters surrounding the study and most importantly the variables that is the focus of observation. The cross-sectional analysis examines observations made at one single moment in time on several different objects. A regression model of this kind can reveal a wide variety of correlations and relationship characteristics between the different variables in the model at one single moment in time. To elaborate with an example; the cross-sectional study can be used to see the differences in equity analysts’ performance depending on geographical location or types of equity. The time-series analysis focuses on studying the development of included variables over time. This type of regression reveals changes in relationship characteristics under a certain period, pinpointing the factors of change (Bryman & Bell, 2005).

Time-series regression analysis will allow our study to see the potential changes in equity analyst performance as a result of changes in the underlying independent variable of credit rating issuing. The aim is explaining the correlation between the credit rating issuing and the information environment (measured with the accuracy of the analysts’ forecasting) on our sample of firms from a wide variety of countries. In our study the actual rating, whether its Aaa or Ccc, is irrelevant to the formulated question of research which means the point of time in which the firm gained a rating is what is central to observe. If, however, the question was formulated differently and the actual rating was the relevant observation, the cross-sectional study would also be sufficient in analyzing the correlation.
The study will practically be split into two parts of testing, with regards to what dependent variables are being tested. The first part is testing the information environment (private and common information, analyst accuracy and dispersion). We call this study the primary long-term study of information environment (hypotheses 1-4). Our primary study will include the rating issuing effects on year-to-year analyst performance and the BKLS calculated information environment proxies (denoted S and H). The second part of testing is what we call a secondary short-term study on instant market effects (hypothesis 5). This will include the studying of instant effect on market price levels with daily observations before and after the issuing of a credit rating.

The primary study will, as mentioned, be constructed as a time-series study over a larger span of time. Firms in this study will be analyzed multiple years before and after they were issued their credit rating. Since the time span here becomes rather long the results will be susceptible to effects of non-incorporated events throughout the studied years. This will demand us to implement a number of control variables in our regression model to minimize the risk of initial credit rating explaining untrue effects on our dependent variables.

The secondary study, in contrast, contains a rather short time-span in its time series regression analysis. Since the market, according to efficient market theory (Fama, 1970), will absorb new information quickly the effect of a new credit rating will most likely be seen instantly. Therefore the event study is made with daily observations around the time of initial credit rating issuing. This will entail a regression analysis on changes in market stock prices as a potential result of credit rating issuing. It will measure stock prices for the focal firm the days before and the days after the issuing of a credit rating. The regression would, without control variables, output a coefficient rather irrelevant, since the stock returns often contain a trend possibly dependent on a large amount of input such as macroeconomic events. Instead, for a regression with outputs such as stock price movement, we need a variable controlling for normal price level movement (in this case index price level). Thus, allowing us to see if the changes in stock price are in fact abnormal. The design of our secondary study will allow us to analyze the instant reaction to credit ratings as an integral part of explaining the informational market effects of credit rating issuing.
4.2 Method of Analysis

Our hypotheses are tested with the fixed-effects Driscoll-Kraay panel-data regressions (Hoechle, 2007). A choice based on our statistical testing of data presented later in this chapter. The model of regression, which is ran on four dependent variables in our primary study, is of a classical build and looks like the following;

\[ Y_{it} = \beta_1 x_{initial\ credit\ rating} + \beta_2 c_{market\ value} + \beta_3 c_{st.dev.RoE} + \beta_4 c_{trading\ volume} + \beta_5 c_{number\ of\ analysts} + \beta_6 c_{earnings\ surprise} + \varepsilon_{it} \]

Where \( Y \) is the dependent variable (accuracy, dispersion, private and common information). The \( x \) is statically the initial credit rating coverage and \( c \) is the control variables. For this long-term study on the effects on information environment we choose five control variables based on previous studies showing effects from these on analyst performance. These are market value of focal firm, standard deviation of returns on equity, focal firm’s stock trading volume, number of equity analysts following focal firm and earnings surprise based on the average stock price over the year. These control variables are explained further in the operationalization part of this chapter. Lastly \( \varepsilon_{it} \) is the residual term in our regression.

For our secondary study on the instant market effects of credit rating issuing we apply the same fixed-effects regression model. In this instance we use the same methodology where \( y \) is the dependent variable of stock price. Our control variables, \( c \), in this regression model are; rating rank (face value of issued rating) as well as index price level. The independent variable, \( x \), is consequently the initial credit rating date. This provides us with the following formula for our secondary regression model;

\[ Y_{it} = \beta_1 x_{initial\ credit\ rating} + \beta_2 c_{rating\ rank} + \beta_3 c_{index\ price\ level} + \varepsilon_{it} \]

The primary and the secondary study use choose a significance level of \( p<0.05 \), where there is a five percent chance that a false hypothesis is accepted. Furthermore, a robustness test will be performed in the shape of a median panel-data regression model with the same build as the ones described above. This chapter now continues with introducing the collection of raw data and the producing of our sample. After which we describe the data and variables used in our studies in more detail, under the operationalization and statistical testing sections.
4.3 Data Description

Previous studies on information environment that examines analyst performance and credit ratings have collected data from market observers and databases such as International Brokers’ Estimate System (I/B/E/S), DataStream (von Koch, Nilsson, Jönsson & Jansson, 2014, Mei & Subramanyam, 2008). Data collected from these types of sources is considered to be secondary data. This means that the data is not gathered from the original or primary source but instead through an intermediary. Bryman and Bell (2005) mentions the danger of relying on secondary data where there is a larger risk for false data compared to when the data is collected from the primary source. The primary source would in the case of our study be the firms themselves, their earnings reports and the analysts forecasting reports respectively. This primary data would demand immense resources to collect from a large enough sample of firms. Instead our study relies, like von Koch et al (2014), Beuselinck, Joos and Khurana (2010), Kim and Shi (2012), Byard, Li & Yu (2011), on secondary data. Our secondary data is collected mainly from Datastream, Google Finance, Yahoo Finance and Investing.com.

Datastream is a market observing company delivering secondary data to students, researchers and market participants alike. The company is owned by the Canadian information and news corporation Thomson Reuters Corp and monitor more than 100 countries around the world with their respective markets (Thomson Reuters, 2016). Datastream has contributed with six variables in our study: analyst mean forecasted earnings per share, analyst forecast dispersion, earnings per share (EPS), stock price, market trading volume, market value and standard deviation of return on equity (StdRoE). Out of these, analyst forecast accuracy and dispersion constitute our main independent variables. Datastream has analyst’s forecasts of future EPS available for every day of the year. We have chosen to use a nine months forecast from 31st of March (forecasting the EPS at year’s end). The logic of choosing March 31st is based on the research of Lang and Lundholm (1996) where they discuss how financial statements increase the accuracy of forecasts. Since the first quarterly financial statement is released after March 31st, by picking this date for capturing the forecasts we eliminate the risk of the additional information available in the financial statement “discretely affecting” our results.

From Investing.com, Yahoo Finance and Google Finance the event study collects daily observations on stock prices, index price levels and exchange rates. Since the firms in our selection are large corporations listed on well-known and adequately “covered” exchanges, the data presented by Yahoo and Google can be monitored and controlled by almost anyone with
insight in said exchanges. The same rationale is applied to the usage of Investing.com, where currency exchange prices are gathered. This gives, by logic, some legitimacy to the data collected from these three sites. The variables constitute observations made at the closing of the markets - meaning for example that we use the closing stock price of a firm.

Concluding, the data for initial coverage of a CRA is collected via Datastream. The observations used for the initial rating is the exact date and time of the rating being published to the public and therefore when it is considered public information.

4.4 Sampling
The selection of firms to include in our study has been largely made with respect to available data and the limited time and resources at hand. This section will present, in chronological order, the process of firm selection first for the primary study and then for the secondary study. Firstly, we gained access to data for 11,405 firms from Datastream - these observations contained variables in the form of our desired control variables and dependent variables (analyst accuracy and dispersion). The criteria was that desired observations for all control variables were included and that the firm was covered by at least two analysts in order to get a dispersion measurement. The listed firms were geographically spread throughout 24 countries. Secondly we gained access to initial credit rating dates. These observations were matched with the sample of 11,405 firms and 68,757 firm/years we already had, resulting in a sample of 1368 firms. These included firms with observations exclusively after or before the initial credit rating year. Additionally, for reliability purposes, we concluded that at least two years of observations should be included prior and after the initial credit rating date. This contributed to a loss of testable firms and resulted in a sample size of 584 firms with a total of 9032 firm/years. Statistical methodological limitations then constricted us from using observations with negative values for our dependent variables H and S - derived from the running of the BKLS model explained in detail in the next section. These negative values were dealt with according to Beuselinck et al (2010) where the BKLS formula altered for the negative observations. Some observations then contained missing values making the final count of observations range between 9000 and 9031 observations, between the years 1991-2010, for the different regression models. With a total amount of 584 firms we then calculate a mean of roughly 15 observations (or firm/years) per firm.
The secondary study take its origin from the original 11,405 firms collected from Datastream. We chose to include 100 firms in the sample, which were included based on a number of criteria. The sample is in chronological order based on when they received their initial credit rating, starting with the most recent. In order to collect the 100 firms needed the following criteria had to be met. (1) The firm needs to be publicly listed prior to receiving the initial rating. (2) The initial rating received had to be in the range of Aaa-Ccc. (3) the firm needs to be the parent company, no subsidiaries are included in the sample. The following criteria were applied until we reached a total of 100 firms. The sample includes firms receiving initial ratings during the years 2012-2016, spanning over 17 countries in total. The ratings received in the sample are in the range of A1-Caa2. Every firm in the sample has 22 days of stock observations (11 days prior to the initial coverage and 11 days after).

4.5 Rationale of Equity Analyst Performance to Measure Information Environment

Barron, Kim, Lim and Stevens wrote an article in 1998 on a mathematical model they had constructed that would use inputs of equity analyst performance and produce a measurement of information environment quality (BKLS model). More specifically the model separates the public and private shares of the total amount of available information on the market. In short, this is done by assuming that equity analysts gain access to private information as well as the easily accessible public information (also denoted common information). The model then analyzes the analyst's performance and the investor’s performance to gain an understanding of how big the difference in accessed information really is. The idea of using equity analysts as a proxy for researching inputs to market information cannot be contributed only to Barron et al (1998). Studies in the beginning of the 1990s also claimed analyst performance to be a good measurement for information environment (Barry & Jennings, 1992; Abarbanell, Lanen & Verrecchia, 1995). The measure of performance is based on the concepts of analyst uncertainty.
and analyst dispersion (derived from analyst consensus). Uncertainty is represented by the forecasting accuracy and measured in the mean error in analysts’ earnings forecasts. The validity of this measure is according to Barron et al (1998) well supported in literature. The article is also reforming in the way it uses dispersion in the model, where it takes into account that dispersion of analysts includes both uncertainty and degree of consensus. Analyst consensus was before the BKLS model something commonly used as either the average forecast or as a pure measure of dispersion (Barron et al, 1998).

The BKLS model is constructed as two simple equations (see below) using no more than three variables; SE, D and N. Standard error (SE) represents the uncertainty variable in the forecasting of a firm’s future earnings. In our study it is derived from the nine months (March 31st to December 31st) mean forecast accuracy of our sample. Next, the dispersion (D) is derived from subtracting common uncertainty from overall uncertainty (or multiplying overall uncertainty with the inverse of a consensus ratio) meaning that dispersion increases as uncertainty increases and consensus decreases. This is represented by the sample variance of analysts’ earnings forecasts (Barron et al, 1998).

\[
h = \frac{SE - D}{[(1 - \frac{1}{N})D + SE]^2} \quad s = \frac{D}{[(1 - \frac{1}{N})D + SE]^2}
\]

\(h\) = the quality of public information
\(s\) = the quality of private information
\(SE\) = the expected squared error in the mean forecast
\(D\) = the expected sample variance in forecasts
\(N\) = the number of forecasts

In summary, the BKLS model used in our study is based on the assumption that equity analysts use public and private information in their forecasting of future earnings. The separation of common and overall uncertainty in the model allows for a measurement of public and private market information to be constructed and hence inputs to information environment analyzed.

The BKLS model has since 1998 suffered some critique in its validity and reliability as an information environment measurement. Sheng and Thevenot (2012) express concerns of the BKLS model not accounting for unanticipated event after the forecast has been made as well as its inability to incorporate \textit{ex ante} uncertainty. This meaning the BKLS model handles \textit{ex-}
post uncertainty and lacks in its ability to achieve a measurement using forecasting before actual returns has been confirmed.

Barron, Kim, Lim and Stevens (1998) also critique their own model in certain situations. One of those situations is where there is a lack of observations in forecasting. The model requires more than one analyst to cover the firm in any given time. Moreover, while two analysts are enough for the BKLS model to produce a result, a low number of analysts covering a firm will threaten the validity of the model output (Barron et al, 1998).

4.6 Operationalization

The operationalization of the research process is important in order to create a reliable and valid study. Therefore it is of importance to use variables that are either the exact information that is needed, or variables that are proxies for what we are trying to explain. The starting point for the operationalization is in the theory discussed in prior chapters and our task is to transfer the theories into variables that are precise and as unambiguous as possible (Holme, Solvang & Nilsson, 1997). Staying clear of ambiguity in our model inputs will enable us to be precise in our estimates and results (Holme et al, 1997). Our operationalization is therefore a way of explaining our variables and thus strengthening them as well as our models. We are using variables that have been used in prior research and often are raw data, which in most variables does not force us to code the data further.

4.6.1 Dependent Variables

In our study, we are aiming to examine credit ratings effect on the information content available to market participants. Therefore the dependent variables have to reflect the information content. A dependent variable is the variable being affected (Bryman & Bell, 2005) and therefore it is important that our dependent variables are thoroughly explained and anchored in prior research.

4.6.1.1 Analyst forecast accuracy

Schipper (1991) describe analysts “as one of the primary users of financial accounting information”. She argues the fact that analysts are sophisticated investors who can interpret accounting information in a way that regular investors cannot. Lang and Lundholm (1996)
further conclude how analysts provide a way to observe the activities and beliefs of investors, which cannot be observed directly. In Barron’s et al (1998) article they discuss further how analysts can be used as a proxy for information. The logic presented by Barron et al (1998) is that when there is a high amount of information available to analysts their accuracy should increase and vice versa (Barron et al, 1998). The correlation between analyst forecast accuracy and information is also described in Krishnaswami and Subramaniam (1999) study where they use analysts forecast as a way of measuring information asymmetry. Based on prior studies mentioned, we find analyst forecast accuracy to be a useful proxy for the information available to investors.

The methodology behind using analyst forecast error and choosing March 31st for forecasted data (before first quarterly) has some implications on our study that we need to take into consideration. The variable is not corrected for exogenous factors, which could not have been foreseen e.g. terrorist attacks, corporate scandals, economic downfall (Sheng & Thevenot, 2012). Therefore the mean error might not always reflect a valid variable for information available. In some cases the analysts would have made forecast that was correct based on the information they had and an exogenous factor made their forecast invalid. To build upon this there is extensive research showing how managers have incentives to meet or beat the forecasts leading to usage of earnings management (von Koch et al, 2014; Degeorge, Patel & Zeckhauser, 1999; Abarbanell et al, 1995). This is problematic for a variable that is assessing the information content based on a comparison between forecasted EPS and actual EPS.

In regards to this, we still find analyst forecast accuracy to be a useful proxy to capture the information content based on prior studies surrounding analysts (Schipper, 1991; Lang & Lundholm, 1996; Krishnaswami & Subramaniam, 1999; Von koch et al, 2014; Barron et al, 1998) and the fact that we are aiming to test a hypothesis based on yearly observations. The problem of earnings management incentives by managers to meet or beat analysts forecast is not remedied in the forecast accuracy variable. We understand this limitation in the variable and build upon it in the following section.

Analyst forecast accuracy is a ratio variable and is measured by comparing forecasted earnings per share on March 31st and actual earnings per share on December 31st. The formula of calculation follows;
The formula provides us with a product describing the level of accuracy in forecasts. An optimal forecast will provide a product of 0. The further from zero the product is located, the worse the accuracy. This becomes vital in analyzing the results. Furthermore, for statistical testing purposes we use the absolute value of the product (no negative value) in order to maintain simplicity in the regression model. Analysts’ forecast accuracy is denoted as ACC in our study.

**4.6.1.2 Analyst forecast dispersion**

In the above section we determined why analysts are able to act as a proxy for information. In order to combat some of the problems with analyst forecast accuracy, we use the variable analyst forecast dispersion as a compliment. Analyst forecast dispersion is gathered through Datastream, and is calculated as the variance within the forecasts. The variable is directly gathered through I/B/E/S via Datastream, which does not require any further calculations in order to be a viable variable for our model.

As mentioned, a problem with analyst forecast accuracy is exogenous factors that can skew the accuracy (Sheng & Thevenot, 2012). By focusing on analyst forecast dispersion some of these problems are remedied. The dispersion of analyst forecast does not require us to compare the actual EPS of the companies with the forecast. It only requires us to see if analysts are converging in their forecasts. To conclude, the dispersion among analysts is not affected by the same measuring issues that we find in accuracy, such as extraordinary events after 31st of March. Based on this we find analyst forecast dispersion to be a variable that complements analyst forecast accuracy and aims to explain the relation between information content available to analysts and the information created by credit ratings without the impact of exogenous factors.

Analyst forecast dispersion is a ratio variable and is measured as the standard deviation in analyst forecast EPS. A positive value indicates an increase in dispersion and a negative a decrease in dispersion. It is denoted as DISP in our dataset.
4.6.1.3 Public information

To extend on the hypothesis regarding analysts forecast accuracy and dispersion, we want to observe the effect of credit ratings on public and private information. In order to examine how they impact the public and private information we will use the BKLS model introduced earlier. Public information in the BKLS model is denoted by \( h \) and is calculated:

\[
h = \frac{SE - \frac{D}{N}}{\left(1 - \frac{1}{N}\right)D + SE}^2
\]

This variable allows us to measure the amount of public information (common information) available to investors. This is one of the few variables that we need to calculate, and therefore it is important that we are precise whilst calculating \( h \) in order to not inflict the variable with human error. As mentioned, \( SE \) (Squared error of mean forecast) and \( D \) (the expected sample variance, dispersion, in forecasts) are two of the main components of the equation. Thus, they face the same problems as discussed in analyst forecast accuracy and analyst forecast dispersion. The other variable used in the model is the number of analysts covering the focal firm (N).

Public information is calculated using the equation illustrated above and is a ratio variable. Public information is based on variables discussed in the earlier section regarding the BKLS model. A positive value for public information in our regression model indicates an increase in public information and a negative value indicates a decrease respectively. Public information is denoted as \( H \) in our dataset.

4.6.1.4 Private information

In order to observe the initial credit rating effect on private information, we will further utilize the BKLS model. Private information is denoted by \( s \) and is calculated by:

\[
s = \frac{D}{\left(1 - \frac{1}{N}\right)D + SE}^2
\]

The variable allows us to measure the amount of private information available to market participants. As mentioned, this is a variable that we need to calculate and it further demands us to be consistent and thorough. This equation faces the same issues mentioned in the equation.
of public information and we base our model on the same studies to validate the usage of the BKLS model to calculate private information.

Private information is a ratio variable and is calculated using variables discussed in the earlier section regarding the BKLS model. A positive value for private information indicates an increase in private information and a negative value a decrease. Private information is denoted as $S$ in our dataset.

4.6.1.5 Stock Price

Further our secondary study on instant market effects aim to examine whether the effects of initial rating affect the price of the stock. This variable is based on the studies made by Branson et al (1998), Demiroglu and Ryngaert (2010) and Li and You (2015) who find an abnormal increase in stock price based on equity analyst’s initial coverage of a stock. This positive effect on stock price is isolated from whether it is a buy, hold or sell recommendation. By using stock prices as a dependent variable our aim is to capture if the initial credit rating of a stock has a similar effect as initial equity analyst coverage.

Price is a ratio variable and is measured by the closing price of the stock. Stock Price is collected on the 22 days surrounding the announcement of the initial credit rating, with 11 observations prior and 11 observations after the initial credit rating. Stock price is denoted in US dollars ($). For foreign (outside of the US) firms and foreign markets the price level has been converted to US dollars by calculating a monthly average from the month of observation of focal firm to present day. Stock Price is denoted as PRICE in our dataset.

4.6.2 Independent Variables

The aim of our research is to observe the effect of initial credit rating on the dependent variables operationalized in the above section. An independent variable is the variable that is affecting and explaining the dependent variable (Bryman & Bell, 2005). We will focus on a single independent variable and use control variables in order to seclude the effect of initial credit rating.
4.6.2.1 Initial coverage

In both the primary and secondary study, initial credit rating will act as the independent variable. The aim of the variable is to capture the effect of the initial credit rating on the dependent variables. The variable is coded as a dummy variable, where 0 pertains to the period prior to the initial credit rating and 1 pertains to the period after receiving the rating.

This type of coding has implications on our primary study’s dataset. As described in earlier sections, the date used to gather data surrounding forecasts is March 31st. This means that it is not possible to code the initial rating based on what year the company received its initial rating, but rather it has to be coded according to whether the initial coverage date was before or after March 31st. Hence, a company that receives an initial rating prior to March 31st will receive a value of 1 for that year and a company that receives an initial rating after March 31st will receive a value of 0 for that year. The secondary study has 11 observations prior to the rating and 11 observations after, resulting in a total of 22 observations per firm in the dataset.

It is denoted as CRI (credit rating indicator) in our dataset.

4.6.3 Control Variables

The control variables used in our two studies aim to capture variables that affect the information environment and stock price. Our primary and secondary studies want to exclude the effect of initial rating on the dependent variables and therefore we have to use a number of control variables to extract this effect alone (Bryman & Bell, 2005).

4.6.3.1 Standard Deviation of Return on Equity

The use of Standard Deviation of Return on Equity as a control variable is based on the study by Lang and Lundholm (1996). Their study aims to explain the different variables affecting analysts and their forecasts. In their study they find a significantly positive correlation between analyst dispersion and Standard Deviation of Return on Equity. The logic behind the variable is that a high volatility, which leads to a higher standard deviation of return on equity, affects the ability to produce correct recommendations and therefore increase dispersion amongst analysts. Thus, Standard Deviation of Return on Equity remedies some of the problems discussed surrounding exogenous factors and earnings management incentive problems. Based on Lang and Lundholm’s (1996) study, we include Standard Deviation of Return on Equity in
our regression to control for this effect, and predict a positive connection between it and all the dependent variables in the primary study, except for dispersion where a negative connection should occur.

Standard Deviation of Return on Equity is calculated as the firm’s standard deviation return on equity over the past three years and is a ratio variable. The base value for the calculation is collected on December 31st. It is denoted as stroe in our sample.

4.6.3.2 Number of analysts
We use the number of analysts as a control variable based on prior studies by Von Koch et al. (2014) and Lang and Lundholm (1996) where they both discuss the impact of having more analysts following a firm. Lang and Lundholm (1996) show how the number of analysts correlates with the amount of information available to market participants. Based on these studies we use number of analyst following each firm as a control variable. Number of analyst should, in regards to Lang and Lundholm (1996), have a positive impact on the information environment. Thus, analyst forecast accuracy, common information and private information should increase and dispersion decrease when the number of analyst following a firm increase.

Number of analysts is a ratio variable and is gathered via Datastream. It is collected on March 31st to reflect the amount of analysts making predictions of future EPS for each firm. It is denoted as N in our dataset.

4.6.3.3 Market Value
Market value as a control variable is based on the same studies by Von Koch et al, (2014) and Lang and Lundholm (1996). It is also based on a different study made by Lang and Lundholm (1993) where they find a likely correlation between disclosure policy and firm size and performance variability, i.e. bigger firms tend to disclose more information as well as having less variability in their performance. The studies mentioned all exhibit how market value is a good proxy controlling for size. The logic being that a bigger firm discloses more information to the public. Thus, using market value as a control variable will enable us to further contain the information content of the initial rating. This indicates a positive connection to analyst accuracy, public information and private information and a negative connection to analyst dispersion.
Market value is a ratio variable and is measured at the beginning of each fiscal year. It is denoted as $mv$ in our dataset.

4.6.3.4 Trading Volume
Trading volume, in combination with market value, controls for firm size. Therefore the same logic and studies based around choosing market value is applied to trading volume. Von Koch et al. (2014) point towards the fact that size should reflect the information available and thus have a positive effect on forecast accuracy and dispersion. Von Koch et al. (2014) also utilize trading volume in a different way, where it is used to control for analysts covering a firm. The logic being that analysts are paid indirectly based on the number of trades they produce based on their recommendations. Thus, using trading volume is a further control for the size argument for information content available to market participants as well as control for the activity that analysts create on the market. Therefore the predicted direction of the connection between trading volume and the dependent variables align with market value.

Trading volume is a ratio variable and is measured as the absolute amount of trades for each stock during the first month of each fiscal year. It is denoted as $vo$ in our dataset.

4.6.3.5 Earnings Surprise
The logic of earnings surprise as a control variable is based around the fact that major events regarding the firms might take place during the year which the analysts are not able to account for. The logic stems from the same research by Lang and Lundholm (1996), as discussed earlier, where they discuss how earnings surprise is a way to control for this effect. Von Koch et al (2014) describe how these major events will most likely interfere with analyst’s ability to make accurate predictions. Earnings Surprise is calculated according to:

$$\frac{(EPS_t - EPS_{t-1})}{Average\ Stock\ Price_t}$$

EPS is the actual EPS of each firm in the sample and therefore is sampled at the end of each fiscal year. It is a ratio variable and is denoted as $ES$ in our dataset.
4.6.3.6 *Index Price*

Using indices is based on prior studies regarding stock prices by Demiroglu and Ryngaert (2010) and Li and You (2015). Both studies use variables that measure the overall market climate. We choose indices as a way to capture the same type of effect on the firms. The logic behind using indices is that they capture the overall mood and trend on each market place, as discussed in section 4.2. If there for example is a bullish mentality, where market participants are in a buying mood, it might explain the single stock price effect on the firms in our sample. Based on this, index price should have a significant impact on stock price. However the direction of the impact depends on the overall trend of the marketplace.

Index Price is a ratio variable and is measured as the price of the index related to the country in which the firm is listed. Index price for each country is denoted in US dollars ($) based on the same exchange rate calculation as the one described in section 4.6.1.5. It ranges the same dates as each individual stock in our sample for the short-term event study and is denoted as `INDEXP` in our dataset.

4.6.3.7 *Rating rank*

In order to assure that the initial ratings effect on stock price is not affected by the “face value” of the actual rating, i.e. whether the firm receives a Aaa-Ccc rating, we use rating rank as a control variable to exclude this effect. The logic behind this is that the face value of the rating should have an effect on the stock price of each firm. This control variable enables us to measure the effect of receiving a credit rating without the face value of said rating affecting the end result. The face value of a rating is perceived differently by the market depending on each individual firm. Thus, a Ba1 rating will affect the stock price in relation to if the market perceives it as good or bad based on current stock price. Thus, rating ranks direction of effect on stock price is difficult to determine prior to the regression results.

Rating rank is based around a rating system where firms are given a rating between Aaa-Ccc, where Aaa is the most favorable and Ccc is the least. In order to process this information in a regression each individual rating is given a rank ranging from 1-23 where 1 represents the least favorable and 23 the most favorable. Rating rank is an ordinal variable and is denoted as `RR` in our dataset.
4.7 Methodological Critique

In order to maintain a high standard in our study and produce reliable results and estimates we continuously and throughout the study work with reliability, legitimacy and validity issues. Following is a description of reliability and validity measures that has been taken into account as well as critique on these two elements surrounding our study.

4.7.1 Reliability

Reliability in relation to a quantitative study concerns consistency, compliance and reliability of the study. If a study is reliable, other researchers would be able to replicate the study and see the same results. In a quantitative study, reliability is shown in how the data is collected and tested. By being reliable, the study proves that it is not affected by random or temporary occurrences (Bryman & Bell, 2005). To assure that our results are reliable, and thus enable other researchers to replicate our results, the sampling process and operationalization is thoroughly described. We evaluate our results based around issues faced during the statistical tests performed on our samples.

Some of these issues regard the number of analysts following a firm. This issue affects the variable dispersion, where we set a minimum of two analysts in order to be included in the sample, resulting in some cases where the dispersion is equal to 0. We are aware of this whilst evaluating the results. Further we might find problems regarding the lack of observations prior or after the initial coverage. We set a minimum of two years prior and two years after the initial coverage to be included in our sample. This issue is in combination with using yearly observations for forecasted and actual earnings per share (EPS). To increase the reliability of the study quarterly report forecasts could be used. We base our choice of using yearly data from the standpoint of Lang and Lundholm (1996) surrounding the fact that it enables us to measure only the information held by analysts. Further, we are aware of how this would increase the reliability and evaluate the results accordingly. It is important to note how certain variables are calculated by us and not directly gathered from the source. This is indicated throughout the study in order to increase reliability. Lastly, one of the major issues at hand is the usage of data from only one of the major rating agencies. The consequence of only having access to one of the major rating agencies data is that an initial credit rating might have been issued prior to the rating available to us. Therefore we understand this limitation on our research and need to evaluate the results regarding it explaining the effect of the initial credit rating data at hand.
4.7.2 Validity

Validity regards the fact that a study measures what it intended to measure (Bryman & Bell, 2005). To assure the validity of the research, the data is gathered from public sources, who often are the direct creator and compiler of the data. We argue that this assures a high degree of validity to the dataset, not saying that the data reflects the absolute truth, but it reflects the data that is conveyed to the public. Being the data available to the public, and thus investors and analysts, and not the absolute truth has small implications in regards to our research approach, since we are aiming to find out if CRA’s ratings affect the information available.

By using variables that are frequently used in prior research, and understanding their limitations, we argue that the validity of the research is strong. We are not relying on information gathered through surveys, and therefore are relieved of the issue of questions being misleading and/or misinterpreted, thus resulting in gathered data not catching the variables that we need to produce generalizable results.

In order to proceed with our research, a proxy for the information available in the marketplace has to be used. There is no clear-cut way of defining what is considered information, and therefore it is hard to validate a variable to act as a proxy. Our research relies on prior research variables on information content. To maintain validity throughout the process we need to understand the limitations of this proxy, as well as constantly evaluate our results in regards to it. Therefore it is of importance that our model has factors that enable us to contain the effect of the rating on the information content. To achieve this our model aim to explain as many factors as possible that are contributing to the information content.

4.8 Statistical Analysis

The aim of the study is to determine the effects on analyst performance and information quality from the initial coverage of a CRA and its issuing of a credit rating. Thus, time and changes over time become central to the analysis. To elaborate, the study aims to identify possible and statistically significant changes in information environment before and after a rating has been issued. This need for time series analysis rules out the ordinary cross-sectional multivariable regressions. We instead possess the variable of time as well as the grouping variable of firm identity which both needs to be incorporated into the multivariable regression. Having a
grouping variable and several time-observations for each group to address is called a panel-dataset. This leaves us with panel-data multivariable regression. This type of analysis is used in similar time-series studies such as Li and You (2015) and Demiroglu and Ryngaert (2010).

To proceed with analyzing the data in this fashion however, we need to identify the characteristics of the statistics. In order to achieve a high level of reliability in our results we need to test the distributions of our independent variables for each test as well as the possibility of autocorrelation between variables and heteroscedasticity. After having tested the data we are able to proceed in choosing the best available tests for our study.

4.8.1 Distribution Tests
Firstly, we introduce our two datasets (from our primary and secondary study) to the Shapiro-Wilk distribution test. This will test the distribution normality of our dependent variables - a prerequisite for trustworthy results of a normal panel-data regression. If the data is not considered normally distributed the irregular outliers on either side of the sample mean will affect the results of a regression without being accounted for (Anderson, 2014). This is based on the underlying assumptions made in a linear regression model where the mean value of the variable should be equal to the median. The entire test outputs can be found in appendix A.1.1.

Secondly, we run a kurtosis and skewness test to see if there is a possibility of one or the other. Kurtosis implies that the distribution contains “fat tails” and relatively more frequent outliers than that of a normal distribution. Whereas skewness refers to the distribution being biased towards one or the other side of the sample mean. Meaning that most observations are located either to the “right or left” of the sample mean. In figure 4.8.1.1 the test results of the distribution tests of the primary study on information environment is illustrated.

<table>
<thead>
<tr>
<th>Probability</th>
<th>Normality Tests</th>
<th>Shapiro-Wilk Test</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Normality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Information (H)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>Private Information (S)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>Analyst Accuracy (ACC)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>Analyst Dispersion (DISP)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>NO</td>
<td></td>
</tr>
</tbody>
</table>

H0: normal distribution
H0: no skewness or kurtosis
The Shapiro-Wilk test shows that none of our dependent variables have a normal distribution since we reject the null hypothesis for each one. Further our tests show that our variables in turn also display characteristics of skewness and kurtosis. These values are all very clear indicators of non-normality. The fact that they all are characterized similarly cannot be considered coincidental. The dependent variables are in a clear way dependent on each other, where for example the accuracy of analysts and the public information is based on the same rough data. Figure 4.8.1.2 shows the normal distribution-curve of the variable Analyst Accuracy (ACC).

This clearly shows a non-normal distribution, since the diagonal straight line constitutes a normal distribution. To further explain the characteristics of this, figure 4.8.1.3 shows the density histogram of observations (also of the ACC variable).
Here we can see the effect of extreme outliers around the value of 200 in the graph. While most observations are found just above 0.0. In the next figure below we present the distribution test results of our short-term event study dataset. The conclusion to be drawn, is that our dependent variables are not-normally distributed and largely affected by outliers.

<table>
<thead>
<tr>
<th>Normality Tests</th>
<th>Shapiro-Wilk Test</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Normality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock Price (P)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>NO</td>
</tr>
</tbody>
</table>

H0: normal distribution
H0: no skewness or kurtosis

Like our primary study, Stock Price (P) also shows signs of non-normality, skewness and kurtosis. This will in a linear regression potentially generate untrustworthy outputs, since it is not in accordance to the underlying assumptions of the non-manipulated regression model. To mitigate the negative effects of non-normality in our dependent variables there are some options available. The variable values can be exchanged with the natural logarithm to portray a normal distribution, the outliers can be dealt with in numerous fashions and lastly the regression model can be modified (Brockwell & Davis, 2010). However a fixed effects panel-data regression shows robust estimations and is considered fair in its hypothesis testing even when confronted with underlying non-normality (Powell & Chay, 2003), which affects our choice of regression technique. Meanwhile we see a fairly large number of outliers in our data (which is illustrated...
4.8.2 Autocorrelation and Heteroscedasticity

To further understand the datasets we perform tests of our error terms (or disturbance terms) focusing on the potential threat of autocorrelation and heteroscedasticity. For a regular multivariable regression model to output trustworthy results, the assumptions of constant variance and independency in the error term need to be true. If the error terms show inconstant variance (heteroscedasticity) in our panel-data we will get an overestimation of standard errors in our regression models. Inconstant variance refers to the variance of the residual gradually increasing or decreasing. Graphically, this could be illustrated with a scatter plot where the “scatter” becomes larger further down the regression line. In the same way, dependence in the error term (autocorrelation) also affects the accuracy of the models (i.e. the standard errors). If the error term shows positive autocorrelation the regression would underestimate the standard errors and vice versa (Anderson, 2014). To test autocorrelation we use a Wooldridge-test in STATA for our regression models. Furthermore, we use a so called LR-test within STATA:s selection of statistics tests. In figure 4.8.2.1 we show the test results for our primary study on information environment. The entire test outputs can be found in appendix A.1.2

<table>
<thead>
<tr>
<th>Statistical Tests</th>
<th>Woolridge AC</th>
<th>Prob&gt;F</th>
<th>LR-Test</th>
<th>Prob&gt;Chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Information (H)</td>
<td>31.094</td>
<td>0.0000</td>
<td>-14619.31</td>
<td>1.0000</td>
</tr>
<tr>
<td>Private Information (S)</td>
<td>53.691</td>
<td>0.0000</td>
<td>-36785.18</td>
<td>1.0000</td>
</tr>
<tr>
<td>Analyst Accuracy (ACC)</td>
<td>14.870</td>
<td>0.0001</td>
<td>19923.72</td>
<td>0.0000</td>
</tr>
<tr>
<td>Analyst Dispersion (DISP)</td>
<td>16.508</td>
<td>0.0001</td>
<td>78789.49</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

H0: no autocorrelation
H0: no heteroscedasticity (with negative LR-results = H0: heteroscedasticity)
The Wooldridge autocorrelation test outputs an F value together with a probability (Prob>F) value. If the probability values are zero or adequately close to zero we reject the null-hypothesis and vice versa (Wooldridge, 2010). In this case the null-hypotheses is that our variables contain no autocorrelation and that the error term is independent. However, in all four instances (four regression models) we must reject the null hypothesis and confirm that the error term in fact is not independent and that a least square regression model will either under- or overestimate the standard errors. Moving on, the LR-test work in a similar fashion, where it outputs a probability factor. However, in this test there are underlying mechanics making the format of the output dependent on the format of the other variables. This makes for duality in the interpretation of Prob>Chi2. If the LR-test shows a negative Chi2 test value the null hypothesis should be rejected at a value at or close to 1,0000, this according to Hoechle (2007). Thus, when interpreting the test results we can confidently reject the null-hypothesis and confirm that there is in fact heteroscedasticity in our regression models. Below in figure 4.8.2.2 we illustrate the test results of our regression models in the secondary event study covering the direct impact on price level movement.

**Figure 4.8.2.2. Dependencies test output for the secondary study.**

<table>
<thead>
<tr>
<th><strong>Statistical Tests</strong></th>
<th><strong>Woolridge AC</strong></th>
<th><strong>Prob&gt;F</strong></th>
<th><strong>LR-Test</strong></th>
<th><strong>Prob&gt;Chi2</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock Price (p)</td>
<td>8.835</td>
<td>0.0037</td>
<td>10774.91</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

H0: no autocorrelation
H0: no heteroscedasticity (with negative LR-results = H0: heteroscedasticity)

Here we can clearly state that the model bring autocorrelation as well as heteroscedasticity in the error term. The issue at hand is to mitigate the effects of these characteristics. According to Hoechle (2007) one can use the Driscoll-Kraay regression model for panel-data in STATA to alleviate the effects of autocorrelation and heteroscedasticity. This model would then be considered to output more precise results with more accurate standard errors that reflect the true correlations of independent and dependent variables.

To conclude from our tests we possess data with non-normal distributions and regression models showing autocorrelation and heteroscedasticity in both our studies. We will, for reference, conduct a median regression model along with the, presumed more accurate, Driscoll-Kraay regression model. The median regression is according to econometric ideas preferred when the underlying distributions are irregular or of an unknown character. This
means it can act as a safety or to solidify the results of a more accurate model that relies more underlying assumptions. The latter is a fixed-effects panel-data regression model that handles dependencies in the residual (Hoechle, 2007) as well as generates robust estimations even when non-normality appears in the data (Powell & Chay, 2003).
5.1 Descriptive Statistics

The statistical tests of primary study are based on a dataset of over 9000 observations on 584 firms of ten different variables and the secondary study is based on a dataset of 2200 observations on 100 firms. This section is a summary of those variables and their respective statistics. Figure 5.1.1. demonstrates the statistical descriptives of our included variables for the primary study on credit rating impact on information environment. Values illustrated are number of observations of each variable, their mean value, the standard deviation of the distribution as well as minimum and maximum values.

<table>
<thead>
<tr>
<th>Variable Descriptives</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Public Information (H)</td>
<td>9031</td>
<td>2.986</td>
<td>4.095</td>
<td>0.001</td>
<td>14.793</td>
</tr>
<tr>
<td>Private Information (S)</td>
<td>9000</td>
<td>14.727</td>
<td>27.488</td>
<td>0.000</td>
<td>342.94</td>
</tr>
<tr>
<td>Analyst Accuracy (ACC)</td>
<td>9010</td>
<td>-195.35</td>
<td>17262</td>
<td>-1613936</td>
<td>30360</td>
</tr>
<tr>
<td>Analyst Dispersion (DISP)</td>
<td>9031</td>
<td>5.6031</td>
<td>135.83</td>
<td>0.000</td>
<td>8011.8</td>
</tr>
<tr>
<td>Credit Rating Indicator (CRI)</td>
<td>9031</td>
<td>0.4336</td>
<td>0.4956</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>St.Dev. of RoE (stroe)</td>
<td>9031</td>
<td>10.189</td>
<td>97.014</td>
<td>0.0050</td>
<td>5998.97</td>
</tr>
<tr>
<td>Number of Analysts (n)</td>
<td>9031</td>
<td>13.635</td>
<td>8.584</td>
<td>2.0000</td>
<td>48.000</td>
</tr>
<tr>
<td>Market Trading Volume (vo)</td>
<td>9031</td>
<td>70042</td>
<td>728465</td>
<td>0.2000</td>
<td>49300000</td>
</tr>
<tr>
<td>Market Value (mv)</td>
<td>9031</td>
<td>22319</td>
<td>112182</td>
<td>0.0100</td>
<td>4191093</td>
</tr>
<tr>
<td>Earnings Surprise (ES)</td>
<td>9028</td>
<td>-0.0706</td>
<td>0.7125</td>
<td>-62.000</td>
<td>12.1620</td>
</tr>
</tbody>
</table>

Firstly, the credit rating indicator (CRI) is the main independent variable of the study. It contains information on when the credit rating was issued for a particular firm. This is done with several firm/year observations with values of 0 and 1 (0 = not issued, 1 = issued), which is known as a dummy variable. Therefore, the range of observation values will be restricted to
0 or 1. The mean value of CRI is found at 0.4336. Which is closer to 0 than 1, thus indicating that the data contains more firm/year observations before the credit rating issuing than after. Second, standard deviation of returns on equity is summarized. This variable describes the volatility of returns on equity for a particular firm. Mean value is 10,189, which would indicate that the average firm in our population has had a volatility (standard deviation) of their last three yearly equity returns of 10,189 percent. The maximum and minimum values range from 0,005 to almost 6000. This spread is relatively large, considering the mean value of 10,189, and suggestively including outliers. Third, number of analyst is considered and illustrates the number of equity analyst following a particular firm at the given time of observations. The minimum number of analysts is 2, since the dataset excluded observations with less than 2 analysts due to the fact that “analyst dispersion” then could not be calculated. The average following among our selection is almost 14 analysts per firm. Subsequently leading to the dispersion being calculated on the consensus among 14 analysts on the average firm in the sample. Market trading volume, market value and earnings surprise all contain a wide spread between minimum and maximum, that when compared with mean value and standard deviation hints at extreme outliers.

The dependent variables in the primary study, as mentioned before, are all based on similar rough data and are therefore of similar characteristics. They all contain non-normal distribution - which is hinted by the comparison of mean values, standard deviations and the value ranges. Public and private information for example have a relatively low mean value, a higher standard deviation and a minimum of zero or just above zero. Thus, this relationship is one of a skewed statistical distribution. Important to note before making conclusions on analyst’s accuracy is that a higher value of the variable means less accuracy.

**Figure 5.1.2. Variable descriptives for the secondary study.**

<table>
<thead>
<tr>
<th>Variable Descriptives</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock Price (PRICE)</td>
<td>2200</td>
<td>15.20</td>
<td>10.01</td>
<td>0.16</td>
<td>86.62</td>
</tr>
<tr>
<td>Credit Rating Indicator (CRI)</td>
<td>2200</td>
<td>0.50</td>
<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Rating Rank (RR)</td>
<td>1100</td>
<td>10.20</td>
<td>2.52</td>
<td>5.00</td>
<td>18.00</td>
</tr>
<tr>
<td>Index Price Level (INDEXP)</td>
<td>2200</td>
<td>10156.75</td>
<td>7491.85</td>
<td>48.36</td>
<td>18312.39</td>
</tr>
</tbody>
</table>

The descriptive statistics for the secondary study are presented in figure 5.1.2. Stock price (\(p\)) display a mean of 15.2 and a standard deviation of 10.01. The minimum in the sample is 0.16
and the maximum is 86.62 for the stock price. Stock price (p) is denoted in USD ($) meaning that the average stock price in the sample is 15.2 $. Stock price exhibit signs of outliers, based on the minimum and maximum values. However, the standard deviation is <15.2 $ indicating a sample that is relatively tightly surrounding the mean. Credit Rating Indicator (CRI) is a dummy variable as shown by a minimum of 0 and a maximum of 1. The mean is 0.5 and standard deviation is 0.5, which exhibit how there is an equal amount of 0 and 1 in the sample. Rating rank (RR) is based around what type of initial credit rating each firm receives. As mentioned, each rating has a ranking where 1 is the least favorable and 23 is the most. In order to examine the descriptives surrounding this variable some modifications has to be done. As one can see in figure 5.1.2 half the observations (1100) has been deleted from the descriptives. This is done due to how the variable is coded, where firms receive a rating on the 12th day in our sample. Prior to this, in order to not inflict the stock price with the face value of the rating, it receives a 0, indicating a state where the firm has no rating rank. Thus, 0 are removed from the descriptive statistics in order to not skew the mean towards the low end of rating rank. Rating rank consequently has a mean of 10.2 indicating that the average rating the companies in our sample received is a Ba3. The standard deviation is 2.52, which exhibits a sample tightly surrounding the mean. The minimum is 5, which correspond to a rating of Caa2, and the maximum is 18 corresponding to a rating of A1. Lastly, Index Price Level (INDEXP) exhibit a mean of 10 156.75 with a standard deviation of 7 491.85. The standard deviation is <10 156.75, displaying a sample surrounding the mean. The minimum of the sample is 48.36 and the maximum is 18 312.39. The minimum and maximum values indicate how the sample might be skewed towards the high range. This can be attributed to the majority of observations stemming from the US, as displayed in Figure 4.4.2, where the Index used is at the high range of INDEXP.

To conclude, the descriptive statistics for the secondary study display some interesting notes. A mean Stock Price of 15.2$ with a relatively small standard deviation enable possibilities to explain the relative price change due to the (CRI). Further, our sample indicates how a vast majority of the ratings issued surround the Ba3 rating with a relative small deviation from the mean. Index price levels indicates a sample skewed towards the high range, which is further proof of the non-normality discussed in prior sections.

The correlation matrix in figure 5.1.3 aims to examine whether our independent variables showcase signs of multicollinearity, where two independent variables correlate and thus the single effect of the variables cannot be separated (Anderson, 2014).
As mentioned, credit rating indicator (CRI) is the focal independent variable whilst the rest work as control variables. The general praxis is to set a threshold value for the correlation between independent variables to be included into the model. This threshold is put in the region of 0.7 correlation, which would indicate that the correlation between the variable, i.e. if they explain the same thing, is 70%. Examining figure 5.1.3. None of the independent variables have a correlation close to a threshold of 0.7. We find low correlation throughout our independent and control variables, which indicate how none of the variables explain the same thing in a high degree, and therefore are not at risk of multicollinearity. An interesting note is the low correlation between market value (MV) and Number of analysts (N). Based on prior studies, and our usage of (n) as proxy for size in regards to these studies, a higher value was expected.

The correlation matrix shown in figure 5.1.4 show the correlation between the independent variables used in the regressions regarding the secondary study on instant market effect on stock price levels. As one might expect the correlation between initial credit rating indicator and rating rank is high, almost at a perfect correlation. This can be attributed to the fact that the 11 first days for each firm receives a 0, thus having the same value. As mentioned rating rank is a more descriptive way of examining the effect of the initial credit rating and its face value on stock price and is therefore used as a way to control for how market participants perceive the rank. The correlation between these variables causes multicollinearity in our dataset. It is possible to exclude one of the variables but we choose to include them both based on rating
rank controlling for the effect of face value of ratings and Credit Rating Indicator (CRI) covering the effect of issuing. Index price level has almost zero correlation with both rating rank and initial credit rating and is therefore not affected by the same issue of multicollinearity.

5.2 Driscoll-Kraay Regression

The hypotheses testing will be conducted via the fixed effects regression model for panel data, called Driscoll-Kraay. As discussed in section 4.8.2, this model allows for non-normality in the underlying data as well as corrects or alleviates errors made as a result from dependencies in the residual (autocorrelation and heteroscedasticity). Following are the empirical results from our hypotheses testing as a result of regression models.

5.2.1 Primary Study on Information Environment

The results of the primary study are exhibited in table 5.2.1 below. The columns represent our dependent variables and the rows are the independent variables and the control variables respective estimated effects on those dependent variables. Hence the table presents four different regression models and their output. In appendix A.2 you find the complete regression outputs including R-square values, t-scores etc.

Table 5.2.1. Regression estimates on the primary study.

<table>
<thead>
<tr>
<th>Regression Estimates</th>
<th>Public</th>
<th>Sig</th>
<th>Private</th>
<th>Sig</th>
<th>Accuracy</th>
<th>Sig</th>
<th>Dispersion</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Rating Indicator (CRI)</td>
<td>-1.120</td>
<td>0.00</td>
<td>-6.776</td>
<td>0.01</td>
<td>0.280</td>
<td>0.78</td>
<td>0.059</td>
<td>0.03</td>
</tr>
<tr>
<td>St.Dev. of RoE (STROE)</td>
<td>0.000</td>
<td>0.53</td>
<td>0.001</td>
<td>0.82</td>
<td>-0.003</td>
<td>0.10</td>
<td>0.000</td>
<td>0.43</td>
</tr>
<tr>
<td>Number of Analysts (N)</td>
<td>-0.047</td>
<td>0.00</td>
<td>0.052</td>
<td>0.38</td>
<td>-0.104</td>
<td>0.02</td>
<td>0.000</td>
<td>0.89</td>
</tr>
<tr>
<td>Market Trading Volume (VO)</td>
<td>0.000</td>
<td>0.19</td>
<td>0.000</td>
<td>0.38</td>
<td>0.000</td>
<td>0.04</td>
<td>0.000</td>
<td>0.77</td>
</tr>
<tr>
<td>Market Value (MV)</td>
<td>0.000</td>
<td>0.00</td>
<td>0.000</td>
<td>0.00</td>
<td>0.000</td>
<td>0.17</td>
<td>0.000</td>
<td>0.00</td>
</tr>
<tr>
<td>Earnings Surprise (ES)</td>
<td>0.419</td>
<td>0.21</td>
<td>1.904</td>
<td>0.15</td>
<td>-19.032</td>
<td>0.26</td>
<td>0.013</td>
<td>0.18</td>
</tr>
</tbody>
</table>

The third column in the table refers to the model testing H1, whether there is a positive connection between analysts forecast accuracy and initial credit rating. This model shows an R-Square value of 0.0861 thus explaining 8.6 percent of what constitutes the delta of analyst forecast accuracy (see appendix A.2.1). Initial credit rating has a significance value of 0.78 which exceeds the threshold of p < 0.05 (95 percent confidence interval) and therefore a statistical connection between analyst forecast accuracy and initial credit rating cannot be confirmed by our model. The effects would otherwise claim, according to the coefficient output,
that CRI has a negative effect on analysts’ accuracy (since the value of the variable is inverted). Another interesting notion is how analysts’ accuracy (ACC) is affected by the number of analysts (N) where we find statistical significance and a negative coefficient (positive effect). This would then mean that a higher number of analysts generate more accurate forecasts. The second model (analysts’ dispersion) aim to test H2, whether there is a negative connection between analyst forecast dispersion (DISP) and initial credit rating, i.e. if analyst forecast dispersion decrease when a company receives a credit rating. The model, which can be found in its entirety in appendix A.2.2, has an R-Square value of 0,078, explaining 7,8 percent of what constitutes analyst forecast dispersion changes. Our independent variable, CRI, has a significance value of 0,03, which is below p<0,05. This indicates a statistically significant connection between a company receiving an initial credit rating and analyst forecast dispersion. However, the way initial credit rating affect analyst forecast dispersion is the opposite direction of what was hypothesized. The model displays a beta value of 0,059, which is indicating that analyst dispersion increase by a factor of 0,059 when a company receives the credit rating. Hence the issuing of a credit rating would in fact slightly increase the dispersion of analysts’ forecasts. Our third model is presented in column one in our table and aims to test H3, if there is an increase in public information (H) after companies receive an initial credit rating. The model can be found in its entirety in appendix A.2.3. This regression exhibits an R-Square value of 0,0381, and thus explains 3,81 percent of what constitute changes in public information (H). Initial credit rating has a significance value of 0,002 which is below p<0,05, indicating a statistical connection between initial credit rating and public information. Initial credit rating has a coefficient of -1,11986. This indicates a moderate decrease in public information available when a company receives an initial credit rating, which is the opposite direction of what was hypothesized. Interestingly enough, the control variable of number of equity analysts (N) in fact decreases the public information (H) with a coefficient of -0,047. Finally, the last regression model of the primary study aim to test H4, whether there is an increase in private information (S) available to analysts after the initial credit rating. The entire model output can be found in appendix A.2.4, and has an R-Square value of 0,0393 thus explaining 3,93 percent of what constitute private information changes. CRI has a significance value of 0,005 which is below p<0,05, indicating a statistically significant connection between initial credit rating and private information. Initial credit rating has a beta value of -6,776, indicating a negative relationship between initial credit rating and private information, i.e. the amount of private information available to analysts decrease due to the initial credit rating. Just as with public information, a
negative connection between initial credit rating (CRI) and private information (S) is the opposite of what was hypothesized.

To conclude the regression outputs of our four Driscoll-Kraay models for our primary study on information environment makes us unable to accept any of our hypotheses. Instead they show opposite effects on market information (public/private) as well as analyst dispersion. The model testing analysts’ accuracy outputs a non-significant result, which makes us unable to make conclusions on a direction of effect - but rather we can purely make the conclusion that the correlation is not significant. The results in total make for immensely intriguing analysis of credit rating impact on information environment.

5.2.2 Secondary Study on Instant Market Effects

The results of the fixed-effects model for the secondary study on instant market effects are presented in table 5.2.2 below. The presentation of results is identical to the one for our primary study and for more information on the regression outputs we refer to appendix A.2.5.

<table>
<thead>
<tr>
<th>Regression Estimates</th>
<th>Stock Price (PRICE)</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Rating Indicator (CRI)</td>
<td>1.087</td>
<td>0.00</td>
</tr>
<tr>
<td>Rating Rank (RR)</td>
<td>-0.107</td>
<td>0.00</td>
</tr>
<tr>
<td>Index Price Level (INDEXP)</td>
<td>0.000</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The regression aim to test H5, whether initial credit rating has a positive effect on stock price. The model produce an R-Square value of 0.1754 (See appendix A.2.5), which indicate how the model explain 17.54 percent of what constitutes the stock price. Initial credit rating, denoted as Credit Rating Indicator (CRI) in the model, has a significance value of 0,00 which is below p<0,05, indicating a statistical significant connection between (CRI) and stock price. The Beta-value for (CRI) is 1,087, where stock price increase by on average 1,087 dollars when a firm receives an initial credit rating. This is a positive value, thus our hypothesis regarding initial credit rating impact on stock price can be confirmed. Further, the control variable Rating Rank (RR) has a significance value of 0,00, which is below p<0,05. The Beta-value is -0.107 indicating a, on average, negative effect of the face value of ratings on stock price. Rating Rank (RR), as mentioned, aim to control for the face value of the rating in our testing. The descriptive
statistics for the secondary study provide evidence of firms receiving on average a rating of Ba3, a rank that is on the bottom half of the rating scale, thus giving an indication of why (RR) display a negative value. Index price level (INEXP) is the final control variable for the secondary study. (INEXP) has a significance value of 0.00, below p<0.05, indicating a statistical significant connection between index and stock price. The Beta-value is 0.00, displaying no effect on stock price. Thus, (INEXP) display the characteristics discussed in prior sections.

To conclude, the regression outputs for the secondary study display a statistical significant positive connection between a firm receiving an initial credit rating and the firm's stock price. This confirms our hypothesis. The percentage increase on stock price, based on the mean value, is 7.15 percent. Thus, relying on our model, the firm stock price will increase 7.15 percent upon receiving a credit rating - controlling for index price level trends as well as the face value of the rating.

5.3 Robustness Test

To maintain reliability in our testing we conduct a robustness test in the form of a median regression model on our hypotheses. This model relies on different assumptions in the dataset and will control for underlying issues in the data - as well as for methodological errors in modeling the Driscoll-Kraay regression. Furthermore, since we possess non-normal data we exclude the OLS regression model as a robustness test in favor of the median regression model. In figure 5.3.1 we show the median regression output for both our studies in a summarized fashion. The row contains the independent variable credit rating indicator (CRI) and the columns show its effect and statistical significance on the dependent variable connected to our hypotheses. The median regression models can be found in their entirety in appendix A.3.

<table>
<thead>
<tr>
<th>Median Regression</th>
<th>H</th>
<th>Sig</th>
<th>S</th>
<th>Sig</th>
<th>ACC</th>
<th>Sig</th>
<th>DISP</th>
<th>Sig</th>
<th>PRICE</th>
<th>Sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Rating Indicator</td>
<td>-0.368</td>
<td>0.00</td>
<td>-2.238</td>
<td>0.00</td>
<td>0.229</td>
<td>0.61</td>
<td>0.031</td>
<td>0.00</td>
<td>0.896</td>
<td>0.43</td>
</tr>
</tbody>
</table>

The model estimates a negative relationship between market information (both public and private) and credit rating indicator (CRI). The output of -0.368 for public information (H) and -2.238 for private information (S) suggest that the effect is lower than that of the Driscoll-Kraay estimates. But the direction of the coefficients as well as the relationship between the two
coefficients is the same as in our main regressions (where private information changes more drastically). The statistical significance is very high for both of these estimates (sig < 0.001). The dispersion of analysts’ forecast (DISP) is estimated to increase slightly upon the credit rating issuing with a coefficient of 0.031. This can be said with a high statistical significance (sig < 0.001). The effect on analysts’ accuracy (ACC) does not however show statistical significance (sig > 0.610) and thus no conclusions can be made out of these results. The secondary study covering stock price (PRICE) movement is also tested for robustness with the median regression. In contrast to the Driscoll-Kraay regression model the median regression does not find statistical significance in this relationship (sig > 0.430). It does however produce a positive coefficient like the one we achieved in the main regression, but no conclusions can be drawn upon it. The robustness of this measure from the Driscoll-Kraay model could then be said to be less robust, than that of the primary study.

To conclude, we find that the test show robustness in three out of five tested dependent variables in our two studies. The dependent variables in our primary study and their respective models show the same characteristics, although not entirely the same coefficients. The robustness test produces a non-statistically significant relationship between stock prices and our variables credit rating indicator - which differ from our main regression. This will have to be taken into account when analyzing these relationships - using these estimates with more caution.
Chapter 6: Analysis and Discussion

In this chapter we discuss the empirical results of our study and explain the acceptance or rejections of the hypotheses with basis in the theoretical framework of the study. We conduct a continuous discussion on the results where our findings and hypotheses are brought together. The discussion starts of by introducing the results and the practical causes of the rejections of hypotheses. After which we discuss the underlying causes of the negative effects we see, the implications it may have and the regulatory measures that might be taken to combat the current situation.

The hypothesized directions of credit rating impact on information environment for our study is based on the theories developed by Rhee (2015) and Duarte et al (2008) (as well as a general public consensus) stating that CRAs in fact does have a vital market function as an information intermediary. These studies are claiming that CRAs contribute information or increase information quality in markets. Thereby, they would be presumed to be positives in the societal endeavor to create efficient markets. Clinton et al (2014) and Wang et al (2011) claim efficient markets and the information environment are by definition connected and dependent. Both of their studies argue the efficiency of market pricing and the information quality of the market are strongly correlated. This in turn should be further theoretical evidence of information intermediaries such as CRAs adding to the efficiency of markets. From our models of testing, however, we see contradicting results. Namely, the amount of information or quality of information seems to drop after the release of an initial credit rating. More precisely the private information seem to be decreased by -6.776 units (calculated from the BKLS model) while public information seem to decrease by -1.120 units. Since both private and public information are decreasing upon the initial credit rating issuing we must reject our hypotheses of increasing market information. Instead, the credit rating issuing could be said to decrease the total amount of information in financial markets. Alternatively, and perhaps more likely considering the study of Rhee (2015), the quality of information is what is decreased rather than the amount. Rhee (2015) suggested that the CRA function is of a sorting and ranking nature and contributes to reduce costs of due diligence for market participants. This might mean that the CRA contributes to lessen the practical investment costs for market participants but in return creates less accurate pricing models than those using other risk assessments, such as the equity analysts’ own investment risk models (Lui et al, 2012). Furthermore, Abad & Robles (2014) argues that these bad ratings and the decreasing of information quality in markets increases the overall
systematic risk in society - in turn increasing the risk for financial crashes like the one we saw in 2008. Thus, motivating more thorough research on the subject of credit rating impact. The question of analysis that arises upon the empirical results of our study are; what causes these negative effects on information?

There has in the last ten years been numerous theoretical works done on the subject of anomalies in the presumed function of CRAs. These studies are based on the recent global financial misfortunes and the suggested villainous role of the CRAs. The agencies in this period were presumed to rate without precision due, a large part, to profit incentives (Wojtowicz, 2014). In the theoretical framework of this study we find two major anomalies on the usefulness of CRAs as an information intermediary. First up is the phenomenon of rating shopping. Bolton et al (2012) describes this as the tendency for competitive tendering from the issuers. An example of this is where the issuer applies for a rating at several (both) CRAs and later chooses to publish the better rating. The CRA producing the better rating gets the business. Therefore it is in the CRAs interest to produce good ratings in order to increase profits. Analyzing this logically, one would presume that these ratings become misleading in the way that they are too good and does not reflect the accurate default risk level of the issuer. If the information that is provided by the CRAs are misleading and, in the way that Mei & Subramanyam (2008) argues, equity analysts as well as investors use this information in their investing assessments there would be inefficiency in the market. This is based on the efficient market theories, where an efficient market is one where equity is fairly priced and reflecting the true value of the asset (Fama, 1970). The fact that our empirical results are showing negative effects on information gives reason to believe that the effect of rating shopping could have a severe impact on the information environment.

The second phenomena surrounding the credit rating issuing that is brought up in the recent flow of research in the field is the tendency of earnings manipulation and rating stickiness (Demitras & Cornaggia, 2013). This could also constitute the reason why we see negative effects on information from a newly issued credit rating. Earnings manipulation (or earnings management) refers in this case to where issuer management delay costs or prematurely account for profits during the time of them getting rated. This is done in order to mislead the ratings analysts into issuing a better than fair rating. Demitras and Cornaggia (2013) finds that the CRA in fact does give a better than fair rating to these firms and, perhaps more interestingly, sticks to this rating for years even after the manipulation of earnings has been detected. This
predicament is called *ratings stickiness* (Demitras & Cornaggia, 2013) and concludes that the initial credit rating in fact stays intact and unchanged longer than it should. To elaborate, this means that the CRA is unwilling to change the rating after it has first been published. The main reason for this is according to Demitras and Cornaggia (2013), the CRAs reluctance to acknowledge an error in the rating. This is based in the competitive environment of the CRAs (characterized by the duopoly of Moody’s and S&P) as well as the urge to keep a high level of integrity in their ratings - not admitting errors in their rating models. The issuers, knowing this, use the stickiness of ratings in their favor by the manipulation of earnings during the rating period to receive a better than fair rating. This phenomenon could constitute the other part of the negative effects we see on information environment in our results. It would mean that the effect we see is a product of a better than fair rating being issued and taken into account in the investing processes (pricing) of market participants (e.g. equity analysts). In this case the rating would give the wrong indications to the participant of the focal firm’s default risk - making for a lower threshold of return on investment (ROI) than that of the accurate default risk level. To conclude, the pricing of assets (embedded in forecasting) conducted by equity analysts is less accurate in our sample after the credit rating has been released – which, with support from recent research, can be contributed to these two anomalies and their underlying causes and motives.

The two anomalies to the market function of CRAs are derived out of conflicts of interest, principal-agent issues and lack of regulation - which seemingly is making the information environment worse in the wake of an initial credit rating. Lynch (2009) explains the business of CRAs and the potential conflicts of interest that might arise in the triangular relationship of CRA-issuer-investor. In the way that Hansen (2015) describes CRAs function, they presumably decrease the information asymmetries between firm and investor. Lynch (2009) however claim the CRAs more often than not *owe* the issuer a better than fair rating. He elaborates on this explaining how CRAs income is derived from paying issuers, meaning the ratings are solicited. With this he means there are inherent dangers in that solicited ratings are allowed, due to the fact that it creates an infected principal-agent relationship (Lynch, 2009) with its annexed conflicts of interests (Eisenhardt, 1989). Further, the CRAs active on the global stage all offer consulting services to issuers such as operational and financial management consulting (Rousseau, 2006). This also offers the potential threat of interest conflicts where the purchasing of these services might lead to better ratings being issued. These conflicts of interest are according to current research very *real* and present in today’s business of credit ratings. It may
also be the basis of our results, where the incentives for CRAs to issue better than fair ratings in fact lead to a decrease in the amount of information or the quality of information. Thus, leading to inefficiencies in markets causing the inaccurate pricing of assets.

Griffin and Tang (2012) discuss the business of CRAs and the societal blame that CRAs and their rating models withstood during the years after the financial crisis of 2008. The CRAs’ models of rating issuers can be somewhat arbitrary and each individual process could mean changes and manipulation of the model in order to fit the focal firm. Griffin and Tang (2012) argue that CRA models are not to be blamed alone, but rather they ask for a higher degree of transparency in the rating process. We find that initial credit ratings decrease the quality of information in markets generating less efficient markets. Breaking the business of CRAs down; it comes down to the rating process and how it produces inaccurate ratings. If the process of credit rating would be more transparent and revealing we conclude that the informational aspects of credit ratings would be better, in accordance to what Griffin and Tang (2012) calls for. The transparency in the rating would, firstly, allow outside market participants to find the errors of the rating and incorporate these in their investment analysis (or indeed allow the equity analysts to use it in their forecasts). Secondly, it would decrease the degree of freedom for the CRA in their ratings processes and to some extent eliminate the arbitrary characteristics of the rating model and rating process. This last part is due to the element of outside monitoring. Today, we find disclosure policies only in some parts of the process (e.g. issuer and CRA relationship, fees for issuers etc.) (Griffin & Tang, 2012; Lynch, 2009; SEC, 2014; European Commission, 2016).

The regulatory environment that CRAs have created for themselves is truly one characterized by self-regulation and maintaining the duopoly of CRA business (Rousseau, 2006; Lynch, 2009). Comparing the CRAs to other information intermediaries such as the accounting firms reveals very different governmental approaches to regulation. Whereas the accounting firms are strictly monitored and obliged to follow certain set guidelines for accounting practice (IFRS, 2016). The CRAs however are under relatively minimal supervision and seemingly abide by their own regulatory space (Rousseau, 2006). The accounting industry today warrants global meta-regulations such as the IFRS and strict monitoring from organizations such as the SEC. This regulatory activity is done in the hopes of creating better information intermediaries in markets, and thereby increasing market efficiency. The results of our study show inefficiencies in the informational aspects of credit ratings, where both public and private information
decrease and the dispersion of analysts’ forecasts increase upon initial credit rating issuing. A question remaining to be answered is how these informational inefficiencies stack against the cost benefits of having CRAs do due diligence that would otherwise fall on the market participants, as discussed earlier in the analysis. Are these benefits larger than the cost of having less/worse information in the market? In any case, the discussion of a regulatory approach to combat these inefficiencies is warranted by the same logic that warrants the monitoring and strict supervision of the accounting standards globally.

Another aspect of our study is the identification of public and private information and the changes over time in the separate categories. Referring to Rhee (2015) one could hypothesize that the credit rating as an information intermediary would increase public information at the expense of privately held information. Mei & Subramanyam (2008) further suggest that equity analysts and credit rating analysts to a degree are substitutes for each other. This would mean that when a credit rating is issued on a firm, the equity analyst ends his/her coverage and shifts focus to another firm in order to look for private information that can be turned into business (Mei & Subramanyam, 2008). Finally, Lui et al (2012) takes this into consideration and find that the risk assessment (overall risk) made by the equity analysts are of a higher accuracy than that of the credit rating analysts. An alternative hypothesis taking into account these studies is that credit ratings would replace the coverage of equity analysts to some degree, resulting in a less accurate risk assessment on the focal firm. This would in turn increase public information (risk assessment becomes public) but decrease private information in a higher degree (risk assessment becomes worse). Our results however find no evidence of this relationship between public and private information. When the rating is issued and published both private and public information declines. Mei & Subramanyam (2012) bring up the cost benefits for the equity analysts to change focus upon the issuing of a credit rating. Since the equity analysts can use the risk assessment of the credit rating in their forecasting, the benefit of making their own assessment diminishes, which gives them the incentive to end that type of coverage. Seeing as our study show the information mediated from the credit rating actually does not increase information quality - the choice of foregoing an independent risk assessment from the equity analyst might need reviewing. This since the benefit of the free credit rating risk assessment for the equity analyst might be worse than currently expected.

The secondary study and our final hypothesis cover the instant market effects upon the issuing of a credit rating. Considering the negative results that we see in the market information upon the issuing of a credit rating one would also expect a negative result on the corresponding stock
price. Logically, worse information about an asset’s risk level should mean a higher risk premium or capital cost of investment. To elaborate, if the investor knew the informational differences between an asset covered purely by equity analysts and one with a credit rating, he might prefer the one where equity analysts have rated the risk level. This means that he would require a higher return on the asset with credit rating coverage – thus making this investment costlier. Considering this effect on capital costs of investment following the reduction of information quality the price effect should be negative. Further, having these results from our primary study beforehand we would perhaps have hypothesized a negative relationship between credit rating issuing and stock price. However, we find that the 11 days after the release of a rating are characterized by abnormally large returns on the focal firm’s stock. This can be contributed to various recent theories on the subject. Demiroglu and Ryngaert (2010) and Hansen (2015) bring up the effect of increased liquidity upon the news of initial coverage for a firm. Meaning an issued rating would increase speculation and trading for a specific stock leading to increased volatility and hence also to increased liquidity. Increased liquidity in turn brings value to a stock (lesser risk of stocks not trading and not allowing exit) and thus adds to the stock price. These studies however focus on equity analyst coverage and the size of the firm could be a factor. More specifically, the firms being issued initial credit ratings would generally be bigger than the firms receiving their first analyst stock recommendation or other types of coverage - meaning that the change in liquidity might be more noticeable in these smaller firms. Hansen (2015) further brings up the market expectations on increased quality in the corporate governance upon initial analyst coverage which can also be a factor to the value adding we see in our empirical results. These effects and the adding of stock value from initial coverage in general can be described as effects of investor recognition (Li & You, 2015). Investor recognition would include the market effects of investors gaining additional awareness, and indeed recognition, of the focal firm, leading to less perceived risk in investments and hence a higher stock value. The empirical results also gives evidence of market participants in fact incorporating the credit rating instantly in their investing process. In other words, the market participants could be said to view the credit rating as additional market information or think of it as higher quality information. In the long run and with support from our primary study, however, the information could be said to be of relatively low quality since it leads to less efficient earnings forecasting and equity pricing. Considering the results, we see two possible ways of analyzing the situation. Either (1) the investors and market participants know of the negative informational effects of credit ratings, but values the increased liquidity and the effects of investor recognition higher than the increased cost of invested capital – (2) or the investors
do not know that the informational quality surrounding the focal asset is worse upon credit rating issuing and the cost of capital-effect is not incorporated in the pricing models.
Chapter 7: Conclusion and Implications

In this final chapter of our study we start of by discussing the conclusions that can be drawn upon our research. We also talk about the theoretical and practical implications these conclusions might have for future research and market participants. Lastly, we finish our study by considering and sharing ideas for future research. What areas we find is still lacking existing research and how our study could be further developed by colleague researchers.

7.1 Conclusion

The study conducted examines the relationship between credit rating issuing and the information environment in financial markets. We use a model developed by Barron et al (1998) in order to proxy the information environment with the performance of equity analysts in their earnings forecasting. The empirical results of the study show that the issuing of a credit rating decreases the level of quality in market information in the long run. Both publicly available information and privately held information (by equity analysts) decreases. Our findings support the idea that information about an assets total risk level, contained in the credit rating, decreases precision in the overall information environment – while the credit rating, in accordance to Rhee (2015) might still have the function of sorting information (hence lowering costs of due diligence for market participants). We credit these negative effects to inaccurate ratings being issued and unwillingness to change ratings after initial issuing. Digging deeper we find theoretical support to our findings, where the rating process is subject to conflicts of interest and the CRAs have profit incentives to produce inaccurate ratings. The main causes we can distinguish are the solicited rating process, where issuers commission the CRA for a rating, the shopping of ratings, where issuers pin CRAs against each other picking the better rating and the unwillingness of CRAs to keep high levels of transparency in the rating models leading to potentially arbitrarily constructed rating processes (Lynch, 2009; Bolton et al, 2012; Griffin & Tang, 2012). Furthermore, we find that the initial market reaction to the issuing of initial credit ratings increase stock prices. This indicates that market participants in fact act on the issuing as additional market information - as opposed to the credit rating only affecting the issuers of credit (commercial banks etc.). Hence, where we find an increase in stock prices, one would logically assume that stock prices would diminish upon the lowering of information quality and increase in investment costs inherent in the initial credit rating. The results provide evidence to support that market participants such as investors and equity analysts act on credit ratings as
additional market information, which in the long run in fact decrease the efficiency of equity pricing and hence the efficiency in markets. Finally, we see huge differences between the regulatory space in which CRAs act and where the accounting firms act. The CRAs are under minimal supervision and abide by relatively lenient restrictions to their rating processes (Rousseau, 2006). We recommend discussions on increased regulation and control in the rating processes. Two approaches can be applied as solutions; the controlling or elimination of conflicts of interest such as the commissioning of ratings or increased transparency in rating models and implementation of stricter guidelines for rating processes.

7.2 Implications

Our study contributes with several implications, both theoretical and practical. The theoretical implications are largely concentrated to the research field of information environment. Potential practical implications pertain to the regulatory actions the might be taken to strengthen the market function of CRAs as well as market participants recognition of credit ratings as relatively bad indicators of overall risk level in an asset.

The empirical result of our study does not align with previous studies on the market function of CRAs (Rhee, 2015; Duarte et al, 2008) arguing the informational benefits of credit rating activities. Other studies have pinpointed separate issues and effects from the credit rating and voiced concern for the rating processes, while our study manages to produce results on the actual informational contributions that credit ratings have on the information environment in markets. We show how information available to market participants gets worse in the long run following a credit rating issuing. These conclusions warrant new research in the field and the revision of old conclusions about the informational contributions of CRAs as information intermediaries.

The practical implications of our results gives regulatory organizations such as ESMA and SEC additional motivation to review the regulation surrounding CRA activities and rating processes. We argue that an effective way of strengthening the credit rating as a provider of market information is to regulate the rating process. Either by forcing increased transparency in their models and need to declare and explain any deviations from the standardized models in any given process - or by generating more standardized models for rating and order the CRAs’ commitment to these models. This being said, we realize these actions are not without
implementation issues, such as that the rating process becomes more rigid and the individual skill of a credit rating analyst would be encroached upon.

Finally, we see practical implications to the investment and forecasting processes of all market participants. Even without regulatory measures being taken, the fact that increased knowledge about the informational benefits of credit ratings reaches the market might have positive effects on asset pricing. If the investor and equity analyst realizes the limitations of the rating and its indication of the underlying asset’s overall risk level increased precision in forecasts and investments can be expected. Another implication for the equity analysts’ is where they previously have left coverage of a firm in favor of a credit ratings risk assessment due to cost/benefit analysis. The cost of leaving coverage of said firm could be said to increase when knowing the limitations of the CRA risk assessment. The substitution effects that can be seen today between equity analysts and credit rating analysts (Mei & Subramanyam, 2008) might diminish with this in mind.

7.3 Future Research

Throughout our research process future research questions have been discussed. Our study aims to quantitatively explain relationships within the information environment. As mentioned in section 2.3, an interesting approach to researching the information environment with regards to CRAs is the qualitative research approach. We urge future researchers to apply a qualitative research approach to analyst in regards to how an initial credit rating is perceived and how it affects their forecasts.

Further, we find it necessary for a replication of our study but with a correction for financial crises. During the time period of our primary study (1991-2010) a number of financial crises has hit the markets. Periods leading up to a financial crisis are often characterized by speculation, which is exhibited during the financial crisis of 2008 where CDOs were overvalued (Wojtowicz, 2014) and the markets contain a high degree of trusting investors (Bolton et al, 2012). We therefore advice future researchers to compare periods prior to a financial crisis with periods after financial crisis with the same methodology as were used in our study, in order to examine the information content of the ratings.
Moreover, the differences in information content of credit ratings among countries would strengthen the understanding of the credit rating. The impact of both geographical and political differences would be highly interesting to research - where differences in corporate governance and investor protection systems would be thought to affect information quality of credit ratings.

In our study we have used analyst performance as the proxy for information quality. We suggest future research also use other proxies for information environment to test the effect of credit ratings. As there are several possible ways of measuring information, one would ask for the testing of other proxies to solidify the validity of our study. It would enhance knowledge surrounding the credit rating information effects as well as give additional inputs in the field of measuring market information.

Finally, we suggest further research on differences in information quality of ratings between the cases of solicited and unsolicited ratings. Based on our conclusions and Griffin and Tang’s (2012) study there is a distinct possibility of a higher quality of the rating when the issuer does not commission the rating. This would enable researchers to examine if CRAs in fact does manipulate their rating models for the worse in order to satisfy paying issuers’ demands. By examining the information quality of solicited and unsolicited ratings in a similar fashion to that of our study this knowledge could be gathered and acted upon.
References


Appendix

A.1 Statistical test outputs

A.1.1 Normality Test (Shapiro-Wilk)

A.1.1.1 Accuracy

<table>
<thead>
<tr>
<th>Normality Test (Shapiro-Wilk)</th>
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<td>Variable</td>
<td>Obs</td>
</tr>
<tr>
<td>ACC</td>
<td>9031</td>
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A.1.1.2 Dispersion

<table>
<thead>
<tr>
<th>Normality Test (Shapiro-Wilk)</th>
<th>DISP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Obs</td>
</tr>
<tr>
<td>DISP</td>
<td>9031</td>
</tr>
</tbody>
</table>

A.1.1.3 Public Information

<table>
<thead>
<tr>
<th>Normality Test (Shapiro-Wilk)</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Obs</td>
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<tr>
<td>H</td>
<td>9031</td>
</tr>
</tbody>
</table>

A.1.1.4 Private Information

<table>
<thead>
<tr>
<th>Normality Test (Shapiro-Wilk)</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Obs</td>
</tr>
<tr>
<td>S</td>
<td>9000</td>
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</table>

A.1.1.5 Stock Price

<table>
<thead>
<tr>
<th>Normality Test (Shapiro-Wilk)</th>
<th>P</th>
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</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Obs</td>
</tr>
<tr>
<td>price</td>
<td>2200</td>
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</tbody>
</table>
A.1.2 Autocorrelation Test (Wooldrige test for autocorrelation in panel data)

A.1.2.1 Accuracy

<table>
<thead>
<tr>
<th>Autocorrelation</th>
<th>ACC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wooldridge test for autocorrelation in panel data</td>
<td></td>
</tr>
<tr>
<td>H0: no first-order autocorrelation</td>
<td></td>
</tr>
<tr>
<td>$F(1, 58) = 16.508$</td>
<td></td>
</tr>
<tr>
<td>Prob $&gt; F = 0.0001$</td>
<td></td>
</tr>
</tbody>
</table>

Heteroscedasticity

- Likelihood-ratio test: $LR \chi^2(571) = 78789.49$
- (Assumption: hetero nested in .)
- $Prob > \chi^2 = 0.0000$

A.1.2.2 Dispersion

<table>
<thead>
<tr>
<th>Autocorrelation</th>
<th>DISP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wooldridge test for autocorrelation in panel data</td>
<td></td>
</tr>
<tr>
<td>H0: no first-order autocorrelation</td>
<td></td>
</tr>
<tr>
<td>$F(1, 58) = 14.87$</td>
<td></td>
</tr>
<tr>
<td>Prob $&gt; F = 0.0001$</td>
<td></td>
</tr>
</tbody>
</table>

Heteroscedasticity

- Likelihood-ratio test: $LR \chi^2(571) = 19923.72$
- (Assumption: hetero nested in .)
- $Prob > \chi^2 = 0.0000$

A.1.2.3 Public Information

<table>
<thead>
<tr>
<th>Autocorrelation</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wooldridge test for autocorrelation in panel data</td>
<td></td>
</tr>
<tr>
<td>H0: no first-order autocorrelation</td>
<td></td>
</tr>
<tr>
<td>$F(1, 58) = 31.094$</td>
<td></td>
</tr>
<tr>
<td>Prob $&gt; F = 0.0000$</td>
<td></td>
</tr>
</tbody>
</table>

Heteroscedasticity

- Likelihood-ratio test: $LR \chi^2(571) = -14619.3$
- (Assumption: hetero nested in .)
- $Prob > \chi^2 = 1.0000$

A.1.2.4 Private Information

<table>
<thead>
<tr>
<th>Autocorrelation</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wooldridge test for autocorrelation in panel data</td>
<td></td>
</tr>
<tr>
<td>H0: no first-order autocorrelation</td>
<td></td>
</tr>
<tr>
<td>$F(1, 58) = 53.691$</td>
<td></td>
</tr>
<tr>
<td>Prob $&gt; F = 0.0000$</td>
<td></td>
</tr>
</tbody>
</table>

Heteroscedasticity

- Likelihood-ratio test: $LR \chi^2(571) = -36785.2$
- (Assumption: hetero nested in .)
- $Prob > \chi^2 = 1.0000$
A.1.2.5 Stock Price

**Autocorrelation**

<table>
<thead>
<tr>
<th>P</th>
<th>Wooldridge test for autocorrelation in panel data</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H0:</strong> no first-order autocorrelation</td>
<td></td>
</tr>
<tr>
<td><strong>F( 1, 99)</strong></td>
<td>8,835</td>
</tr>
<tr>
<td><strong>Prob &gt; F</strong></td>
<td>0.0037</td>
</tr>
</tbody>
</table>

**Heteroscedastics**

<table>
<thead>
<tr>
<th>Likelihood-ratio test</th>
<th><strong>LR chi2(571)= 10774.91</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>(Assumption: hetero nested in .)</td>
<td><strong>Prob &gt; chi2 = 0.0000</strong></td>
</tr>
</tbody>
</table>

A.2 Driscoll-Kraay Panel Data Regression

**A.2.1 Accuracy**

<table>
<thead>
<tr>
<th>ACC</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>0.2795973</td>
<td>0.991764</td>
<td>0.28</td>
<td>0.781</td>
<td>-1.796189 - 2.355383</td>
</tr>
<tr>
<td>stdroe</td>
<td>-0.0033821</td>
<td>0.0019508</td>
<td>-1.73</td>
<td>0.099</td>
<td>-0.0074652 - 0.000701</td>
</tr>
<tr>
<td>n</td>
<td>-0.1035448</td>
<td>0.0414608</td>
<td>-2.25</td>
<td>0.022</td>
<td>-0.1903233 - 0.01677</td>
</tr>
<tr>
<td>vo</td>
<td>-4.96E-07</td>
<td>2.30E-07</td>
<td>-2.15</td>
<td>0.044</td>
<td>-9.79E-07 - 1.37E-08</td>
</tr>
<tr>
<td>mv</td>
<td>-1.86E-06</td>
<td>1.31E-06</td>
<td>-1.42</td>
<td>0.171</td>
<td>-4.59E-06 - 8.77E-07</td>
</tr>
<tr>
<td>ES</td>
<td>-19.03221</td>
<td>16.52994</td>
<td>-1.15</td>
<td>0.264</td>
<td>-53.62978 - 15.56536</td>
</tr>
<tr>
<td>_cons</td>
<td>12.92812</td>
<td>1.381083</td>
<td>9.36</td>
<td>0.000</td>
<td>10.03748 - 15.81876</td>
</tr>
</tbody>
</table>

| R-square | 0.0861 |
| Obs | 9028 |
| Groups | 584 |

**A.2.2 Dispersion**

<table>
<thead>
<tr>
<th>DISP</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>0.0594703</td>
<td>0.0254248</td>
<td>2.34</td>
<td>0.030</td>
<td>0.0062555 - 0.112685</td>
</tr>
<tr>
<td>stdroe</td>
<td>0.0000359</td>
<td>0.0000448</td>
<td>0.8</td>
<td>0.433</td>
<td>-0.0000579 - 0.000013</td>
</tr>
<tr>
<td>n</td>
<td>-0.0001589</td>
<td>0.0010961</td>
<td>-0.14</td>
<td>0.886</td>
<td>-0.002453 - 0.002135</td>
</tr>
<tr>
<td>vo</td>
<td>8.88E-10</td>
<td>3.05E-09</td>
<td>0.29</td>
<td>0.774</td>
<td>-5.49E-09 - 7.27E-09</td>
</tr>
<tr>
<td>mv</td>
<td>6.91E-07</td>
<td>6.47E-08</td>
<td>10.67</td>
<td>0.000</td>
<td>5.55E-07 - 8.26E-07</td>
</tr>
<tr>
<td>ES</td>
<td>0.0126176</td>
<td>0.0091239</td>
<td>1.38</td>
<td>0.183</td>
<td>-0.0064789 - 0.031714</td>
</tr>
<tr>
<td>_cons</td>
<td>0.150575</td>
<td>0.0133746</td>
<td>11.26</td>
<td>0.000</td>
<td>0.1225817 - 0.178568</td>
</tr>
</tbody>
</table>

| R-square | 0.078 |
| Obs | 9028 |
| Groups | 584 |
### A.2.3 Public Information

**Driscol-Kraay Panel-Data Regression**

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>-1.119863</td>
<td>0.3211004</td>
<td>-3.49</td>
<td>0.002</td>
<td>-1.791933 -0.44779</td>
</tr>
<tr>
<td>stdroe</td>
<td>0.00034</td>
<td>0.0005311</td>
<td>0.64</td>
<td>0.530</td>
<td>-0.0007716 0.001452</td>
</tr>
<tr>
<td>n</td>
<td>-0.0474343</td>
<td>0.005663</td>
<td>-8.38</td>
<td>0.000</td>
<td>-0.0592871 -0.03558</td>
</tr>
<tr>
<td>vo</td>
<td>9.19E-08</td>
<td>6.81E-08</td>
<td>1.35</td>
<td>0.193</td>
<td>-5.07E-08 2.34E-07</td>
</tr>
<tr>
<td>mv</td>
<td>-2.22E-06</td>
<td>3.19E-07</td>
<td>-7.03</td>
<td>0.000</td>
<td>-2.88E-06 -1.56E-06</td>
</tr>
<tr>
<td>ES</td>
<td>0.4190449</td>
<td>0.3245644</td>
<td>1.29</td>
<td>0.212</td>
<td>-0.2602761 1.098366</td>
</tr>
</tbody>
</table>

_cons    | 4.183737    | 0.1253722 | 33.37 | 0.000 | 3.92133 4.446144     |

R-square | 0.0381      |
Obs       | 9028        |
Groups    | 584         |

### A.2.4 Private Information

**Driscol-Kraay Panel-Data Regression**

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>-6.776304</td>
<td>2.138285</td>
<td>-3.17</td>
<td>0.005</td>
<td>-11.25179 -2.30082</td>
</tr>
<tr>
<td>stdroe</td>
<td>0.0007356</td>
<td>0.0031513</td>
<td>0.23</td>
<td>0.818</td>
<td>-0.0058601 0.007331</td>
</tr>
<tr>
<td>n</td>
<td>0.0521481</td>
<td>0.0573696</td>
<td>0.91</td>
<td>0.375</td>
<td>-0.0679278 0.17224</td>
</tr>
<tr>
<td>vo</td>
<td>1.76E-07</td>
<td>1.95E-07</td>
<td>0.9</td>
<td>0.378</td>
<td>-2.32E-07 5.85E-07</td>
</tr>
<tr>
<td>mv</td>
<td>-8.31E-06</td>
<td>1.79E-06</td>
<td>-4.64</td>
<td>0.000</td>
<td>-0.0000121 -4.56E-06</td>
</tr>
<tr>
<td>ES</td>
<td>1.903588</td>
<td>1.258008</td>
<td>1.51</td>
<td>0.147</td>
<td>-0.7294532 4.536629</td>
</tr>
</tbody>
</table>

_cons    | 15.30386    | 1.022469  | 14.97 | 0.000 | 13.16381 17.44391    |

R-square | 0.0393      |
Obs       | 9028        |
Groups    | 584         |

### A.2.5 Stock Price

**Driscol-Kraay Panel-Data Regression**

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICR</td>
<td>1.087283</td>
<td>0.0227189</td>
<td>47.86</td>
<td>0.000</td>
<td>1.040036 1.134529</td>
</tr>
<tr>
<td>RR</td>
<td>-0.1070431</td>
<td>0.0020861</td>
<td>-51.31</td>
<td>0.000</td>
<td>-0.113815 -0.1027</td>
</tr>
<tr>
<td>INDEXP</td>
<td>0.0003531</td>
<td>2.26E-07</td>
<td>1560.77</td>
<td>0.000</td>
<td>0.0003526 0.000354</td>
</tr>
</tbody>
</table>

_cons    | 10.69626    | 0.0041407 | 2583.18| 0.000 | 10.68765 10.70487    |

R-square | 0.1754      |
Obs       | 2200        |
Groups    | 100         |
## A.3 Median Regression outputs

### A.3.1 Accuracy

<table>
<thead>
<tr>
<th>ACC</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>0.2290472</td>
<td>0.4503742</td>
<td>0.51</td>
<td>0.611</td>
<td>-0.6537885 1.111883</td>
</tr>
<tr>
<td>stdroe</td>
<td>0.0000437</td>
<td>0.0022963</td>
<td>0.02</td>
<td>0.985</td>
<td>-0.0044575 0.004545</td>
</tr>
<tr>
<td>n</td>
<td>-0.0066974</td>
<td>0.0260553</td>
<td>-0.26</td>
<td>0.797</td>
<td>-0.0577717 0.044377</td>
</tr>
<tr>
<td>vo</td>
<td>1.18E-07</td>
<td>3.06E-07</td>
<td>0.39</td>
<td>0.700</td>
<td>-4.82E-07 7.18E-07</td>
</tr>
<tr>
<td>mv</td>
<td>3.31E-07</td>
<td>1.99E-06</td>
<td>0.17</td>
<td>0.868</td>
<td>-3.58E-06 4.24E-06</td>
</tr>
<tr>
<td>ES</td>
<td>-154.1717</td>
<td>0.3126251</td>
<td>-493.15</td>
<td>0.000</td>
<td>-154.7845 -153.559</td>
</tr>
<tr>
<td>_cons</td>
<td>0.2522116</td>
<td>0.4663722</td>
<td>0.54</td>
<td>0.589</td>
<td>-0.6619838 1.166407</td>
</tr>
</tbody>
</table>

R-square: 0.1851

### A.3.2 Dispersion

<table>
<thead>
<tr>
<th>DISP</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>0.0310647</td>
<td>0.0029295</td>
<td>10.6</td>
<td>0.000</td>
<td>0.0253223 0.036807</td>
</tr>
<tr>
<td>stdroe</td>
<td>0.0000221</td>
<td>0.000149</td>
<td>1.48</td>
<td>0.140</td>
<td>-7.23E-06 5.13E-05</td>
</tr>
<tr>
<td>n</td>
<td>-0.0000746</td>
<td>0.0001695</td>
<td>-0.44</td>
<td>0.660</td>
<td>-0.0004068 0.000258</td>
</tr>
<tr>
<td>vo</td>
<td>-8.31E-10</td>
<td>1.99E-09</td>
<td>-0.42</td>
<td>0.676</td>
<td>-4.74E-09 3.07E-09</td>
</tr>
<tr>
<td>mv</td>
<td>6.88E-07</td>
<td>1.30E-08</td>
<td>53.06</td>
<td>0.000</td>
<td>6.63E-07 7.13E-07</td>
</tr>
<tr>
<td>ES</td>
<td>0.0021185</td>
<td>0.0020335</td>
<td>1.04</td>
<td>0.298</td>
<td>-0.0018675 0.006105</td>
</tr>
<tr>
<td>_cons</td>
<td>0.049607</td>
<td>0.0030335</td>
<td>16.35</td>
<td>0.000</td>
<td>0.0436606 0.055553</td>
</tr>
</tbody>
</table>

R-square: 0.0344

### A.3.3 Public Information

<table>
<thead>
<tr>
<th>H</th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>-0.367986</td>
<td>0.0647944</td>
<td>-5.68</td>
<td>0.000</td>
<td>-0.4949978 -0.24097</td>
</tr>
<tr>
<td>stdroe</td>
<td>-0.0002594</td>
<td>0.0003304</td>
<td>-0.79</td>
<td>0.432</td>
<td>-0.000907 0.000388</td>
</tr>
<tr>
<td>n</td>
<td>-0.0224045</td>
<td>0.0037485</td>
<td>-5.98</td>
<td>0.000</td>
<td>-0.0297525 -0.01506</td>
</tr>
<tr>
<td>vo</td>
<td>4.84E-08</td>
<td>4.40E-08</td>
<td>1.1</td>
<td>0.272</td>
<td>-3.80E-08 1.35E-07</td>
</tr>
<tr>
<td>mv</td>
<td>-1.17E-06</td>
<td>2.87E-07</td>
<td>-4.07</td>
<td>0.000</td>
<td>-1.73E-06 -6.04E-07</td>
</tr>
<tr>
<td>ES</td>
<td>1.483342</td>
<td>0.0497674</td>
<td>32.98</td>
<td>0.000</td>
<td>1.395177 1.571506</td>
</tr>
<tr>
<td>_cons</td>
<td>1.91204</td>
<td>0.067096</td>
<td>28.5</td>
<td>0.000</td>
<td>1.780517 2.043564</td>
</tr>
</tbody>
</table>

R-square: 0.0346
### A.3.4 Private Information

**Median Panel-Data Regression**

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>creditrating</td>
<td>-2.237692</td>
<td>0.3024181</td>
<td>-7.4</td>
<td>0.000</td>
<td>-2.830501 -1.64488</td>
</tr>
<tr>
<td>stdroe</td>
<td>0.0004258</td>
<td>0.0015419</td>
<td>0.28</td>
<td>0.782</td>
<td>-0.0025967 0.003448</td>
</tr>
<tr>
<td>n</td>
<td>0.0520148</td>
<td>0.0174957</td>
<td>2.97</td>
<td>0.003</td>
<td>0.0177193 0.08631</td>
</tr>
<tr>
<td>vo</td>
<td>4.85E-07</td>
<td>2.06E-07</td>
<td>2.36</td>
<td>0.018</td>
<td>8.22E-08 8.88E-07</td>
</tr>
<tr>
<td>mv</td>
<td>-2.98E-06</td>
<td>1.34E-06</td>
<td>-2.23</td>
<td>0.026</td>
<td>-5.61E-06 -3.61E-07</td>
</tr>
<tr>
<td>ES</td>
<td>4.838912</td>
<td>0.209922</td>
<td>23.05</td>
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R-square: 0.0241

### A.3.5 Stock Price

**Median Panel-Data Regression**

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<th>Std. Err.</th>
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<th>P&gt;t</th>
<th>[95% Conf. Interval]</th>
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R-square: 0.1043