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The impact of credit rating watchlist and effect of underwriter reputation on IPO underpricing

Jing Liu

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**The impact of credit rating watchlist and effect of underwriter reputation on
IPO underpricing**

by

Jing Liu

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

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2007

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ABSTRACT

This paper first sets up a theoretical model to describe a credit rating agency's (CRA) two roles, namely rating and monitoring. Through CRA's monitoring role, bonds no longer represent loan contracts without monitoring. In the model, bond issuers have to decide whether to go through CRA or borrow directly, and whether to take action to prevent future risk or not. CRA's monitoring ability is shown to be crucial. If CRA can observe creditworthiness changes more accurately so as to offer ratings with less noise, there will be more issuers willing to signal their qualities and take action. If CRA can attract issuers to take action but cannot function in its monitoring role well enough, social welfare will be reduced after introducing CRA into the market.

This paper then examines price adjustments in bond and equity markets according to Moody's bond rating watchlist announcements and actual rating change announcements afterwards. Based on different methods of calculating excess returns, we find that asset prices react in response to Moody's rating announcements, suggesting that they convey valuable information to both bond and equity markets and investors adjust prices according to both upgrading and downgrading directions. When we control for bond rating grades, the evidence of market reactions is more significant than without the control; in contrast, controlling for a stock's beta is not so beneficial. Stronger evidence of market reactions is found in bond markets than in equity markets.

Lastly, Generalized Linear Models (GLMs) with fixed and mixed effects are applied to describe how an issuer matches with an underwriter for an initial public offering (IPO). The study focuses on the issuer's preference over underwriter reputation. From GLM with fixed effects, we find that the issuer tends to choose a high-reputation underwriter when the IPO's expected offer size is large, the expected offer price is high, the issuer is a young firm, there is venture capital backing, the issuer has more assets, or the issuer's leverage ratio is small. From the random effect in GLM with mixed effects, we find that issuers in the state of California or in the Service and Utility industries are more likely to choose high-reputation underwriters than issuers in other states or industries. Underwriters with high reputation tend to have larger sales forces and have headquarters in New York. Using propensity score

matching methods, we find that underwriters with high reputation are generally associated with larger underpricings. The subsamples by the location of offer price in the filing range confirm such positive relation. However, evidence from subperiods shows that the larger underpricing is likely to be both an issuer's industry effect and an underwriter's reputation effect.

CHAPTER 1. THE IMPACT OF CREDIT RATING WATCHLIST

1.1 Introduction

Credit Rating Agencies (CRAs) are important for financial markets. They serve as a guide for investors to make investment decisions. They have two main roles, namely, rating and monitoring. For corporate bonds, they decide ratings based on private and/or public information they obtain. It is to be expected that higher credit ratings will lead to lower funding costs. Monitoring happens after the initial rating is published. If CRAs find that something unusual happens regarding a particular bond issuer, they can decide to put its bond on watchlist¹ for review. An issuer who is put on watchlist and wants to prevent a downgrade or promote an upgrade needs to provide more private information to the CRA. Ultimately, the CRA will report an updated rating. For example, on August 27 1990, the Wall Street Journal reported that on June 11 1990 S&P placed McDonnell Douglas Finance Corp.'s senior debt on its Credit-Watch list for possible downgrade. On August 27 1990, S&P downgraded the issues from single-A-plus to single-A-minus and removed the issues from its Credit-Watch list. The rating concern cited the corporation's real-estate and auto loans problem, and the negative outlook for its aerospace business. Through the credit watch procedure, the CRA can inform investors of potentially enlarged/reduced risk at maturity, so that investors can adjust their pricing decisions accordingly.

Traditionally, bonds have been characterized as direct borrowing without monitoring. However, the CRA can put bonds on credit watchlist for review. This means that bonds are not monitor-free if issuers choose to go through a CRA. The existence of CRA's monitoring raises the questions of how a CRA monitors bonds, how issuers and investors react to CRA's action, and what is the social welfare impact of such monitoring. Answers to those questions are important but still missing from the literature, especially from a theoretical standpoint. Therefore, the main objective of the present paper is to analyze the mechanism of CRA's monitoring role and its impact.

¹ There are different terminologies for credit rating watchlist. S&P usually refers to it as "Credit Watch List" and Moody's uses "Rating Review List" or "Watchlist (Review)". So we call it "Credit Rating Watchlist" in the paper and use "watchlist" for short.

Previous theoretical studies can be classified into two strands, based on market failures in direct credit markets. One strand shows the role of contractual covenants as a method to control agency problems between insiders and outsiders. The second strand focuses on specialized monitoring institutions, for instance financial intermediaries, which are characterized as delegated monitoring. Diamond (1984) assumes asymmetric information and costly monitoring and develops a theory of financial intermediation. Berlin and Loeys (1988) consider a firm's choice between loan contracts with covenants but no monitoring, and loan contracts enforced by a monitoring specialist (or financial intermediary). They show that the firm's choice depends on its credit quality, the accuracy of financial indicators of its creditworthiness, and the cost of monitoring. Diamond (1991) shows that borrowers with median credit qualities rely on loans from banks, which have monitoring function. Borrowers with either high- or low-credit quality will borrow directly by issuing a bond without monitoring.

The present study lays out a model of a firm's choice to issue bonds either directly or through the CRA. The model emphasizes CRA's monitoring role and relates to the literature on specialized monitoring institutions. However, CRAs are different from financial intermediaries in the literature. Diamond (1984) states that

"... a financial intermediary raises funds from many lenders (depositors), promises them a given pattern of returns, lends to entrepreneurs, and spends resources monitoring and enforcing loan contracts with entrepreneurs which are less costly than those available without monitoring.

Therefore, for incentive purposes for depositors and entrepreneurs, financial intermediaries need to bear repayment risks. However, they do not publish information monitored to the lenders. Similarly, CRAs perform rating and monitoring tasks. However, unlike traditional financial intermediaries, CRAs charge issuers and then provide ratings to the public for free. They do not raise or lend funds, as investors directly lend money to issuers. The CRA is a specialized monitoring institution which only signals an issuer's creditworthiness to the public, and the signal helps investors make investment decisions on

their own. From the point of signalling, our model relates to the literature on signalling games with imperfect information.

The most closely related contribution is Boot, Milbourn and Schmeits (2006), who study the role of credit rating from a theoretical standpoint. They show that a CRA can represent a coordination mechanism for investors. They focus on initial ratings and show how they affect the market by introducing institutional investors. Boot et al. also model the appeal process for initial ratings and attempt to describe the credit watch procedure. Different from their interest, our paper focuses on CRA's monitoring role. We explicitly model the credit watch procedure and study its impact on financial markets. Similarly to the "recovery effort" in their model, we assume that issuers can take action as an ex ante hedging strategy. This relates our model to the literature on risk management (e.g., Leland (1998)², Smith and Stulz (1985)³).⁴ However, the preference over hedging strategies is not pursued here.

As reviewed in Ederington and Yawitz (1987), early empirical studies found mixed results when examining the market response to rating changes. However, most recent studies find a significant market reaction to bond downgrades (e.g., Dichev and Piotroski (2001), Griffin and Sanvicente (1982), Goh and Ederington (1993), Hand, Holthausen and Leftwich (1992), Holthausen and Leftwich (1986), Wansley and Clauretje (1985)). Generally, they do not find a significant market response to bond upgrades. Except for Hand et al. (1992) and Wansley and Clauretje (1985), these studies examine only equity market reactions. The most probable reason is that daily bond price data are not easily accessible. Another reason could be that it is difficult to get a purely uncontaminated sample to focus solely on the watchlist. Here "uncontaminated" means there are no concurrent disclosures from other sources except CRAs.

Wansley and Clauretje (1985) suggest that the placement of firms on watchlist is unexpected to investors; there are significant price adjustments caused by placement on watchlist with negative reasons. Hand, Holthausen and Leftwich (1992) find significantly

² Leland mainly examines the joint determination of capital structure and investment risk. In the analysis of risk management, he shows that the ex ante hedging strategy performs always better than the ex post strategy and the strategy to hedge all the time. He also points out that the current understanding of why firms hedge is incomplete.

³ Smith and Stulz point out that although ex post hedging is in stockholders' best interest, less hedging will occur than with an ex ante hedging strategy.

⁴ Most of the studies in this field support our selection of an ex ante hedging strategy in the model.

negative daily excess bond returns (DEBRs) for either unexpected or uncontaminated watchlist for downgrades, significantly negative DEBRs for expected watchlist for upgrades, and significantly positive DEBRs for unexpected and uncontaminated watchlist for upgrades. For actual rating changes after watchlist, they find significantly negative DEBRs for downgrades and significantly positive DEBRs for upgrades. These two results are both consistent with our assumption that CRAs have limited ability to correctly put bonds on watchlist. If investors believe CRAs have perfect ability to put bonds on watchlist, they would only react to the watchlist and assume that the actual rating change will be the same as watchlist shows. But Hand et al. (2006) emphasize that investors react to both watchlist and the following actual rating changes, which implies that these two are not exactly the same for investors.

Following the aforementioned empirical results, we set up a theoretical model and analyze the impact of credit rating watchlist on issuers' equilibrium strategies and social welfare. Issuers face two decisions, namely (i) going through a CRA or borrowing directly, and (ii) taking action to prevent future risk or not. We mainly explore CRA's interaction with issuers and its credit rating watchlist. The changes in bond prices predicted by our model coincide with those obtained by empirical studies. In the model there exist three Pure Strategy Nash Equilibria and CRA's ability to correctly put issuers on watchlist is crucial. The welfare analysis suggests that introducing a CRA into the financial market does not always improve social welfare.

The rest of this chapter is organized as follows. Section 1.2 introduces the credit rating market and the watchlist process. Section 1.3 describes the model setup. Section 1.4 analyzes the impact of credit rating watchlist on bond prices. Section 1.5 shows the issuer's subgame equilibrium, equilibrium strategy and outcome, and section 1.6 analyses the effects on social welfare. Section 1.7 concludes, points out limitations of the model, and suggests paths for future study.

1.2 Credit Rating Market and Watchlist Process

Many observers accept the CRA as an important component of financial markets. S&P states [S&P (2005)] that

"Ratings are based on information supplied to Ratings Services by the issuer or its agents and information obtained by Ratings Services from other sources it considers reliable."

S&P writes [S&P (2006)] that

"Ratings Services must comply with securities laws in many jurisdictions that limit or in some cases prohibit the improper use of non-public information...All Confidential Information that is obtained by Ratings Services employees in the course of their employment with rating services must be kept confidential."

The aforementioned statements indicate that some of the information provided by issuers to a CRA is private. As issuers do not want to make their private information public, they use a CRA as an intermediary to signal their quality to the markets. However, there are some ratings that are initiated by CRAs and generally do not involve the participation of an issuer's management. In such instances, private information is less likely to be included in the rating process. In the present model, we exclude the latter and assume that ratings are solely based on private information.

Many economists are of the opinion that credit rating itself has little information value and is more likely to be a method for information release. However, there are documents from S&P and Moody's supporting the view that there is new information revealed by the rating. S&P asserts [S&P (2005)] that

"Ratings are current opinions regarding future creditworthiness of issuers or issues...Ratings are not verifiable statements of fact..."

Moody's reports [Cantor and Fons (1999)] that

"...credit rating is by nature subjective. The role of the rating committee is to introduce as much objectivity to the process as possible by bringing an understanding of the relevant risk factors and viewpoints to each and every analysis. For each rating, Moody's relies on the judgment of a diverse group of credit risk professionals to weigh those factors in light of a variety of business scenarios for the issuer and then

come to a conclusion on what the rating should be...Moody's rating is an opinion forecast of an issuer's future relative creditworthiness."

From all of the above, it can be concluded that credit rating is not only a signal for existing facts, but also CRA's subjective opinion about the issuer's future creditworthiness. It seems reasonable for credit ratings to have information value themselves.

Analysts from CRAs try to inform the issuer immediately after the rating committee determined rating and prior to the publication of the rating. It is possible that the issuer is not satisfied with CRA's rating and starts an appeal process. Moody's states [Hilderman (1999)] that

"An appeal process may be considered for a first-time rating, if the issuer is able to provide new and material information that might lead the rating committee to reconsider the rating...This (the appeal process) does not frequently occur because the analyst works with the issuer throughout the original rating process to make sure that all relevant information is brought forth and considered prior to the convening of the rating committee."

This implies that the issuer almost always accepts the first-time rating. For the purpose of our model, the appeal process will not be considered, by assuming that the CRA has perfect rating ability. This assumption can be justified on the grounds that the CRA can get a substantial amount of private information about the issuer and can ask for more if needed.

Moody's reports [Mahoney (2002)] that between 1970 and 2001, about 7.15% of 'Aaa' ratings, 7.44% of 'Aa' ratings, 4.68% of 'A' ratings and 4.51% of 'Baa' ratings were downgraded by one grade to the lower adjacent grade on a one- year-average basis. Thus, the original investment rating has been downgraded with average probability less than 10% per year over 30 years. However, the probability of downgrades can be much higher when considering periods of several years. Thus, it is relevant for investors to take possible future downgrades into account when making investment decisions.

The main focus of our model is the impact of CRA's watchlist, which is expected to improve the quality of ratings and also provides a way to help us understand the market

reaction to the informational content of watchlist placement. Boot et al. (2006) show the fundamental mechanism of CRA's role of rating in the market by introducing institutional investors. We will not focus on that aspect, but rather on CRA's monitoring role after the initial rating is assigned. According to S&P (2005):

"...once a rating is assigned Ratings Services shall monitor on an ongoing basis and update the rating by: a. regularly reviewing the issuer's creditworthiness; b. initiating a review of the status of the rating upon becoming aware of any information that might reasonably be expected to result in a Rating Action..."

Similarly, Moody's states [Fons (2002)] that

"If changing circumstances contradict the assumptions or data supporting the current rating, we will place the rating under review (on the watchlist). The watchlist highlights issuers whose rating is formally on review for possible upgrade, downgrade, or direction uncertain ... between 66%-76% of all ratings have been changed in the same direction (and rarely in the opposite direction) as indicated by their watchlist review."

The fact that historically only 66%-76% of watchlist placements were followed by a change in rating in the same direction suggests that CRA has a limited ability to observe the changing circumstances contradicting the assumptions supporting the current rating. Compared to an initial rating, the issuer may not provide detailed private information to the CRA for updating purposes. The CRA may suspect of changing circumstances but can not be completely sure. Thus, it is possible for the CRA to put an issuer on watchlist by mistake, or to not put an issuer on watchlist when it should. Therefore, in our model, it assumes that the CRA has limited ability to correctly put an issuer on watchlist.

Investors are believed to trust the rating. For example, Moody's reports [Fons (2002)] that

"Investors follow and react to multiple aspects of the rating system-- e.g., rating outlooks and the watchlist--for indications of potential

changes in credit quality...rating agency behavior is believed to influence security prices..."

This is Moody's interpretation of the commentary from meetings with issuer organizations, investors, asset management firms, and the like. It suggests that investors base their investment decisions on the rating and adjust them following watchlist placement.

If an issuer is put on watchlist, it may provide further private information to the CRA. This allows the CRA to reach an updated conclusion regarding the issuer's future creditworthiness. Based on the new rating, investors may adjust their investment decisions so that the market price may change as well. Thus, our analysis also looks at the price change after the publication of the updated rating.

1.3 Model Setup

To focus on the essential issues regarding CRAs, we assume perfectly competitive financial markets, risk neutrality, and a zero risk-free interest rate. There are two types of projects in the market, either safe or risky. A safe project has default rate 0 and a risky project has default rate $1-\gamma$, $0 < \gamma < 1$. Both projects have gross rate of return R_p (>1) when not in default, and zero otherwise. An issuer raises funds directly from the bond market and invests them in the project. Each bond pays investors one dollar at maturity if it is not in default, and zero otherwise.

At the beginning (i.e., $t=0$), bond issuers can be either initially good (G) with probability β or initially bad (B) with probability $(1-\beta)$. The distribution is common knowledge to every player including the issuer, who does not know its initial type⁵. Initially good issuers end up investing in the safe (risky) projects with probability $(1-\alpha)$ (α), whereas initially bad issuers invest in the risky projects with probability 1. Later on (i.e., $t=2$), a negative⁶ shock might happen randomly with probability α to initially good issuers. If a

⁵ It may be argued that issuers usually have private information about themselves and they should know their initial types. The reason that we employ the assumption that issuers do not know their initial types is laid out in Appendix A.

⁶ We do not model positive shocks because previous empirical work does not support significant market reaction to watchlist for possible upgrade. According to Goh and Ederington (1998), possible reasons for this stylized fact are that either companies voluntarily release favorable information but are reluctant to release unfavorable information, or that CRAs spend more resources in detecting deteriorations in credit quality than improvement.

shock happens, the initially good issuer invests in the risky project with probability 1^7 . Otherwise, the initially good issuer invests in the safe project for sure. We assume that α is common knowledge to all game participants but the shock is private information to the issuer. Therefore, the probabilities of issuers investing in safe and risky projects are $\beta(1-\alpha)$ and $[(1-\beta)+\beta\alpha]$, respectively.

Assumption 1: $\alpha < 1/2$.

The assumption means that the negative shock is not very likely. The reason for restricting $\alpha < 1/2$ is that we do not want shocks to dominate the impact of watchlist, and the players' beliefs and actions will not be normal if shocks happen frequently. It is straightforward to extend the model to allow for $1/2 < \alpha < 1$.

If there were no CRA in the market, investors would make investment decisions based on market average quality (see figure 1.1). In contrast, in the presence of CRAs with both rating and monitoring roles, the timeline⁸ when issuers choose to go through the CRA is extended as shown in figure 1.2. The events at times 1 and 3 correspond to CRA's rating role, whereas events at time 2 relates to CRA's monitoring role. If issuers do not go through the CRA, investors will make investment decisions based on public information (or market average quality), which is the same as the game with no CRAs in the market.

We assume there is only one CRA, as a simplification of many identical CRAs. If an issuer chooses to go through a CRA (at $t=1$), the CRA will charge it a flat-rate service fee C_r , which makes the CRA break even. The rating contract requires an issuer to provide enough confidential information (at $t=1$) for the initial rating and also some confidential information on a frequent basis for monitoring purposes. The CRA uses the same effort to rate each project and gives rating results mainly based on the private information provided by the issuers. Ratings can be either high quality (h)⁹ or low quality (l).¹⁰ Once the CRA determines the rating, it commits to publicly report it. We assume that the CRA has perfect rating ability,

⁷ As there is only a one-time shock by assumption, a project's type will not change afterwards. Thus, it is permanent after the shock.

⁸ As a simplification, we assume that issuers are always more sensitive to the rating grades than investors, such that issuers always react to the rating grades faster/earlier than investors.

⁹ In the real world, ratings on corporate bonds can vary from a highest quality of Aaa to a lowest quality of C. For example, Moody's uses Aaa, Aa, A, Baa, Ba, B, Caa, Ca, and C, and there are two modifiers, '+' and '-', in each rating grade. Here we restrict ratings to only two categories, 'h' and 'l', to make the model tractable.

¹⁰ The same rating grade at different times may have different interpretations. It will be addressed in detail below.

so that it can correctly rate an initially good (or bad) issuer as ‘h’ (or ‘l’). Thus, after the initial rating, an issuer will know its initial type. As the initial rating is based on current available information that the CRA gets (at $t=1$), the initial rating is a short-term rating (for $t=1$ only). Because there may be negative shocks for initially good issuers, an initial rating ‘h’ (at $t=1$) is a signal indicating that the issuer is likely to invest in the safe project, while an initial rating ‘l’ (at $t=1$) is a signal indicating that the issuer invests in the risky project for sure.

$t=0$
• Nature assigns an initial type (initially good or initially bad) to an issuer.
$t=1$
• Investors invest in bonds and issuers invest the resulting funds in projects.
$t=2$
• Negative shocks happen.
$t=3$
• Projects and bonds pay off.

Figure 1.1. The Timeline of the Game in the Absence of CRA

$t=0$
• Nature assigns an initial type (initially good or initially bad) to an issuer.
$t=1$
<ul style="list-style-type: none"> • An issuer offers private information to the CRA. • The CRA gives the bond a rating grade, which is published for free. • An initially good issuer chooses to take action or not. • Investors invest in bonds and issuers invest the resulting funds in projects.
$t=2$
<ul style="list-style-type: none"> • Negative shocks happen. • The CRA decides whether to put bond on watchlist. • If a bond is not on watchlist, the issuer keeps initial rating. If a bond is put on watchlist, the issuer chooses whether to provide more private information or not. • Investors adjust bond prices according to rating changes, and issuers adjust investment in projects accordingly.
$t=3$
<ul style="list-style-type: none"> • If an issuer is put on watchlist, the CRA announces rerating grade. • Investors adjust bond prices according to rating changes, and issuers adjust investment in projects accordingly. • Projects and bonds pay off.

Figure 1.2. The Timeline of the Game when Issuers Go Through the CRA

Immediately after an issuer knows its initial rating and before a shock happens, an initially good issuer may take action to reduce the probability of the future negative shock. The action has private cost C_a and the action's probability of success is θ . If an issuer's action is successful, it will receive no shock for sure; otherwise, the shock will happen with probability α as usual. During the CRA's monitoring role, we assume that an issuer's action is observable to the CRA and so is the result of the action.

After the negative shock happens (at $t=2$), if the CRA finds that changing circumstances contradict the assumptions or data supporting the current bond rating, it will place that bond on watchlist with rating 'w'. As a result of our assumption, the rating 'w' is a signal indicating that the bond is on review for possible downgrade. We assume that the CRA has limited ability to correctly put an issuer on watchlist such that with probability $(1-\eta)$ (or η) the CRA will put a non-shocked (or shocked) issuer on watchlist. However, if an issuer's action succeeds the CRA will not put it on watchlist because the CRA can observe the action result. Then, the issuer of the bond on watchlist will choose to provide more private information or not. As the CRA has perfect rating ability, an issuer who has no shock but is put on watchlist will provide more information; otherwise, it will not.

Assumption 2: $1 \geq \eta > 1/2$.

Assumption 2 means that most of the time the CRA makes correct decisions when putting issuers on watchlist. It is straightforward to extend the model to allow for $1/2 \geq \eta \geq 0$.

Finally (at $t=3$), the CRA will report the rerating result for each bond on watchlist, either downgrading to rating 'l' or reaffirming its initial rating 'h'. Because of CRA's perfect rating ability, a rerating of 'h' (or 'l') is a signal indicating that the issuer invests in the safe (or risky) project for sure.

1.4 Impact of Credit Rating Watchlist on Bond Prices

The impact of credit rating watchlist on bond prices can be shown by comparing bond prices at $t=1$, $t=2$ and $t=3$. The price change from $t=1$ (initial rating) to $t=2$ (being put on watchlist) shows the market reaction to watchlist placement. The price change from $t=2$ (watchlist) to $t=3$ (rerating) shows the market reaction to the actual rating change after being put on watchlist.

The repayment from a safe project is $F^s=1$, and from a risky project is $F^r=\gamma$, where $1-\gamma$ is the default rate and $1>\gamma>0$. It is obvious that $P_{3h}=1$ and $P_{3l}=\gamma$.

As we assume the CRA has perfect rating ability, issuers who receive initial ratings 'h' at $t=1$ are good types at that time. We call them initially good issuers. Similarly, we name issuers who receive initial rating 'l' as initially bad issuers. As shocks only happen to good type issuers, only initially good issuers have an incentive to hedge the risk. Therefore, issuers initially rated 'l' will not take action, and only issuers initially rated 'h' will decide to take action or not.

There are two cases that we will not consider to conform with the existing empirical evidence. One case is when issuers choose not to be rated by the CRA so that good issuers are mixed up with bad issuers sharing the same price. Thus, the bond price at date $t=1$ is

$$P_1 = \beta(1-\alpha)F^s + [1-\beta(1-\alpha)]F^r = \beta(1-\alpha) + \gamma(1-\beta) + \gamma\beta\alpha,$$

where the proportion of issuers investing in the safe projects is $\beta(1-\alpha)$, and the proportion of issuers investing in the risky projects is $[1-\beta(1-\alpha)]$. As there is no CRA and investors decide repayment based on expected average market quality, there is no price change after $t=1$. The other case occurs when an issuer chooses the CRA and it is initially bad. As there is no shock for initially bad issuers, $P_{1l}=\gamma$ and there is no price change afterwards. Thus, the only case we discuss below is when issuers choose the CRA and they are initially good.

1.4.1 Bond Prices

1.4.1.1 Issuers Go Through the CRA and Take Action

There are three types of issuers receiving rating h at $t=2$, namely, (a) initially good issuers with successful action, (b) initially good issuers with unsuccessful action and no shock for which the CRA makes correct decision of not putting them on watchlist, and (c) initially good issuers with unsuccessful action and shock happening for which the CRA makes incorrect decision of not putting them on watchlist. Thus, the price for rating h at $t=2$ is

$$P_{2h}^a = \left\{ \frac{[(1-\theta)(1-\alpha)\eta + \theta]}{[(1-\theta)(1-\alpha)\eta + \theta + (1-\theta)\alpha(1-\eta)]} \right\} F^s \\ + \left\{ \frac{[(1-\theta)\alpha(1-\eta)]}{[(1-\theta)(1-\alpha)\eta + \theta + (1-\theta)\alpha(1-\eta)]} \right\} F^r$$

$$=(\eta-\alpha\eta-\eta\theta+\eta\theta\alpha+\theta+\alpha\gamma-\alpha\gamma\eta-\alpha\gamma\theta+\alpha\gamma\eta\theta)/(\eta-2\alpha\eta-\eta\theta+2\eta\theta\alpha+\theta+\alpha-\theta\alpha),$$

where the superscript ‘a’ means initially good issuers who take action.

There are two types of issuers placed in watchlist at $t=2$, namely, (a) initially good issuers with unsuccessful action and no shock for which the CRA makes incorrect decision of putting them on watchlist, and (b) initially good issuers with unsuccessful action and shock happening for which the CRA makes correct decision of putting them on watchlist. Thus, the price for bonds in watchlist at $t=2$ is

$$\begin{aligned} P_{2w}^a &= \{[(1-\alpha)(1-\eta)]/[(1-\alpha)(1-\eta)+\alpha\eta]\} F^s + \{(\alpha\eta)/[(1-\alpha)(1-\eta)+\alpha\eta]\} F^r \\ &= (1-\eta-\alpha+\alpha\eta+\alpha\gamma\eta)/(1-\eta-\alpha+2\alpha\eta). \end{aligned}$$

An issuer with rating h at $t=1$ may have future price P_{2h}^a , P_{3h}^a or P_{3l}^a . Thus, P_{1h}^a is the weighted average of those three prices, where

$$\begin{aligned} P_{1h}^a &= [(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)] P_{2h}^a + (1-\theta)(1-\alpha)(1-\eta) P_{3h}^a + (1-\theta)\alpha\eta P_{3l}^a \\ &= \alpha\gamma-\alpha\gamma\theta+1-\alpha+\theta\alpha. \end{aligned}$$

By comparing prices P_{3h}^a , P_{2h}^a , P_{1h}^a , P_{2w}^a and P_{3l}^a , it is straightforward to obtain the following Lemma.

Lemma 1. *When issuers go through the CRA and those who receive rating ‘h’ take action, bond prices are characterized by the following ordering: $P_{3h}^a > P_{2h}^a > P_{1h}^a > P_{2w}^a > P_{3l}^a$.*

Proof. See Appendix A.2.

1.4.1.2 Issuers Go Through the CRA and Take No Action

There are two types of issuers receiving rating h at $t=2$, namely, (a) initially good issuers with no shock for which the CRA makes correct decision of not putting them on watchlist, and (b) initially good issuers with a shock happening for which the CRA makes incorrect decision of not putting them on watchlist. Thus, the price P_{2h}^{na} is given by

$$\begin{aligned} P_{2h}^{na} &= \{[(1-\alpha)\eta]/[(1-\alpha)\eta+\alpha(1-\eta)]\} F^s + \{[\alpha(1-\eta)]/[(1-\alpha)\eta+\alpha(1-\eta)]\} F^r \\ &= (-\eta+\alpha\eta-\alpha\gamma+\alpha\gamma\eta)/(-\eta+2\alpha\eta-\alpha). \end{aligned}$$

where the superscript ‘na’ means initially good issuers who take no action.

There are two types of issuers placed on watchlist at $t=2$, namely, (a) initially good issuers with no shock for which the CRA makes incorrect decision of putting them on watchlist, and (b) initially good issuers with a shock happening for which the CRA makes correct decision of putting them on watchlist. Thus, the price P_{2w}^{na} is

$$\begin{aligned} P_{2w}^{na} &= \{[(1-\alpha)(1-\eta)]/[(1-\alpha)(1-\eta)+\alpha\eta]\}F^s + \{(\alpha\eta)/[(1-\alpha)(1-\eta)+\alpha\eta]\}F^r \\ &= (1-\eta-\alpha+\alpha\eta+\alpha\eta)/(1-\eta-\alpha+2\alpha\eta). \end{aligned}$$

As an issuer with rating h at $t=1$ may have price P_{2h}^{na} at $t=2$ or P_{3h}^{na} and P_{3l}^{na} at $t=3$, the price at $t=1$ (P_{1h}^{na}) is given by the weighted average of those three future prices, where

$$P_{1h}^{na} = \alpha[\eta P_{3l}^{na} + (1-\eta) P_{2h}^{na}] + (1-\alpha)[\eta P_{2h}^{na} + (1-\eta) P_{3h}^{na}] = \alpha\eta - \alpha + 1.$$

The following Lemma can be obtained by comparing prices P_{3h}^{na} , P_{2h} , P_{1h}^{na} , P_{2w}^{na} and P_{3l}^{na} .

Lemma 2. *When issuers go through the CRA and nobody takes action, bond prices are characterized by the following ordering: $P_{3h}^{na} > P_{2h}^{na} > P_{1h}^{na} > P_{2w}^{na} > P_{3l}^{na}$.*

Proof. See Appendix A.2.

1.4.2 Comparison with Empirical Results

By comparing Lemma 1 and Lemma 2, we can easily obtain the following proposition.

Proposition 3. *Under both strategies, prices satisfy the ordering $P_{3h} > P_{2h} > P_{1h} > P_{2w} > P_{3l}$, in which $P_{2w} < P_{1h}$ shows the price drop after putting on watchlist for potential downgrade, and $P_{3l} < P_{2w}$ shows the price drop after the actual downgrade.*

Proof. See Lemma 1 and Lemma 2.

No matter which strategy issuers choose, those two price changes are consistent with the empirical results from Hand, Holthausen and Leftwich(1992) and Wansley and Clauret(1985). One of the reasons may be that the setup of our model matches one of their important sample specifications that all of the actions of watchlist are unexpected (e.g., the weight of F^r in P_{2w} is $(\alpha\eta)/((1-\alpha)(1-\eta)+\alpha\eta)$), which is substantially different from zero).

The consistency of the present price changes with empirical results shows that the proposed model replicates the empirical literature findings about watchlist for negative reasons and actual downgrades.

1.5 Equilibrium Results

We use backward induction to solve this model. First, we solve for subgame pure strategy Nash equilibrium at the decision node for initially good issuers to decide whether to take action or not. Then, based on the subgame pure strategy Nash equilibrium, we solve for pure strategy Nash equilibrium at the decision node for issuers to decide to go through the CRA or not.

1.5.1 Subgame Equilibrium

The players of this subgame are those issuers who receive initial rating ‘h’ and the decision is whether to take action or not. As a simplification, we assume that only the final price of a bond will impact an issuer’s payoff from a project. It is the same as setting a weight 1 to the final price of a bond and 0 to other prices. Thus, it is easy to extend the current assumption to other types of weighted average over all bond prices.

1.5.1.1 Subgame Equilibrium Utilities

When issuers take no action, there are four possibilities: shock and on watchlist (with probability $\alpha\eta$), shock and not on watchlist (with probability $\alpha(1-\eta)$), no shock and on watchlist (with probability $(1-\alpha)(1-\eta)$), and no shock and not on watchlist (with probability $(1-\alpha)\eta$). Therefore, the subgame utility of this strategy is

$$U_{na} = (1-\alpha)\{R_p [\eta P_{2h}^{na} + (1-\eta) P_{3h}^{na}] - 1\} + \alpha\gamma\{R_p [\eta P_{3l}^{na} + (1-\eta) P_{2h}^{na}] - 1\} - C_r,$$

where $P_{2h}^{na} = (-\eta + \alpha\eta - \alpha\gamma + \alpha\gamma\eta) / (-\eta + 2\alpha\eta - \alpha)$, $P_{3h}^{na} = 1$ and $P_{3l}^{na} = \gamma$.

When issuers take action, there is one more possibility compared to the strategy of ‘no action’, which is successful action and then neither shock nor watchlist. Therefore, the subgame utility of this strategy is

$$U_a = \theta(R_p P_{2h}^a - 1) + (1-\theta)(1-\alpha)\{R_p [\eta P_{2h}^a + (1-\eta) P_{3h}^a] - 1\}$$

$$+(1-\theta)\alpha\gamma\{R_p[\eta P_{3l}^a+(1-\eta)P_{2h}^a]-1\}-C_a-C_r,$$

where $P_{2h}^a = (\eta-\alpha\eta-\eta\theta+\eta\theta\alpha+\theta+\alpha\gamma-\alpha\gamma\eta-\alpha\gamma\theta+\alpha\gamma\eta\theta)/(\eta-2\alpha\eta-\eta\theta+2\eta\theta\alpha+\theta+\alpha-\theta\alpha)$, $P_{3h}^a = 1$ and $P_{3l}^a = \gamma$.

1.5.1.2 Subgame Equilibrium Condition

Clearly, initially good issuers will take action when the utility from doing so (U_a) is greater than the utility from no action (U_{na}). Otherwise, they will take no action.

Proposition 4. *In the subgame equilibrium, there exists a threshold $\bar{\theta}_a$ for the probability that the action is successful, such that*

1. *If $\theta > \bar{\theta}_a$ (effective action), issuers who receive initial rating ‘h’ will take action.*
2. *If $\theta < \bar{\theta}_a$ (ineffective action), nobody will take action.*

Proof. *See Appendix A.3. Note that we need $\underline{C}_a < C_a < \bar{C}_a$ to get $\bar{\theta}_a \in [0, 1]$.*

The intuition is straightforward. When initially good issuers decide whether to take action, they have to compare the gain and the loss. The gain is the reduction in the probability of a shock happening and then having P_{3l} . That is, the larger probability of the action to succeed, the smaller the risk from shocks and the higher the bond price. The loss is given by the private cost C_a , which is too high to afford when there is no credit rating watchlist by assumption. Therefore, there is a threshold value for θ , at which issuers will be indifferent between taking action or not. When θ is higher than the threshold value, the gain exceeds the loss so that initially good issuers will take action. Otherwise, taking action is not worthwhile.

As the threshold $\bar{\theta}_a$ is a function of η , it is useful to explore their relation.

Lemma 5. *The threshold value $\bar{\theta}_a$ for the probability that the action is successful, which makes initially good issuers indifferent to take action or not, is decreasing in CRA’s ability to correctly put issuers on watchlist (i.e., $\partial \bar{\theta}_a / \partial \eta < 0$).*

Proof. *See Appendix A.3.*

This Lemma states that the greater the ability of the CRA to correctly put issuers on watchlist, the smaller the threshold value $\bar{\theta}_a$ needs to make initially good issuers take action. Intuitively, when the CRA can find larger proportion of shocks happening, there will be more risk for an issuer when a shock happens. Then initially good issuers have more incentive to escape from the shock and the watchlist. The only way to be shock-free is to take action. As they are more eager to reduce the risk from potential shocks, they care less about the probability of action to be successful.

Another effect of greater CRA's ability to correctly put issuers on watchlist is that it will give initially good issuers higher bond price if they are not put on watchlist. As the CRA is less likely to make mistakes of leaving shocks unnoticed (e.g., $1-\eta$ is smaller), there will be fewer bad issuers with risky projects sharing rating h at $t=2$ with good issuers. This higher bond price will increase issuers' utilities so that it will make no action more attractive. This will let issuers care more about the probability of successful action.

From the above Lemmas, we can conclude that the second effect is dominated by the first one. The intuition is that we have assumptions $\alpha < 1/2$ and $\eta > 1/2$. Thus, the price for an issuer with rating h at $t=2$ (e.g., P_{2h}) is closer to 1 than to γ . The expected loss of price decreasing from P_{2h} to γ if shock happens is much more important than the expected gain of price increasing from P_{2h} to 1. Then, the most important things issuers worry about are possible shocks and watchlist, so that the effect of higher P_{2h} is dominated.

Lemma 5 tells us that if the CRA can improve its ability to correctly put issuers on watchlist, it will be easier to induce initially good issuers to take action. Thus, CRA's monitoring ability plays an important role.

1.5.2 Equilibrium

The utility formula of an issuer investing in a safe project is $U^G = (R_p P - 1) - C$, whereas it of an issuer investing in a risky project is $U^B = \gamma(R_p P - 1) - C$, where P is the corresponding bond price and C is the cost depending on issuer's selection of the CRA and the decision of taking action or not. There are four possibilities for an issuer, namely (a) hit by shock and put on watchlist, (b) no shock but put on watchlist, (c) hit by shock but not put on watchlist, (d)

no shock and not put on watchlist. With the probabilities and bond prices for those four cases, the issuer's expected utility can be calculated.

To solve the model, we make the following assumptions. If issuers do not go through the CRA, they will not take action as the cost of taking action is very high (i.e., $C_a > \underline{C}_a$, proof see Appendix A.2).¹¹ If issuers go through the CRA and the CRA has perfect (or no) ability to put issuers on watchlist, initially good issuers will always (or never) take action. If issuers go through the CRA and the action is always successful (or unsuccessful), initially good issuers will always (or never) take action.

1.5.2.1 Equilibrium Utilities

1.5.2.1.1 Issuers Go Through the CRA

The utility for initially bad issuers is the same, regardless of whether initially good issuers take action or not:

$$U^B = \gamma(R_p \gamma - 1) - C_r,$$

where the superscript 'B' means 'for initially bad issuers'. The bond price is γ , as the bond pays \$1 with probability γ and \$0 with probability $(1-\gamma)$.

If issuers take no action, the utility for initially good issuers who take no action is

$$U_{na}^G = U_{na} - C_r,$$

where the subscript 'na' means 'no action' and its superscript 'G' means 'for initially good issuers', U_{na} has the same functional form as in Subgame Equilibrium. Thus, the issuer's expected utility is

$$E(U_{na}) = \beta U_{na}^G + (1-\beta) U^B.$$

If issuers take action, the utility for initially good issuers who take action is

$$U_a^G = U_a - C_r,$$

¹¹ As we focus on CRA's monitoring role, our model wants to show that watchlist can attract issuers to take action. If issuers take action even when there is no rating, watchlist is not particularly interesting. Therefore, in the present paper we assume $C_a > \underline{C}_a$ is always true. It is straightforward to extend the model from assumption $C_a > \underline{C}_a$ to $C_a \geq 0$.

where the subscript ‘a’ means ‘taking action’, U_a has the same functional form as in Subgame Equilibrium. Thus, the issuer’s expected utility is

$$E(U_a) = \beta U_a^G + (1-\beta) U^B.$$

1.5.2.1.2 Issuers Do Not Go Through the CRA

Under our assumption that an initially good issuer will not take action if it does not go through the CRA, its expected utility is

$$E(U_{nr}) = [1-\beta(1-\alpha)]\gamma(R_p P_1^{na} - 1) + \beta(1-\alpha)(R_p P_1^{na} - 1),$$

where the subscript ‘nr’ means ‘no rating’, and $P_1^{na} = \beta(1-\alpha) + \gamma(1-\beta) + \gamma\beta\alpha$.

1.5.2.2 Equilibrium Condition

Comparing expected utilities, $E(U_{na})$, $E(U_a)$ and $E(U_{nr})$, we can get conditions for equilibrium strategies as reported in the following proposition.

Proposition 6. *There exist three Pure Strategy Nash Equilibria and two thresholds η_a and η_{na} for CRA’s probability of correctly putting issuers on watchlist, (and combine the result from proposition 4) such that*

1. *If $\eta > \eta_a$ and $\theta > \bar{\theta}_a$, issuers will go through the CRA and issuers who receive initial rating ‘h’ will take action.*
2. *If $\eta < \eta_{na}$ and $\theta < \bar{\theta}_a$, issuers will go through the CRA and nobody will take action.*
3. *Otherwise, issuers will not go through the CRA.*

Proof. *See Appendix A.4. Note that we need constraint $\underline{C}_r^a < C_r < \bar{C}_r^a$ to get $\eta_a \in [0,1]$ and $\underline{C}_r^{na} < C_r < \bar{C}_r^{na}$ to get $\eta_{na} \in [0,1]$.*

According to proposition 6, the CRA plays an important role for issuers to decide their strategies. There are two primary factors for issuers to consider, η and θ . Clearly, η is directly related to the CRA’s monitoring ability and θ is indirectly related to the CRA as its threshold value $\bar{\theta}_a$ is decreasing in η . If we use β to define the equilibrium, we will get

results similar to Diamond (1991)¹². However, the present paper focuses on the interaction between issuers and the CRA, especially credit rating watchlist. We choose η to define the equilibrium, instead of β .

Intuitively, in the first equilibrium CRA's ability to correctly put issuers on watchlist is good ($\eta > \eta_a$) and the action is likely to succeed ($\theta > \bar{\theta}_a$). Therefore issuers trust the CRA to signal their types and are willing to take action to reduce the risk from possible shocks if they are initially good. As $\bar{\theta}_a$ is decreasing in η , the larger η is, the smaller $\bar{\theta}_a$ is, which augments the region for issuers to choose this strategy.

The first equilibrium strategy also includes the condition that the cost of rating should be neither too high nor too low. It is straightforward to understand that cost of rating should not exceed the benefit to issuers from going through the CRA to signal their types. However, the lower bound of cost of rating shows that the rating should not be free and has to cost something to keep some potential quality or standard. This attracts us to explore the relationship between \underline{C}_r^a and β .

Lemma 7. *The lower bound of the cost of rating \underline{C}_r^a in strategy condition for issuers going through the CRA and taking action is increasing in the probability of issuers to be initially good (i.e., $\partial \underline{C}_r^a / \partial \beta > 0$).*

Proof. *See Appendix A.4.*

Lemma 7 indicates that the larger proportion of initially good issuers in the market, the more issuers can gain from the strategy of going through the CRA and taking action. The gain comes from two effects. One effect is that issuers can signal their initial qualities to the market. The second effect is that initially good issuers can take action to help prevent themselves from possible shocks. When the probability of issuers to be initially good is small, the effect of the initial rating dominates the effect of taking action. When the probability of issuers to be initially good is large, the effect of the initial rating is dominated by the effect of taking action. Thus, \underline{C}_r^a is always increasing with β .

¹² When market quality is median, issuers will go through the CRA and issue bonds under monitoring. In contrast, when market quality is high or low, issuers will not go through the CRA but borrow directly without monitoring.

For a given value of \underline{C}_r^a , define $\beta(\underline{C}_r^a)$ such that issuers will go through the CRA and take action if $\beta > \beta(\underline{C}_r^a)$. Because, when the average market quality is sufficiently bad, the lower bound on the cost of rating (i.e., \underline{C}_r^a) prevents issuers from choosing the CRA. Then, \underline{C}_r^a requires a market quality for the case when issuers go through the CRA. In other words, when the average market quality is bad enough, issuers would rather take pooled prices than signal their qualities.

According to the second equilibrium strategy stated in Proposition 6, issuers still trust the CRA to signal their types but they are no longer willing to take action. The conditions are that CRA's ability to correctly put issuers on watchlist is poor ($\eta < \eta_{na}$), and the action is unlikely to succeed ($\theta < \bar{\theta}_a$). Intuitively, as the CRA has low ability to correctly put issuers on watchlist, issuers have little risk of being put on watchlist. Then, it is worthy to go through the CRA and signal their initial types to the market. However, the action is unlikely to succeed now and the private cost of taking action is relatively high. Thus, it is a waste of money to take action. As $\bar{\theta}_a$ is decreasing in η , a larger η will result a smaller region for issuers to choose the second equilibrium strategy.

The third equilibrium strategy states that, if either CRA's ability to correctly put issuers on watchlist is bad ($\eta < \eta_a$) and the action is likely to succeed ($\theta > \bar{\theta}_a$), or CRA's ability to correctly put issuers on watchlist is good ($\eta > \eta_{na}$) but the action is unlikely to succeed ($\theta < \bar{\theta}_a$), issuers would rather mix up with others and ignore their own types. There are two effects stemming from a greater CRA's ability to correctly put issuers on watchlist. One effect is that an issuer will have less risk if no shock happens and higher price if not on watchlist. As the CRA can observe potential shocks with more precision, it is less likely for a no-shock-hit issuer to be put on watchlist. As there will be a larger proportion of good issuers sharing price P_{2h} , investors anticipate that and are willing to pay more for the bond with rating h at $t=2$. Thus, the price P_{2h} will be larger and closer to 1. The second effect is that an issuer will have more risk if a shock happens and lower price if put on watchlist. As the CRA can observe potential shocks with more precision, it is more likely for a shock-hit issuer to be

put on watchlist. Then the price P_{2w} will be lower and closer to γ , as there will be a larger proportion of bad issuers sharing price P_{2w} . When the action is likely to succeed, the first effect dominates the second one, such that the worse the monitoring ability, the greater the probability for issuers to not go through the CRA. When the action is unlikely to succeed, the first effect is dominated by the second one, such that the better the monitoring ability, the more probable for issuers to not go through the CRA. As $\bar{\theta}_a$ is decreasing in η , the higher η is, the smaller is $\bar{\theta}_a$, which makes larger region of the first condition and smaller region of the second one. Whether the whole region for issuers not going through the CRA changes or not depends on the relative sizes of η_a and η_{na} .

1.5.3 Value of Thresholds

One interesting question derived from the third equilibrium in Proposition 6 is whether threshold η_a is larger than η_{na} or not. It is mathematically difficult to compare them directly, but different parameter values can be used to compare them numerically.

Conjecture 8. *When action is more likely to succeed and issuers take action, issuers will demand more for CRA's ability to correctly put shock-hit issuers on watchlist, that is $\eta_a > \eta_{na}$.*

This conjecture is consistent with our equilibrium analysis that when issuers' actions have more chance to succeed, they care more about CRA's ability to correctly put issuers on watchlist. The intuition is that if issuers are attracted to take the costly action, they expect the CRA to be able to observe shocks more accurately. If the CRA can reduce the probability of not putting shock-hit issuers on watchlist, the price with rating 'h' after the shock will be higher and closer to 1. Only this can give issuers enough incentive/benefit to take action, besides the action being likely to succeed. Thus, the threshold value of η to make issuers indifferent to take action or not is larger when the probability for action to be successful is larger.

We set $\theta = \bar{\theta}_a$, $\gamma = 0.67$, $\beta = 0.5^{13}$, $R_p = 2$, $\eta = 0.7$ and let α take values of 0.05, 0.1, 0.2 and 0.3. For C_r and C_a , we use 75% quantile of the constraint in calculation. The results are shown in table 1.1.

From three sets of trial values, we can get an approximate idea of how large the parameters would be. Take $\alpha = 0.1$, $\gamma = 0.67$, $\beta = 0.5$, $R_p = 2$ as an example, the threshold value θ for action to be successful is 50%, the value for η_a and η_{na} is 0.757 and 0.341, respectively. We need the cost of rating to be between 0.054 and 0.081. The cost of action needs to be positive and smaller than 0.579. Thus, under these values, if $\eta > 0.757$ and $\theta > 0.5$, issuers will go through the CRA and initially good issuers will take action. If $\eta < 0.341$ and $\theta < 0.5$, issuers will go through the CRA and nobody will take action. Otherwise, issuers will not go through the CRA.

Table 1.1 Trial Values for Parameters

	$\alpha = 0.05$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$
C_r	(0.057, 0.086)	(0.054, 0.081)	(0.044, 0.050)	(0.025, 0.046)
C_a	(0.223, 0.562)	(0.269, 0.579)	(0.329, 0.614)	(0.365, 0.648)
$\bar{\theta}_a$	0.560	0.500	0.350	0.420
η_a	0.897	0.757	0.853	0.916
η_{na}	0.414	0.341	0.253	0.186

Moody's states [Fons (2002)] that "Between 66%-76% of all ratings have been changed in the same direction (and rarely in the opposite direction) as indicated by their watchlist review." Compared to the historical range of η , the trial value 75.7% when $\alpha = 0.1$ is a higher standard for the CRA in reality. Maybe one of the reasons is that the values of other deep parameters we choose are not realistic enough. It could be that shock happens more than 10% of the time.

¹³ The value for β is selected based on the initial issuer ratings collected from Fitch Ratings, Inc. during 1/1/2004 and 6/20/2007 in table 2 in Appendix A. There are 5,515 initial issuer ratings in the sample, 77.4% of which are investment grades and 22.6% of which are speculative grades. Since there are more initially good issuers, we assume $\beta = 0.5$ as a fair game.

All of the above shows that CRA's monitoring ability is important. If the CRA can provide more precise ratings, there will be larger region for the favorable case that issuers go through the CRA and take action to reduce risk from possible shocks.

1.6 Social Welfare Analysis

The social welfare analysis proceeds in two steps. First, we compare the social welfare of two setups, CRA without the monitoring role and CRA with the monitoring role. Second, we compare the social welfare according to issuer's strategy in the setup that CRA has the monitoring role. We call them 'Inter-setup' and 'Intra-setup' analyses, respectively. As we assume investors and the CRA break even, social welfare is solely about issuers.

1.6.1 Inter-setup Analysis

Comparing the social welfare of those two setups, we can obtain the result stated in Proposition 9.

Proposition 9. *As long as the CRA can monitor issuers' creditworthiness after initial ratings, when issuers choose to go through the CRA and take no action the social welfare will be increased compared to the CRA without the monitoring role.*

Proof. *See Appendix A.5.*

This proposition establishes that when issuers choose to go through the CRA and take no action, no matter how good/bad the CRA is at monitoring, social welfare will be increased as long as the CRA has a monitoring role. This indicates that the benefit of CRA's monitoring role is greater than its cost. The benefit is that the signals of watchlist and the rating changes afterwards give investors more information about the issuer's future creditworthiness. Based on more information, investors are able to price bonds more precisely so as to invest more in safe projects and less in risky projects. This will increase the social welfare by having a larger proportion of safe investment in the market. However, the cost of monitoring is negligible compared to initial rating. As the CRA regularly monitors the general market situation and the individual industry development, there is no significant additional cost associated with monitoring bonds. The benefit dominates the cost, so that CRA's monitoring role can improve social welfare when issuers choose to go through the CRA and take no action. This shows that even if CRA's monitoring cannot attract issuers to

take action, it can still improve the social welfare by providing more information to the market. However, this case may not be efficient and is discussed below.

1.6.2 Intra-setup Analysis

According to section 1.5, we know that issuers have three types of equilibrium strategies when the CRA has a monitoring role. If issuers choose the strategy corresponding to the equilibrium condition, social welfare will be maximized. However, not all of the equilibria are efficient. The equilibrium when issuers go through the CRA and take action is an "Efficient Equilibrium". As issuers are willing to not only signal their initial types and accept CRA's monitoring but also take action to prevent future risk, CRA's rating role and monitoring role are both effective. The equilibrium when issuers go through the CRA and take no action is a "Semi-Efficient Equilibrium", as CRA's rating role is effective but its monitoring role is not attractive for issuers to take action. The equilibrium when issuers do not go through the CRA is an "Inefficient Equilibrium", as none of CRA's roles is effective.

Obviously, going through the CRA is not always the optimal choice for issuers. When CRA's ability to correctly put issuers on watchlist is relatively low and the action is likely to succeed, or CRA's ability to correctly put issuers on watchlist is good and the action is unlikely to succeed, issuers should choose direct borrowing instead of going through the CRA. Some policies that always force issuers to have ratings before issuing may reduce social welfare. For example, institutional investors can only invest in bonds with investment grades. Thus, the rating service from the CRA does not necessarily improve social welfare.

However, if the CRA can improve its monitoring ability, the threshold $\bar{\theta}_a$ will be smaller. There will be a larger range for the "Efficient Equilibrium" and a smaller range for the "Semi-Efficient Equilibrium". Thus, we will have greater probability of having a favorable equilibrium.

1.7 Conclusion

This chapter primarily sets up a theoretical model to describe CRAs' rating and monitoring roles. As a CRA is a specialized monitoring institution, bonds can also be monitored by a CRA, which is different from bonds' characteristics in the literature. In the

proposed model, issuers have to choose between going through the CRA (issuing bond with monitoring) and direct borrowing without monitoring, and they need to decide whether to take action to prevent future risk or not. Bond price changes due to watchlist implied by the model are consistent with previous empirical studies. There exist three Pure Strategy Nash Equilibria. The results show that CRA's ability to correctly put issuers on watchlist is crucial. If the CRA can monitor creditworthiness changes more effectively so as to offer ratings with less noise, there will be more issuers willing to choose credit rating service and take action. From a social welfare standpoint, we find that even when CRA's watchlist cannot attract issuers to take action, CRA's monitoring role can still improve social welfare by sending more information to the market. However, when issuers are attracted to take action, having the CRA in the market may not improve welfare, unless it can observe creditworthiness changes well enough. Thus, it is vital for the CRA to improve its ability to monitor issuers' carrying on after initial ratings, especially the ability to observe creditworthiness changes.

Some limitations of our model are that we only consider an uncontaminated environment and issuer-requested bond ratings. Also, our focus is on watchlist for negative reasons, actual downgrades afterwards and reconfirmation of initial ratings afterwards. Some potential fruitful extensions of the present model are the following. 1) People can introduce positive shocks to the model, such that there will be watchlists for positive reasons and actual rating upgrades as well. 2) If people assume that good issuers can access not only safe projects but also risky ones, there will be additional moral hazard problem to consider. 3) If the CRA is assumed to have imperfect rating ability, the equilibrium strategies will be more complicated. Another interesting topic for future research is the comparison of the efficiency of firms' choices between issuing bonds through a CRA with a monitoring role and borrowing through financial intermediation with delegated monitoring.

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CHAPTER 2. MARKET REACTIONS TO MOODY'S RATING ANNOUNCEMENTS: TESTS ON BOND AND EQUITY MARKETS

2.1 Introduction

This paper examines the reaction of bond and equity markets to two types of credit rating announcements, namely, watchlist placement and actual rating changes after watchlist placement. Here is an example of the two announcements.¹⁴ On January 31st 2005, Moody's placed the 'Baa2' senior unsecured debt rating of AT&T Corp. (AT&T) on rating watchlist for possible upgrades following the announcement for SBC's proposed acquisition of AT&T for approximately \$15 billion in SBC common stock and the assumption of approximately \$6 billion of net debt. Including a \$1 billion special dividend to be paid to AT&T shareholders at the close of the transaction, the total value of the transaction is approximately \$22 billion. On December 19th 2005, Moody's upgraded the "Baa2" senior unsecured debt rating to "A2" following the acquisition by SBC Communications, Inc. of AT&T Corp. The upgrading also reflects the December 16th, 2005, AT&T Inc. announcement that it has unconditionally and irrevocably guaranteed the payment of interest and principal on three issues of its subsidiary AT&T Corp.

Previous studies suggest that there are significant price adjustments in equity markets to rating announcements. For example, Griffin and Sanvicente (1982) examine the stock price adjustment according to the rating change announcement from 1960 through 1975. They control public information around announcement and get return differences by matching a control group of stocks based on beta, industry, and key financial variables. They also employ a two-factor model to get return residuals. Both of the two measures support the hypothesis that rating downgrade announcements release new information to the equity markets. However, for rating upgrade announcements, equity markets show no significant reaction in the month of the event.

¹⁴ This information is collected from the Business News section in the LexisNexis Academic Search database.

Goh and Ederington (1993) separate announcements for bond rating downgrades¹⁵ from 1984 through 1986 into those due to financial prospect deterioration, and those due to leverage increases. They find negative equity market reactions to downgrades in the former group but no reaction in the latter group. This finding shows that equity markets are generally sensitive to the new information associated with future performance but not sensitive to past known information.

Ederington and Goh (1998) analyze forecast revisions around the announcement and find that equity markets react to downgrades but not to upgrades. Their explanations are that companies voluntarily release positive information but hesitate to release negative information, and rating agencies spend more time and resources in finding deterioration in future credibility than improvements in it.

Dichev and Piotroski (2001) examine abnormal long-run stock returns through a matching beta and market-to-book ratio portfolio in the first three years following Moody's bond rating change announcements between 1971 and 1997. They find no reliable mean abnormal returns following upgrades, but a negative mean abnormal return following downgrades. Also, downgrades underperform on average in the long-run and in all years of the sample period, which indicates that there is an under-reaction to the announcement for rating downgrades.

Larrymore, Liu and Rimbey (2003) examine the announcement for rating downgrades of 40 firms from 1974 through 1999. They find a significantly negative average cumulative abnormal return based on a market model.

Studies about bond markets are much fewer and the evidence is mixed. However, equity markets are generally found to react more strongly to the rating announcements than bond markets. Two studies directly examining bond market reactions and comparing them to equity market reactions are Wansley and Clauretje (1985), and Hand, Holthausen and Leftwich (1992). Wansley and Clauretje (1985) use a sample of 164 watchlist announcements from Standard and Poor's between November 1981 and December 1983.

¹⁵ The rating change announcements they focus on are not the same as the ones we focus on. Theirs have only information about rating change announcements, regardless of whether there is a watchlist placement before it or not. However, we look at rating change announcements following watchlist placement. So, our study can separate the market reaction to watchlist announcements from the market reaction to rating change announcements afterwards.

They use bonds with the same rating grades by Standard and Poor's but which have been rerated without being placed on watchlist as control. They show that the average monthly bond price change after watchlist placement is significantly negative compared to the control group, and there is a significant adjustment lag for negative watchlist placement and actual downgrades. For positive watchlist placement and actual upgrades, there are relatively negative price changes which contradict intuition. They argue that maybe investors cannot separate rating agency's announcements and treat each announcement as new negative information. They also find a significant average monthly price change associated with actual downgrades but no reaction to actual upgrades or affirmation of previous rating. For equity markets, they calculate the daily abnormal return based on a market model and find that there is a significantly negative (positive) average abnormal return for companies that are placed on watchlist for possible downgrades (upgrades). However, there is no evidence related to other announcements.

Hand *et al.* (1992) separate watchlist (rating change) announcements¹⁶ between November 1981 and December 1983 (1977 and 1982) into two types of groups, contaminated (with one or more other concurrent disclosures) versus noncontaminated (without any concurrent disclosures), and expected (the yield-to-maturity of a bond is greater (less) than the benchmark for downgrades (upgrades)) versus unexpected (the yield-to-maturity of a bond is less (greater) than the benchmark for downgrades (upgrades)). For watchlist announcements for possible downgrades, unexpected announcements for both contaminated and noncontaminated groups have significantly negative average excess returns in bond and equity markets. For watchlist announcement for possible upgrades, only unexpected announcement for the noncontaminated group has a significantly positive average excess return in the bond market. For rating downgrades (upgrades), only stock (bond) markets show a significantly negative (positive) average excess return. There are some asymmetric results associated with the rating change announcements, but when they control for prior expectations they find symmetric results. Hence, they conclude that there are reactions in both bond and equity markets to rating announcements.

¹⁶ It is clear that watchlist announcements in their sample are not related to rating change announcements.

In contrast to the aforementioned literature, the present study examines market reactions to a complete watchlist action of Moody's including placement and removal, from January 2005 through June 2006. For the bond market, we calculate bond excess returns based on T-bond rates and excess bond rating returns based on Standard and Poor's composite bond rates. For equity markets, we calculate stock excess returns based on a market model and stock excess beta returns based on the corresponding beta portfolio.

We find that there are no statistically significant average excess returns associated with either rating announcement for either direction in either market. However, if we focus on the association between rating announcements and signs of excess returns, both bond and equity markets show significant reactions to watchlist announcements for both possible downgrades and upgrades, watchlist announcement in general, and rating change announcement in general. Additionally, there is a significant bond market reaction to rating downgrade and upgrade announcements, while no evidence is found in equity markets. Results also suggest that controlling for a bond's default risk premium is a better way to exclude the noise that is not associated with the rating announcement, while controlling for a stock's beta coefficient is not so beneficial.

The rest of this chapter is organized as follows. Section 2.2 describes the sample and section 2.3 explains the methodology. Section 2.4 shows the empirical results and section 2.5 concludes.

2.2 Sample Description

We collect Moody's credit watchlist and rating change announcements from January 2005 through June 2006 from Moody's Investors Service. The sample includes only parent companies domiciled in the United States at all rating levels (investment grades and speculative grades). The sample includes three sectors, Industrial, Utility, and Finance.¹⁷ Within the above criteria, we get the complete data set for the period.

Because the sample data do not specify whether there is a watchlist placement before a rating change, we match rating change announcements with watchlist announcements by

¹⁷ The sample that Moody's Investors Service provides includes only those three sectors. It is a limit for this study.

event dates and rating grades¹⁸. Our intention is to focus on events related to watchlist actions, so that we exclude rating change announcements for firms that have not been placed on watchlist for review. The matched sample consists of 262 complete watchlist events including placement and removal, 175 of which are in 2005 and 87 are from January 2006 through June 2006.

Daily bond prices are collected from TRACE in Wharton Research Data Services. Bond information, such as maturity date, coupon payment date, priority (senior or junior), and redemption features (callable, puttable, or convertible) are collected from NASD BondInfo database. Because bonds are traded Over-the-Counter and their market is less active than the stock market, some events are lost if no daily bond transaction prices are available during a specified event window. Also, if there is a coupon payment during an event window, we delete the event to minimize noise. The entire sample having daily bond prices contains 166 events¹⁹ with complete watchlist action (see summary in table 2.1). The majority of actual rating changes are consistent with watchlist directions and most of the companies are in the Industrial sector. When placed on watchlist, most of the companies have ratings A, Baa (investment grades), and Ba and B (speculative grades).

Daily stock prices, market indexes, and daily excess beta returns are collected from the Center for Research in Security Prices (CRSP). Because some firms do not have either stock prices or excess beta returns in CRSP during a specified event window or some firms are privately held, some events are lost. The entire sample having either daily stock prices or daily excess beta returns consists of 192 events (see summary in table 2.2). The sample characteristics are very similar to the bond market sample reported in table 2.1, as the majority of the events for the two samples overlap.

¹⁸ The rating change announcement following a watchlist placement should be the first rating change after watchlist placement. So its event date should be the closest after the date of watchlist placement. Also, since we match by rating grades, the old rating grade of a rating change announcement should be the same as the rating grade of a watchlist announcement.

¹⁹ A few events have daily bond prices for only one announcement, either watchlist placement or actual rating changes. Since the sample size is not large, we keep them in the study. We adopt the same approach to construct the sample for equity markets.

Table 2.1. Bond Market Sample Description

	Actual Downgrades	Actual Upgrades
Possible Downgrades	99	7
Direction Uncertain	3	2
Possible Upgrades	1	54

Sector	
Finance	15
Industrial	131
Service	20

Old rating ¹	
Aa	2
A	22
Baa	56
Ba	31
B	41
Caa	9
None	5

¹Old rating is the company's rating when it is placed on watchlist.

Table 2.2. Equity Market Sample Description

	Actual Downgrades	Actual Upgrades
Possible Downgrades	112	3
Direction Uncertain	3	1
Possible Upgrades	0	73

Sector	
Finance	19
Industrial	150
Service	23

Old rating	
Aa	2
A	24
Baa	68
Ba	43
B	41
Caa	11
None	3

2.3 Methodology

2.3.1 Estimation of Bond Gross Returns

We define the event date to be day 0, such that each announcement date is day 0. As bond trading is not as active as stock, we set up an event window larger than the event day and the following day to calculate the “window-spanning” bond gross return. The event window for watchlist placement (WL) is (-36, 56) and for rating changes (RC) is (-37, 76). We use the last price before day 0 in the event window as P_0 and the first price on or after day 0 in the event window as P_1 . Then we calculate the bond gross return as $\frac{P_1 - P_0}{P_0}$. The

following example illustrates the calculation of the gross return of a bond with trading activities on days -10, -5, +3, and +6. The last pre-event transaction date before day 0 is day -5 and the first post-event transaction date on or after day 0 is day +3. Hence, the bond gross return is calculated as the difference of the prices on day -5 and day +3 divided by the price on day -5.

The summary statistics of event window reported in table 2.3 indicates that 95% of our sample events fall into either WL window (-17, 19) or RC window (-20, 24), and 70% of our sample events fall into either WL window (-11, 11) or RC window (-13, 14). As the power to statistically test the market reaction of announcement will be larger for a shorter event window, considering the inactive trading in the bond market our event windows are sufficiently qualified for the tests.

Table 2.3. Summary Statistics of Event Window for Bond Market

WL	Mean	Median	STD	MIN	MAX
Pre-event	-4.7	-3	6.3	-36	-1
Post-event	3.2	0	7.8	0	56
RC	Mean	Median	STD	MIN	MAX
Pre-event	-5.7	-3	7.3	-37	-1
Post-event	4.1	0	9.7	0	76

Usually a company has more than one bond issued in the market. In such instances, we use an equal-weighted average gross return for the test of a company. The selection and calculation follow three steps. If a company has issued at least one straight-debt bond²⁰, then first we choose corporate straight-debt bonds from all the issues that the company has. Second, we choose maximum three (if available) bonds from the set of bonds obtained in the first step, which have the longest time until maturity than all other bonds that we select in the first step.²¹ Third, if there are at least two bonds obtained in the second step, we take the average bond gross return of selected bonds in the second step as a single observation for the company. If there is only one straight-debt bond selected in the second step, we utilize that bond's gross return for the company. However, if there is not a single straight-debt issue, we choose corporate non-straight-debt bonds²² instead in the first step. The second and third steps are the same.

2.3.2 Estimation of Bond Excess Returns

We measure the bond excess return as the bond gross return less the return on a risk-free bond matched by the maturity year. We use U.S. Treasury bonds (T-bonds) as a substitute for the risk-free bond. The return of the T-bond is calculated as the difference between the estimated post-event²³ and pre-event T-bond prices divided by the estimated pre-event T-bond price.

The daily U.S. Treasury rates are collected from the website <http://www.ustreas.gov/>. As reported U.S. Treasury rates have fixed maturities, 1, 2, 3, 5, 7, 10 and 20 years during the sample period (January 2005 through June 2006); we use linear interpolation to get yield curve rates for the missing maturity years up to 19 years. If the maturity year of a corporate bond is longer than 20 years, the corporate bond is compared to a U.S. T-bond with 20 years maturity as a long-term risk-free match.

²⁰ Corporate straight-debt bonds have no redemption features such that they are neither callable/puttable nor convertible.

²¹ If a company issues at least four straight-debt bonds, we choose three bonds with the longest time until maturity from the selected bonds in the first step. If a company issues less than four straight-debt bonds, we choose all of them in the second step.

²² Corporate non-straight-debt bonds have redemption features such that they are at least callable, puttable or convertible.

²³ The post-event date for the T-bond is matched as the first transaction day after the event of the sample corporate bond. So is the pre-event date for the T-bond.

We convert daily Treasury yield rates into daily T-bond prices by the following formula²⁴:

$$P_d = \left(\frac{1}{\left(1 + \frac{1}{2} rm\right)^{N_{tc}/182.5}} \right) \times \left[\frac{C}{rm} \left(\left(1 + \frac{1}{2} rm\right) - \frac{1}{\left(1 + \frac{1}{2} rm\right)^{n-1}} \right) + \frac{M}{\left(1 + \frac{1}{2} rm\right)^{n-1}} \right],$$

where;

P_d is the dirty price of the bond;

rm is the yield to maturity;

N_{tc} is the number of days between the current date and the next coupon date;

C is the value of each coupon payment;

n is the number of coupon payments before redemption;

M is the face value of the bond;

Daily Treasury yield rates are commonly referred to as “Constant Maturity Treasury” rates (CMTs), which provide estimated yields for various maturity years starting from the current date. Hence, “ $N_{tc}=182.5$ ” and “ $n = 2 * \text{maturity years}$ ” for all U.S. T-bonds with semi-annual coupon payments. The yield to maturity of a T-bond with a specific maturity year is assumed to be the average yield of that T-bond during the sample period.

2.3.3 Estimation of Bond Excess Rating Returns

We measure the bond excess rating return as the bond gross return less the average return for all the bonds with the same rating grade. We use Standard and Poor’s Corporate Bond Rates (CBRs) based on Industrial and Utility bonds of different ratings as the control for the default risk premium. The CBR is expressed in terms of yields and is released from the weekly edition of Standard and Poor’s Creditweek. Following the same formula in section 2.3.2 to convert bond yields to bond prices, the return of the CBR is calculated as the difference between the estimated post-event and pre-event composite bond prices divided by the estimated pre-event composite bond price.

²⁴ The formula is in page 9 of the book “Analysing and Interpreting the YIELD CURVE” by Moorad Choudhry, *John Wiley & Sons (Asia) Pte ltd.*

We collect CBRs from January 2005 through June 2006 from the Bloomberg database. The available CBRs have ratings AA, A, and BBB for 5, 10, 15, and 20 maturity years, and rating BB for 5, 10, and 15 maturity years.²⁵ Because the CBR is available every Tuesday during the sample period, we take steps to estimate daily rates for different ratings with different maturity years. First, we calculate the composite default risk premium on each Tuesday as the yield difference between the available CBRs and T-bonds with matched maturity years. Second, we assume that the change of the composite default risk premium is smooth between consecutive Tuesdays. By linear interpolation, we calculate the daily composite default risk premiums during the whole period for available ratings (AA, A, BBB, and BB) and available maturity years (5, 10, 15, and/or 20). Third, we assume that the change in composite default risk premium is smooth between adjacent rating grades for available maturity years. By linear interpolation, we get daily composite default risk premiums for other rating grades (B and CCC) with 5, 10, 15, and/or 20 maturity years. Fourth, for each rating grade we assume that the change of the composite default risk premium is smooth between adjacent maturity years. By linear interpolation, we complete the CBRs for all rating grades (AA, A, BBB, BB, B and CCC) with all maturity years (1 to 20 years), after adding back the corresponding T-bond rates.

2.3.4 Estimation of Stock Excess Returns

We measure the stock excess return as the average prediction errors calculated from the market model on days 0 and +1 for each event. As trading in equity markets is frequent, the event window can be set up narrowly as (0, +1). We include day +1 in the event window because sometimes the rating news is released in the Wall Street Journal the day after Moody's announcement. We take the equity market index as the CRSP value-weighted New York, American and NASDAQ stock exchange index. The market model parameters (alpha and beta) are estimated using the combined data of pre-event window (-214, -31) and post-event window (+31, +214). Because previous studies show that there is a negative average excess return before downgrades and a positive average excess return before upgrades,

²⁵ Standard and Poor's uses a similar but different rating grade as Moody's. AAA, AA, A, BBB, BB, B, CCC from Standard and Poor's are equivalent to Aaa, Aa, A, Baa, Ba, B, Caa, respectively, from Moody's.

researchers have recently utilized post-event data for the estimation of market parameters. However, post-event data are associated with the rating announcements, either watchlist placement or a new rating, which are different from pre-event data representing the situation before/without the event. Hence, we use both of them as controls.

2.3.5 Estimation of Stock Excess Beta Returns

Similar to controlling bond returns by rating grades discussed in section 2.3.3, stock returns can be controlled by means of beta coefficients. We collect daily excess beta returns from the CRSP, which is measured as the excess return of a specific issue less the average return of all issues in its beta portfolio for each trading day. We measure the stock excess beta return as the average excess beta return of day 0 and day +1 for each event.

2.3.6 Tests

Besides the *t*-test for a variety of mean returns with one degree of freedom fewer than the number of announcements in the sample, we also employ other tests, i.e. sign tests, Pearson's chi-square tests, Goodman and Kruskal's gamma statistics, and first order stochastic dominance tests.

2.3.6.1 Sign Tests

The null hypothesis for a sign test is that the probability of observing successes in all trials is 0.5. For watchlist announcement with possible downgrades/upgrades, success is an observed negative/positive excess return. Success is similarly defined for rating change announcements. We report a one-sided p-value in each test, showing the probability of observing more than the current number of successes in the sample if success and failure happened with equal probability. The smaller the one-sided p-value is, the more significant the evidence that announcements affect prices.

2.3.6.2 Pearson's Chi-square Tests

The Pearson's chi-square test is used to test whether the relative frequency of occurrence of observed events follows a specified frequency distribution. The events are assumed to be independent and have the same distribution, and the outcomes of each event to

be mutually exclusive. The null hypothesis is the same as the sign test explained above. The chi-square statistic, which has 1 degree of freedom²⁶ in our case, is defined as:

$$\chi^2 = \sum_{i=1}^n \frac{(O_i - E_i)^2}{E_i},$$

where

O_i is the frequency of an observed event i ;

E_i is the theoretically expected frequency of an event i under the null hypothesis.

For a given degree of freedom, the larger the chi-square statistic is, the more confident we are in rejecting the null hypothesis of equal probability.

2.3.6.3 Goodman and Kruskal's Gamma Statistics

Goodman and Kruskal's Gamma is a symmetric measure based on the difference between the concordant pairs²⁷ and the discordant pairs²⁸, and is defined as follows:

$$\gamma = \frac{C - D}{C + D},$$

where

$C = \sum_i \sum_j n_{ij} \cdot \sum_{k>i} \sum_{l>j} n_{kl}$ is the number of concordant pairs,

$D = \sum_i \sum_j n_{ij} \cdot \sum_{k>i} \sum_{l<j} n_{kl}$ is the number of discordant pairs.

The gamma statistic shows the proportionate reduction in error when the independent variable is used to predict the rank of the dependent variable. For this matter, the larger the absolute value of gamma, the stronger the evidence of association between the two variables. In the analysis, the rank of credit rating announcement for (possible) upgrades is set higher than for (possible) downgrades and the rank of associated positive returns is set higher than the rank of associated negative returns. So the contingency table which is used to record the relationship between two or more variables, is as follows:

²⁶ The degree of freedom is $(m-1)(n-1)$, where m is the number of rows of the contingency table and n is the number of columns. In our case, $m=n=2$.

²⁷ A concordant pair is a pair of a bivariate observation (m, n) and (s, t) , such that in a contingency table if m ranks higher (lower) than s , n ranks higher (lower) than t as well.

²⁸ A discordant pair is a pair of a bivariate observation (m, n) and (s, t) , such that in a contingency table if m ranks lower (higher) than s , n ranks higher (lower) than t .

Table 2.4. Example of the Contingency Table

		Direction of rating announcements	
		Downgrades	Upgrades
Sign of returns	Negative	n_{11}	n_{12}
	Positive	n_{21}	n_{22}

where n_{ij} denotes the number of events falling into the i^{th} row and the j^{th} column of the contingency table. Obviously, n_{11} and n_{22} are set as concordant pairs, while n_{21} and n_{12} are set as discordant pairs. Under multinomial sampling, $\hat{\gamma}$ has an asymptotically normal distribution²⁹. The values for γ range from -1 to 1, with $\gamma = \pm 1$ indicating a perfectly linear positive/negative relationship between the two variables. When the two variables are statistically independent, gamma equals zero.

2.3.6.4 First Order Stochastic Dominance Tests

Tests for stochastic dominance are used to compare the distributions between pairs of random variables with application in asset management and welfare economics. The advantage of this approach is that it utilizes the entire density function rather than a few moments such as the mean, the variance, and the skewness. In the present study, we test for the first order stochastic dominance of rating announcements with upgrades over downgrades.

Suppose that we have a random sample of n independent observations y_i , $i = 1, \dots, n$, from a population with distribution function $F_y(\cdot)$, and a random sample of m independent observations z_i , $i = 1, \dots, m$, from another population with distribution function $F_z(\cdot)$. The probability function $f_z(x)$ is said to stochastically dominate the probability function $f_y(x)$ by first-order, if and only if, $F_z(x) \leq F_y(x)$ for all values of x with strict inequality for at least one value of x . We follow Davidson and Duclos (2000) that the test statistic is as follows:

$$T(x) = \frac{\hat{d}y(x) - \hat{d}z(x)}{\sqrt{\hat{V}(x)}}$$

²⁹ For reference information about the mean and the variance, see Liebetrau, Albert M. (1983), *Measures of association*. Newbury Park, CA: Sage Publications, Quantitative Applications in the Social Sciences Series No. 32.

where

$$\hat{d}_y(x) = \frac{1}{n} \sum_{i=1}^n I(y_i \leq x),$$

$$\hat{d}_z(x) = \frac{1}{m} \sum_{i=1}^m I(z_i \leq x),$$

$$\hat{V}(x) = \frac{1}{n} \hat{d}_y(x)[1 - \hat{d}_y(x)] + \frac{1}{m} \hat{d}_z(x)[1 - \hat{d}_z(x)].$$

The null hypothesis is $dy(x) = dz(x)$ under which $T(x)$ is asymptotically distributed as a standard normal variate. It is empirically impossible to carry the test over the full support. So we follow Bishop, Formby and Thistle (1992) by taking the union-intersection test at fixed values x_1, x_2, \dots, x_k that are evenly spread out in the range of the sample. There are four hypotheses as defined:

1. H_0 : $dy(x_i) = dz(x_i)$ for all x_i ,
2. H_A : $dy(x_i) \neq dz(x_i)$ for some x_i ,
3. H_{A1} : Y first order stochastically dominates Z,
4. H_{A2} : Z first order stochastically dominates Y.

The conclusions are made based on following rules:

1. If $|T(x_i)| < M_{\infty, \alpha}^k \forall i$, do not reject H_0 ,
2. If $-T(x_i) > M_{\infty, \alpha}^k$ for some i and $T(x_i) < M_{\infty, \alpha}^k \forall i$, accept H_{A1} ,
3. If $T(x_i) > M_{\infty, \alpha}^k$ for some i and $-T(x_i) < M_{\infty, \alpha}^k \forall i$, accept H_{A2} ,
4. If $T(x_i) > M_{\infty, \alpha}^k$ for some i and $-T(x_i) > M_{\infty, \alpha}^k \forall i$, accept H_A ,

where $M_{\infty, \alpha}^k$ is the studentized maximum modulus statistic with k and infinite degrees of freedom with $(1 - \alpha)$ percentile and the corresponding table is in Stoline and Ury (1979).

In our event, Y is the return associated with rating (possible) downgrade announcements and Z is the return associated with rating (possible) upgrade announcements. We are expected to accept H_{A2} in most of the cases that the return associated with rating downgrades are stochastically dominated by the return associated with rating upgrades by order 1.

2.4 Results

2.4.1 Reactions of Bond Markets

We employ three bond returns in the present section, namely, gross returns, excess returns, and excess rating returns. We perform tests in two samples, one consisting of the entire sample with both straight-debt and non-straight-debt bonds, and the other one containing straight-debt bonds only. As we select non-straight-debt bonds as a substitute when there are no straight-debt bonds available, the size of the former is larger than the size of the latter.

2.4.1.1 Moody's Credit Watchlist Announcements

2.4.1.1.1 Entire Sample

Detailed results for bond market reactions to watchlist placement for the entire sample are reported in tables 2.5 and 2.6. The sign tests in table 2.5 show significant bond price adjustments for watchlist with possible downgrades, but little evidence of adjustment for watchlist with possible upgrades. The bond market exhibits significant reactions to watchlist announcements, when we consider the effect of possible downgrades and upgrades together (see table 2.6).

In the case of watchlist for possible downgrades, table 2.5 shows that none of the three returns has significant *t*-statistics (-0.440 for gross return, -0.401 for excess return, and -0.403 for excess rating return), even though each mean (-1.10% for gross return, -1.05% for excess return, and -1.23% for excess rating return) and median (-0.46% for gross return, -0.52% for excess return, and -0.79% for excess rating return) are negative as expected. However, the sign test shows significant evidence of more negative gross returns, excess returns, or excess rating returns in the entire sample, and the significance level (1.4% for gross return, 0.8% for excess return, and 0.5% for excess rating return) is increasing when we control for the risk-free rate and the default risk premium in succession. Taking excess rating return as an example, the sign test indicates that there is a 0.5% chance of observing 64 negative excess rating returns in a total 101 events if the actual probability of negative excess

rating returns is 50%. Then at the 0.5% significance level, we reject the null hypothesis of equal probability, and conclude that it is much more likely to observe negative excess rating returns when watchlist placement is for possible downgrades.

In the case of watchlist for possible upgrades, the mean for each of the three bond returns is positive (0.20% for gross return, 0.21% for excess return, and 0.51% for excess rating return), but none of them is significantly different from zero (t -statistics are 0.099 for gross return, 0.082 for excess return, and 0.218 for excess rating return). Two of the three bond median returns are negative (-0.10% for gross return, -0.0004% for excess return, and 0.27% for excess rating return). The sign test shows more significant evidence when we control for the risk-free rate and then the default risk premium; however, the smallest one-sided p -value is 0.284 (with excess rating return). Hence, there is no significant evidence to be observed of a positive bond return when watchlist placement is for possible upgrades.

When we consider the effect of watchlist announcements (regardless of the possible direction), the joint tests reported in table 2.6 show that there is a significant reaction in bond markets. All three gammas (0.2438 for gross return, 0.2477 for excess return, and 0.3714 for excess rating return) are positive. Gamma increases from gross returns, to excess returns, to excess rating returns, and the associated z -statistics (9.39 for gross return, 9.45 for excess return, and 14.87 for excess rating return) increases as well. These indicate that the association between watchlist announcements and bond returns is significantly positive and the significance level increases as we control for the risk-free rate and the default risk premium in succession. Taking the excess rating return as an example, the gamma statistic is 0.3714, which shows that if we know the possible direction of a watchlist announcement, it can help us forecast the sign of an excess rating return by reducing 37.14% of the prediction error. Since the variance is only 0.0006 and the z -statistic is 14.87, the significance level is less than 0.01%. On the other hand, Pearson's Chi-square statistics (19.81 for gross return, 19.70 for excess return, and 26.04 for excess rating return) indicate that all of them are significant at a level less than 0.01%, and that excess rating return is more significant than the other two. For example, the significant chi-square statistic 26.04 for excess rating return indicates that we can reject the null hypothesis of equal probability and conclude that watchlist announcements and the sign of excess rating returns are highly correlated.

Table 2.5. Results Summary for Watchlist Announcements for the Entire Sample in the Bond Market

t-test:

	Raw return		Excess return		Excess rating return	
	DOWN ¹	UP ²	DOWN	UP	DOWN	UP
Mean	-1.10%	0.20%	-1.05%	0.21%	-1.23%	0.51%
Median	-0.46%	-0.10%	-0.52%	-0.0004%	-0.79%	0.27%
Std. Dev.	2.40%	2.00%	2.61%	2.59%	3.06%	2.35%
Max	5.60%	8.70%	5.88%	8.76%	5.88%	9.01%
Min	-7.22%	-6.10%	-7.18%	-6.67%	-11.52%	-5.62%
t-statistic	-0.440	0.099	-0.401	0.082	-0.403	0.218
One-sided p-value	0.331	0.461	0.345	0.468	0.344	0.414

Sign Test:

	Raw return		Excess return		Excess rating return	
	DOWN	UP	DOWN	UP	DOWN	UP
Sample size	101	55	99	54	101	49
No. of Negatives	62	28	62	27	64	22
No. of Positives	35	26	36	26	36	27
No. of Zeros	4	1	0	1	1	0
One-sided p-value	0.014	0.606	0.008	0.554	0.005	0.284

¹DOWN denotes the watchlist announcement is for possible downgrades.

²UP denotes the watchlist announcement is for possible upgrades.

Table 2.6. Results of Joint Tests for Watchlist Announcements for the Entire Sample in the Bond Market

<i>Goodman and Kruskal's Gamma</i>	Gross Return	Excess return	Excess rating return
Gamma	0.2438	0.2477	0.3714
Variance	0.0007	0.0007	0.0006
z-statistic	9.39	9.45	14.87
<i>Pearson's Chi-square</i>	Gross Return	Excess return	Excess rating return
Chi-square	19.81	19.70	26.04
p-value	<0.0001	<0.0001	<0.0001

2.4.1.1.2 Straight-debt Bonds Only

When we limit the bond sample to U.S. corporate straight-debt bonds, the sample size is reduced from 156 events to 102. We find as strong reactions for this reduced sample as for the entire sample. (See table 2.7 and 2.8)

For watchlist with possible downgrades, both the mean and median of the three bond returns are negative as expected, but none of the means is significantly different from zero. The sign tests show that all three bond returns have significantly more negative than positive observations. Taking the excess rating return as an example, the sign test indicates that there is a 1.2% chance of observing 42 successes in 65 events if the probability of observing success is 50%. Then at the 1.2% significance level we reject the null hypothesis and can conclude that it is more likely to observe a negative bond return when the watchlist announcement is for possible downgrades.

For watchlist with possible upgrades, the means of the three bond returns are all positive, but none of them is statistically significant. For the sign tests, only excess rating return shows a significant reaction at the 10% level. There is only a 7.5% chance of observing 20 positive excess rating returns in 31 events if equal probability is true, from which we can conclude that there are more positive excess rating returns associated with watchlist placement for possible upgrades. However, gross returns and excess returns can not reject the null at the 10% significance level.

In the case of the joint tests reported in table 2.8, all three gammas are significantly positive (all z -statistics are greater than 1.96), which indicates that bond returns are significantly associated with watchlist placement. For example, the gamma of excess rating returns (i.e. 0.5371) indicates that the information of the watchlist direction can reduce by 53.71% the prediction error in forecasting the sign of an excess rating return. In the case of Pearson's chi-square test, we find that all three returns show a significant correlation between watchlist announcements and signs of bond returns at the 0.05% significance level.

Table 2.7. Results Summary for Watchlist Announcements for Straight-debt Bonds*t*-test:

	Gross return		Excess return		Excess rating return	
	DOWN ¹	UP ²	DOWN	UP	DOWN	UP
Mean	-1.22%	0.83%	-1.02%	0.33%	-1.13%	0.88%
Median	-0.50%	-0.06%	-0.51%	-0.001%	-0.86%	0.66%
Std. Dev.	2.42%	2.47%	2.63%	3.04%	2.90%	2.79%
Max	2.99%	8.66%	4.89%	8.76%	5.49%	9.01%
Min	-6.65%	-1.70%	-6.47%	-6.67%	-11.32%	-5.62%
t-statistic	-0.503	0.337	-0.386	0.110	-0.389	0.315
One-sided p-value	0.308	0.369	0.350	0.457	0.349	0.378

Sign Test:

	Gross return		Excess return		Excess rating return	
	DOWN	UP	DOWN	UP	DOWN	UP
Sample size	67	35	67	35	65	31
No. of Negatives	43	16	41	18	42	11
No. of Positives	24	18	26	17	23	20
No. of Zeros	0	1	0	0	0	0
One-sided p-value	0.014	0.5	0.043	0.5	0.012	0.075

¹DOWN denotes the watchlist announcement is for possible downgrades.²UP denotes the watchlist announcement is for possible upgrades.**Table 2.8. Results of Joint Tests for Watchlist Announcements for Straight-debt Bonds**

<i>Goodman and Kruskal's Gamma</i>	Gross Return	Excess return	Excess rating return
Gamma	0.3368	0.1966	0.5371
Variance	0.0014	0.0016	0.0011
z-statistic	8.97	4.91	16.21
<i>Pearson's Chi-square</i>	Gross Return	Excess return	Excess rating return
Chi-square	15.98	13.24	23.92
p-value	0.0001	0.0003	<0.0001

2.4.1.2 Moody's Rating Change Announcements Following Watchlist Placements

2.4.1.2.1 Entire Sample

For rating change announcements after watchlist placement, there is no significant evidence of effects on bond returns from the *t*-test on mean returns. However, other tests

indicate significant bond market reactions to rating upgrade announcements and rating change announcements regardless of the direction. (See tables 2.9 and 2.10)

For rating downgrade announcements, the three mean and median returns are all negative, but the mean returns are not significant in value. Only gross returns show a significant reaction in sign test at the significance level 0.2%. The significance levels of the sign tests for excess return and excess rating return are 21.1% and 24.0%, respectively. For rating upgrade announcements, the means of the three returns are positive but they are not statistically significant. However, at the significance level 0.4% excess rating returns show a significant reaction according to the sign test. This indicates that there are more positive excess rating returns observed when the rating change announcement is for upgrading.

For rating change announcements regardless of directions, the gammas are all significantly positive. This supports the hypothesis that the association between rating change announcements and signs of bond returns is positive. For example, the gamma 0.4369 for excess rating returns means that the prediction error when forecasting the sign of the return can be reduced by 43.69% if we know the direction of rating changes. All three chi-square tests are significant, as well, which rejects hypothesis that there is no correlations between rating change announcements and signs of returns.

It is interesting to notice that for the above analysis, the gross return usually shows a more significant reaction than the excess return, and that the excess rating return is always the most significant one among the three. Hence, it seems important to control for the default risk premium in addition to the risk-free rate when testing for bond market reactions.

2.4.1.2.2 Straight-debt Bonds Only

The sample of straight-debt bond reaction following rating changes consists of 108 events; which is considerably smaller than entire sample of 162 events. However, the results reported in tables 2.11 and 2.12 suggest that the detected market reaction is somewhat more significant for the reduced sample.

**Table 2.9. Results Summary for Rating Change Announcements for the Entire Sample
in the Bond Market**

t-test:

	Raw return		Excess return		Excess rating return	
	DOWN ¹	UP ²	DOWN	UP	DOWN	UP
Mean	-1.00%	0.10%	-0.40%	0.20%	-0.37%	0.89%
Median	-0.50%	0%	-0.18%	0.25%	-0.19%	0.69%
Std. Dev.	2.30%	1.50%	2.14%	1.81%	2.35%	1.97%
Max	4.10%	4.50%	3.97%	6.28%	5.69%	6.28%
Min	-9.30%	-4.90%	-7.29%	-3.28%	-7.89%	-3.50%
t-statistic	-0.409	0.053	-0.188	0.109	-0.160	0.452
One-sided p-value	0.342	0.479	0.426	0.457	0.437	0.327

Sign Test:

	Raw return		Excess return		Excess rating return	
	DOWN	UP	DOWN	UP	DOWN	UP
Sample size	99	63	99	62	98	57
No. of Negatives	64	31	54	30	53	18
No. of Positives	30	32	43	32	45	39
No. of Zeros	5	0	1	0	0	0
One-sided p-value	0.002	0.5	0.211	0.450	0.240	0.004

¹DOWN denotes the rating changes announcement is for downgrades.

²UP denotes the rating changes announcement is for upgrades.

**Table 2.10. Results of Joint tests for Rating Change Announcements for the Entire
Sample in the Bond Market**

<i>Goodman and Kruskal's Gamma</i>	Gross		
	Return	Excess return	Excess rating return
Gamma	0.3754	0.1451	0.4369
Variance	0.0005	0.0006	0.0005
z-statistic	16.59	5.77	19.22
<i>Pearson's Chi-square</i>	Gross		
	Return	Excess return	Excess rating return
Chi-square	17.47	9.31	28.62
p-value	<0.0001	0.0023	<0.0001

For rating downgrades, the means of all three returns are insignificantly negative but all sign tests reject the null of equal probability at the 10% significance level. Taking the excess rating return as an example, there is an 8.8% chance of observing 39 negative excess rating returns in 66 events if they were equal probable. So, there are significantly more negative excess rating returns associated with rating downgrades. For rating upgrades, all three returns are insignificantly positive at the mean, and only sign test for excess rating returns reject the null of equal probability at the 8.8% significance level. The conclusion is that more positive excess rating returns are observed with rating upgrade announcements.

Considering general rating change announcements, all gammas are significantly positive and all chi-square statistics are significantly nonzero (see table 2.12). For example, the gamma of excess rating returns shows that the information of the direction of a rating change announcement can reduce the prediction error by 41.94% in estimating the sign of an excess rating return. Its chi-square statistic 16.98 also indicates a significant correlation between rating change announcements and signs of excess rating returns.

2.4.1.3 Summary

The *t*-tests show negative/positive average returns associated with watchlist announcements for possible downgrades/upgrades or with rating change announcements for actual downgrades/upgrades following watchlist placements. However, none of them is statistically significant. Figures 2.1-2.4 show the density and cumulative density plots of bond excess rating returns of straight-debt bonds. Plots of other results are displayed in appendix B. As straight-debt bonds' excess rating returns associated with watchlist announcements for either possible downgrades or upgrades are well spread out, the size of the standardized mean returns are too small to reject the *t*-tests. Comparing for different directions of watchlist placement, it appears that the two cumulative distributions (in figure 2.3) are clearly different from each other, but the area of overlapping of the two density distributions (in figure 2.1) is not small. The situation is similar for straight-debt bonds with rating change announcements and for the entire sample with both announcements.

Table 2.11. Results Summary for Rating Change Announcements for Straight-debt Bonds

t-test:

	Gross return		Excess return		Excess rating return	
	DOWN ¹	UP ²	DOWN	UP	DOWN	UP
Mean	-0.51%	0.04%	-0.42%	0.03%	-0.42%	0.63%
Median	-0.85%	0.07%	-0.22%	-0.04%	-0.39%	0.64%
Std. Dev.	2.47%	1.49%	2.10%	1.77%	2.40%	1.89%
Max	4.11%	3.44%	3.97%	5.09%	5.39%	5.55%
Min	-9.25%	-4.86%	-7.29%	-3.28%	-7.89%	-3.50%
t-statistic	-0.343	0.049	-0.199	0.016	-0.176	0.330
One-sided p-value	0.366	0.481	0.421	0.494	0.430	0.372

Sign Test:

	Gross return		Excess return		Excess rating return	
	DOWN	UP	DOWN	UP	DOWN	UP
Sample size	69	39	69	39	66	35
No. of Negatives	43	19	42	21	39	13
No. of Positives	24	20	26	18	27	22
No. of Zeros	2	0	1	0	1	0
One-sided p-value	0.027	0.5	0.046	0.625	0.088	0.088

¹DOWN denotes the rating change announcement is for downgrades.

²UP denotes the rating change announcement is for upgrades.

Table 2.12. Results of Joint Tests for Rating Change Announcements for Straight-debt Bonds

<i>Goodman and Kruskal's Gamma</i>	Gross Return	Excess return	Excess rating return
Gamma	0.3070	0.1613	0.4194
Variance	0.0013	0.0015	0.0012
z-statistic	8.60	4.23	11.89
<i>Pearson's Chi-square</i>	Gross Return	Excess return	Excess rating return
Chi-square	12.15	11.61	16.98
p-value	0.0005	0.0007	<0.0001

The sign tests report significant associations between the signs of three types of bond returns and credit rating announcements, i.e., for watchlist placement, rating changes,

watchlist for possible downgrades, and rating downgrades. However, only when we control for the default risk premium, we find such associations significant for watchlist announcements with possible upgrades or rating upgrade announcements. The frequency plots of bond returns associated with credit rating announcements shown in figures 2.5-2.8 explicitly display the results. Watchlist with possible downgrades in all four figures and rating downgrades in figures 2.5, 2.6, and 2.8 show clear frequency differences between negative and positive returns, while only watchlist with possible upgrades in figure 2.8 and rating upgrades in figures 2.7 and 2.8 show such clear differences.

The bond market reaction to the announcements for both watchlist placement and removal indicates that bond investors consider Moody's watchlist placement as new information; however it appears they do not fully trust it. If investors believe that the watchlist is correct for sure, they will fully adjust bond prices after watchlist placement, without any reactions to rating changes afterwards. However, they save a part of the price adjustment until Moody's confirms the watchlist direction in the rating change announcement.

Even though the average bond excess return and the average bond excess rating return are not significantly different from zero, we can still get the relative size of each price adjustment. Taking excess rating returns for straight-debt bonds as an example, its average for watchlist placement with possible downgrades (upgrades) is -1.13% (0.88%), and for rating downgrades (upgrades) is -0.42% (0.63%). The absolute size of price adjustments for watchlist announcements is larger than for rating change announcements, supporting the conclusion that bond investors do trust the watchlist announcements, but not fully so.

Interestingly, we find that for corporate straight-debt bonds the relative size of mean returns associated with watchlist announcements to mean returns associated with both watchlist and rating change announcements, is close to the probability of the watchlist announcement with a correct direction. From the results in tables 2.7 and 2.11, computed relative sizes are 70.54% for gross returns, 70.83% for excess returns, and 72.72% for excess rating returns. In Moody's report, Fons (2002) states that "...between 66%-76% of all ratings have been changed in the same direction (and rarely in the opposite direction) as indicated by their watchlist review." All three relative sizes fall into the range of 66%-76%, which

suggests that bond investors have rational expectations regarding the likelihood of watchlist announcements being followed by rating changes in the same direction.

Comparison of the entire sample and the one with only corporate straight-debt bonds reveals that the former shows a gradually decreasing significance level with watchlist announcements when we control for the risk-free rate and the default risk premium in succession. However, for watchlist announcements in the latter sample, the significance level for gross returns is smaller than for excess return, and that for excess rating return is always the smallest. For rating changes, the significance level is even gradually increasing. The inconsistency between the reactions of different types of bonds to two types of announcements is difficult to interpret. However, the size of the average excess rating return is always the largest among the three averages for each type of announcement. All three returns associated with watchlist announcements for possible downgrades reject the null using sign tests in both samples, and average excess rating returns show the most significant evidence. Also, Figures 2.5 and 2.6 depict more negative excess returns associated with watchlist for upgrades or rating upgrades, which contradict intuition, while the frequencies of excess rating returns in figures 2.7 and 2.8 are consistent with prior expectations. Hence, we argue that controlling for the risk-free rate is not sufficient and that it is necessary to also consider the default risk premium.

2.4.2 Reactions of Equity Markets

We employ two types of returns in equity markets, i.e. excess returns based on a market model and excess beta returns based on a beta portfolio.

2.4.2.1 Moody's Credit Watchlist Announcements

There is no significant evidence of equity market reactions to watchlist announcements by the *t*-test on mean returns, but other tests report strong associations between announcements and equity returns. Excess beta returns indicate somewhat more significant reactions than excess returns. (See table 2.13 and 2.14)

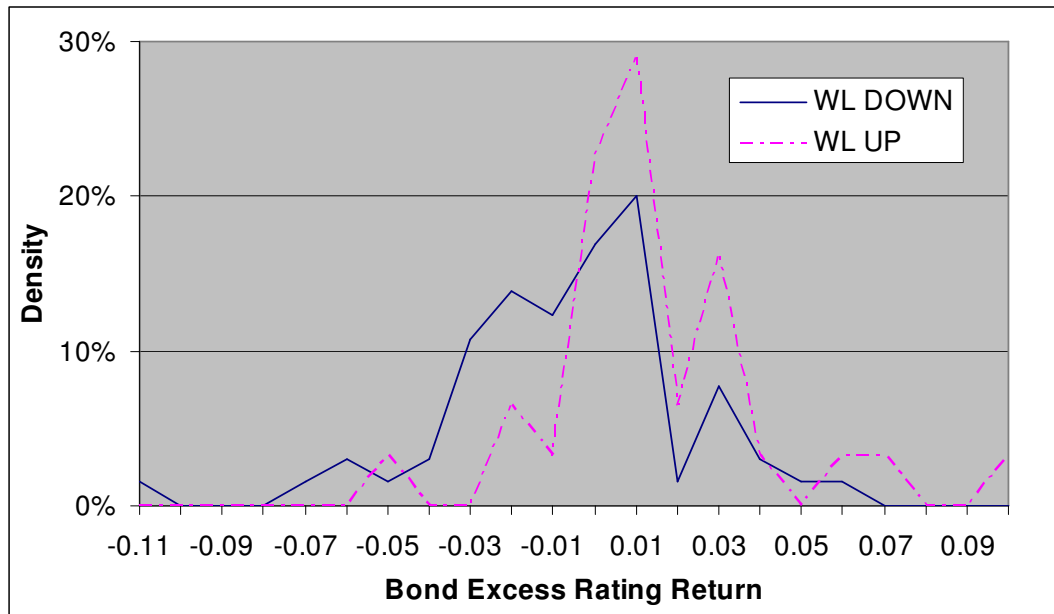


Figure 2.1. Density of Bond Excess Rating Returns of Straight-debt Bonds Associated with Watchlist Announcements

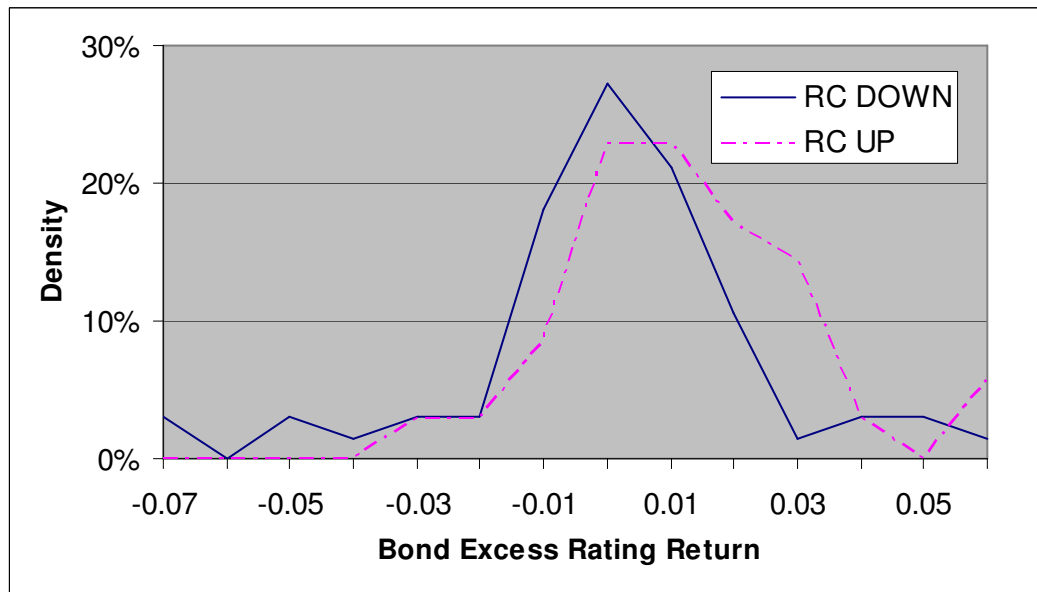


Figure 2.2. Density of Bond Excess Rating Returns of Straight-debt Bonds Associated with Rating Change Announcements

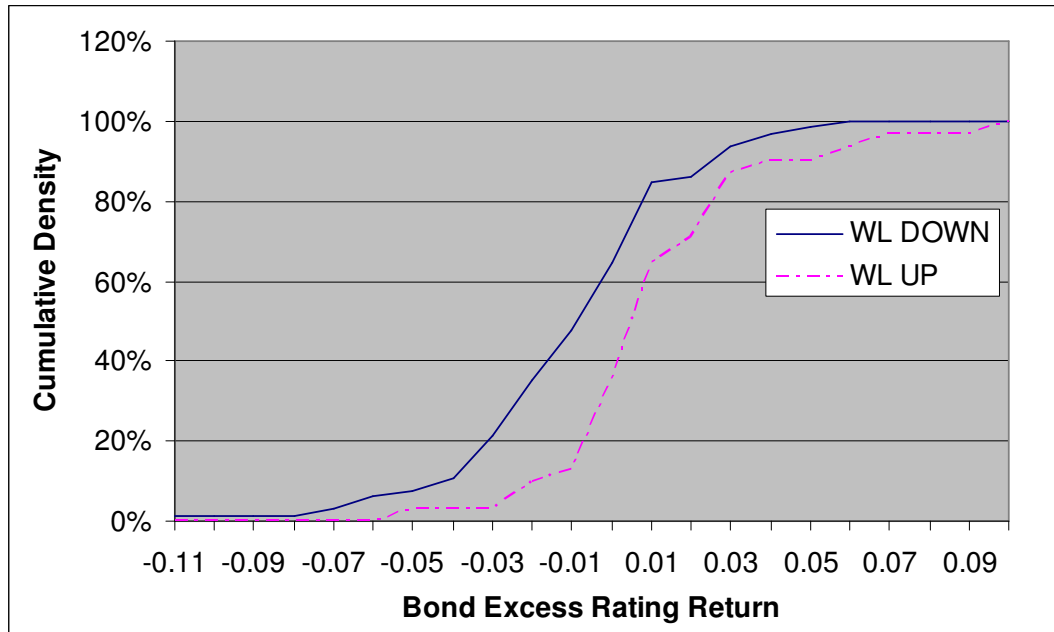


Figure 2.3. Cumulative Density of Bond Excess Rating Returns of Straight-debt Bonds Associated with Watchlist Announcements

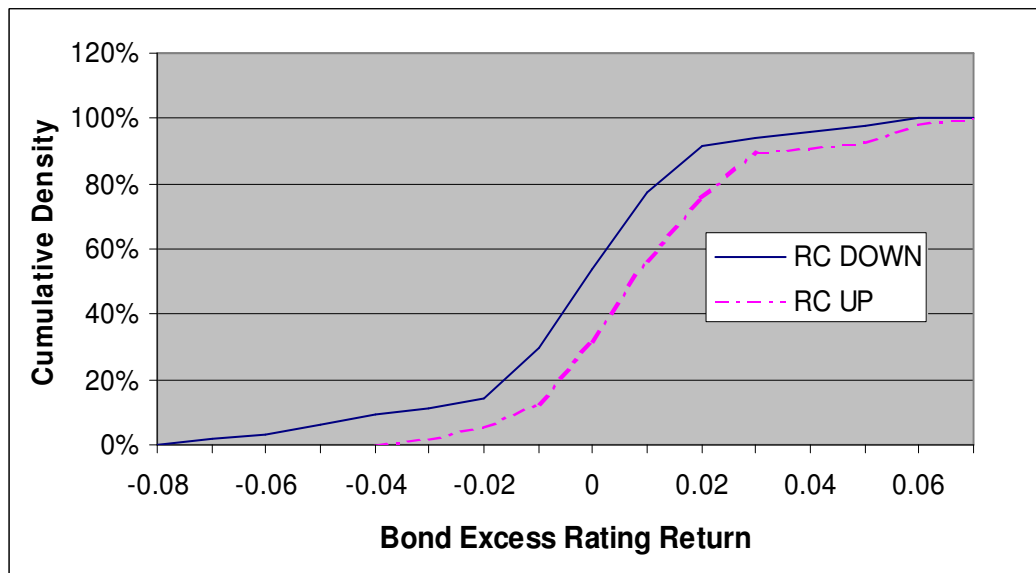


Figure 2.4. Cumulative Density of Bond Excess Rating Returns of Straight-debt Bonds Associated with Rating Change Announcements

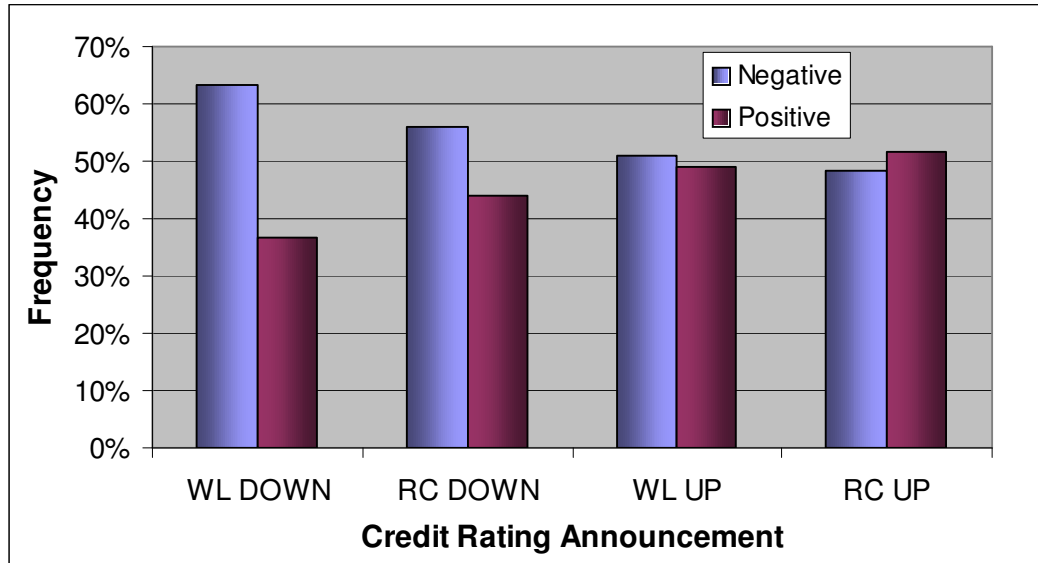


Figure 2.5. Frequency of Negative and Positive Bond Excess Returns of the Entire Sample Associated with Credit Rating Announcements

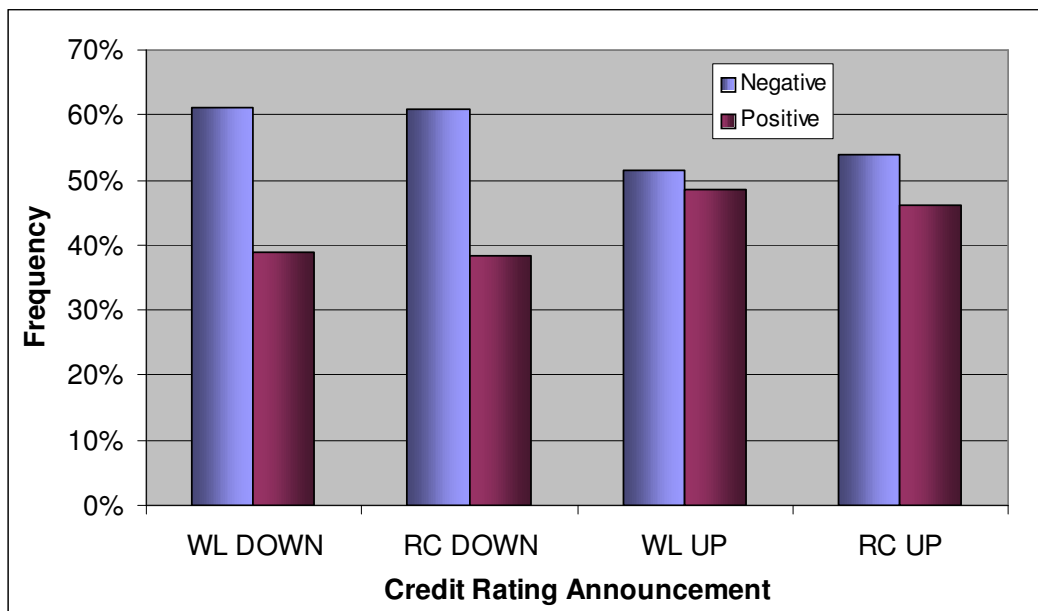


Figure 2.6. Frequency of Negative and Positive Bond Excess Returns of Straight-debt Bonds Associated with Credit Rating Announcements

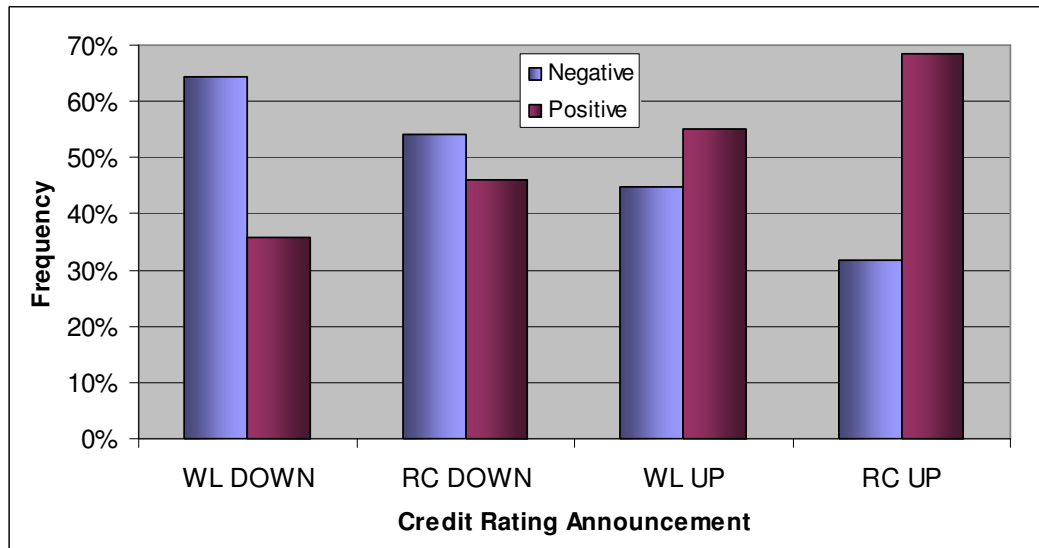


Figure 2.7. Frequency of Negative and Positive Bond Excess Rating Returns of the Entire Sample Associated with Credit Rating Announcements

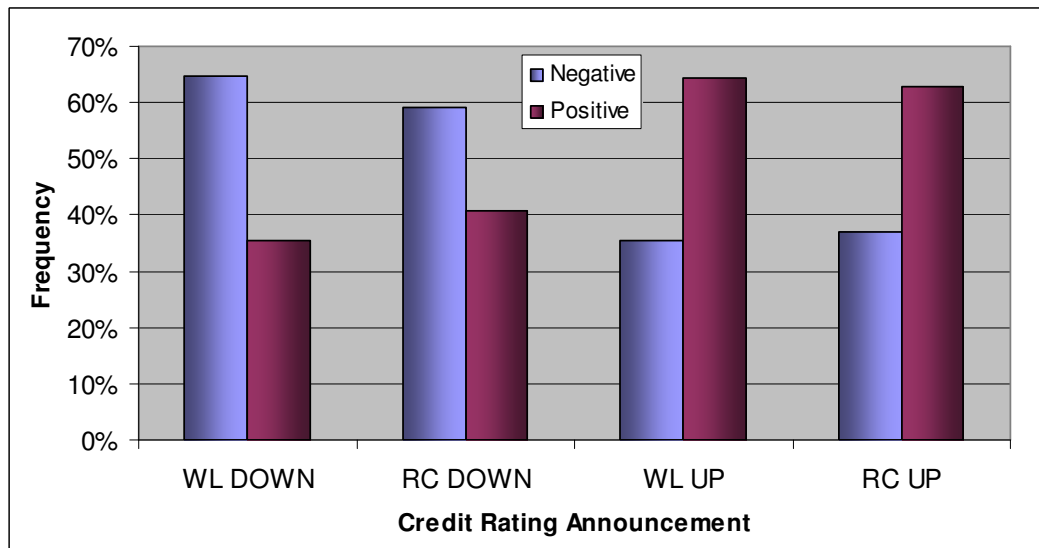


Figure 2.8. Frequency of Negative and Positive Bond Excess Rating Returns of Straight-debt Bonds Associated with Credit Rating Announcements

In the case of watchlist placements for possible downgrades, the average excess return and the average excess beta return are insignificantly negative. However the sign test reports that there are significantly more negative excess (beta) returns. The significance level of excess beta returns is 5.4%, which is smaller than the 11.0% level according to excess returns.

For watchlist announcements for possible upgrades, the averages are positive but not significant for both excess returns and excess beta returns. However, sign test reports a strong relation between such announcements and signs of excess (beta) returns at the 8.1% (4.9%) significance level.

The results in table 2.14 indicate that for watchlist announcements in general, equity market reaction is significant at the 0.01% level using the chi-square statistics. If the possible direction of watchlist placement is known, the excess beta return reports a 38.3% reduction of prediction error when forecasting signs of associated returns, while the excess return reports a 29.5% reduction.

Table 2.13. Results Summary for Watchlist Announcements in the Equity Market

<i>t</i> -test:				
	Excess return		Excess beta return	
	DOWN ¹	UP ²	DOWN	UP
Mean	-0.53%	0.50%	-0.47%	0.60%
Median	-0.07%	0.19%	-0.18%	0.14%
Std. Dev.	3.02%	2.08%	3.01%	2.04%
Max	10.09%	11.47%	10.23%	10.98%
Min	-16.65%	-3.31%	-17.36%	-2.44%
t-statistic	-0.176	0.239	-0.156	0.293
One-sided p-value	0.430	0.406	0.438	0.385

Sign Test:				
	Excess return		Excess beta return	
	DOWN	UP	DOWN	UP
Sample size	112	68	99	62
No. of Negatives	63	28	58	24
No. of Positives	49	40	41	38
One-sided p-value	0.110	0.091	0.054	0.049

¹DOWN denotes the watchlist announcement is for possible downgrades.

²UP denotes the watchlist announcement is for possible upgrades.

Table 2.14. Results of Joint Tests for Watchlist Announcements in the Equity Market

<i>Goodman and Kruskal's Gamma</i>	Excess return	Excess beta return
Gamma	0.295	0.383
Variance	0.0004	0.0005
z-statistic	13.92	17.18
<i>Pearson's Chi-square</i>	Excess return	Excess beta return
Chi-square	16.42	16.58
p-value	0.0001	<0.0001

2.4.2.2 Moody's Rating Change Announcements Afterwards

There is no significant evidence of equity market reactions from either the *t*-test or sign test (see table 2.15). However, both Goodman and Kruskal's gamma and Pearson's chi-square report significant evidence (see table 2.16).

For rating downgrade or upgrade announcements, the signs of the two average excess returns are consistent with expectations, but none is significantly different from zero at any reasonable level.

However, considering rating change announcements as a whole, the gamma of excess returns shows that the direction of rating changes can reduce 7.53% of prediction error in forecasting signs of returns at the 5% significance level. Similarly, the gamma of excess beta returns reports a 4.08% reduction, which is significant at the 0.05% level. Both chi-square statistics are significant at the 1% level, rejecting the null hypothesis of no relation between such announcements and signs of returns.

2.4.2.3 Summary

The equity market shows a strong reaction to watchlist announcements, regardless of directions, while no significant reactions are found to rating downgrade/upgrade announcements except when we take rating change announcements in general.

Figures 2.9-2.12 show the density and cumulative density distributions of stock excess beta returns associated with the events. The cumulative density distributions of stock excess beta returns (in figures 2.11 and 2.12) can be clearly differentiated by announcement directions, but density distributions (in figures 2.9 and 2.10) have substantial overlapping.

Table 2.15. Results Summary for Rating Change Announcements in the Equity Market

<i>t</i> -test:				
	Excess return		Excess beta return	
	DOWN ¹	UP ²	DOWN	UP
Mean	-0.15%	0.21%	-0.55%	0.21%
Median	0.06%	-0.07%	-0.06%	0.01%
Std. Dev.	0.92%	1.56%	2.36%	1.84%
Max	2.69%	3.79%	4.92%	5.53%
Min	-2.24%	-1.83%	-12.78%	-8.39%
t-statistic	-0.163	0.137	-0.232	0.112
One-sided p-value	0.435	0.446	0.409	0.456

Sign Test:				
	Excess return		Excess beta return	
	DOWN	UP	DOWN	UP
Sample size	105	72	98	66
No. of Negatives	55	35	51	33
No. of Positives	50	37	47	33
One-sided p-value	0.348	0.453	0.381	0.5

¹DOWN denotes the rating changes announcement is for downgrades.

²UP denotes the rating changes announcement is for upgrades.

Table 2.16. Results of Joint Tests for Rating Change Announcements in the Equity Market

<i>Goodman and Kruskal's Gamma</i>	Excess return	Excess beta return
Gamma	0.0753	0.0408
Variance	0.0005	0.0006
z-statistic	3.29	1.64
<i>Pearson's Chi-square</i>	Excess return	Excess beta return
Chi-square	6.63	6.61
p-value	0.010	0.010

However, all of them are better than the plots of stock excess returns (in appendix B.13-B.16). Watchlist announcements for both directions in figures 2.13 and 2.14 show considerably different frequencies of negative and positive returns. However, the evidence for excess beta returns is somewhat stronger. Hence, controlling for a stock's beta is recommended in such studies.

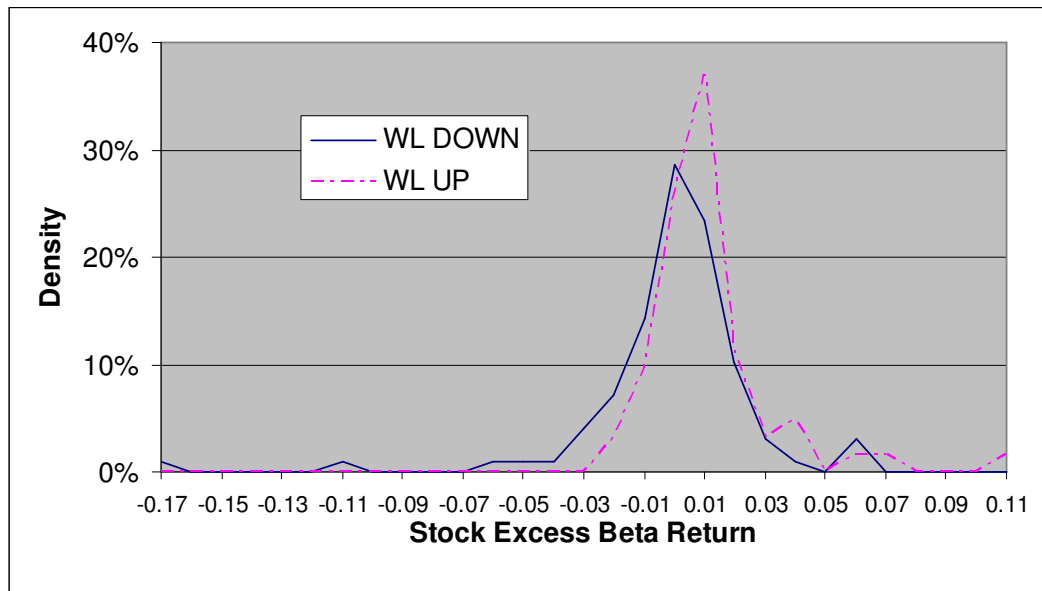


Figure 2.9. Density of Stock Excess Beta Returns Associated with Watchlist Announcements

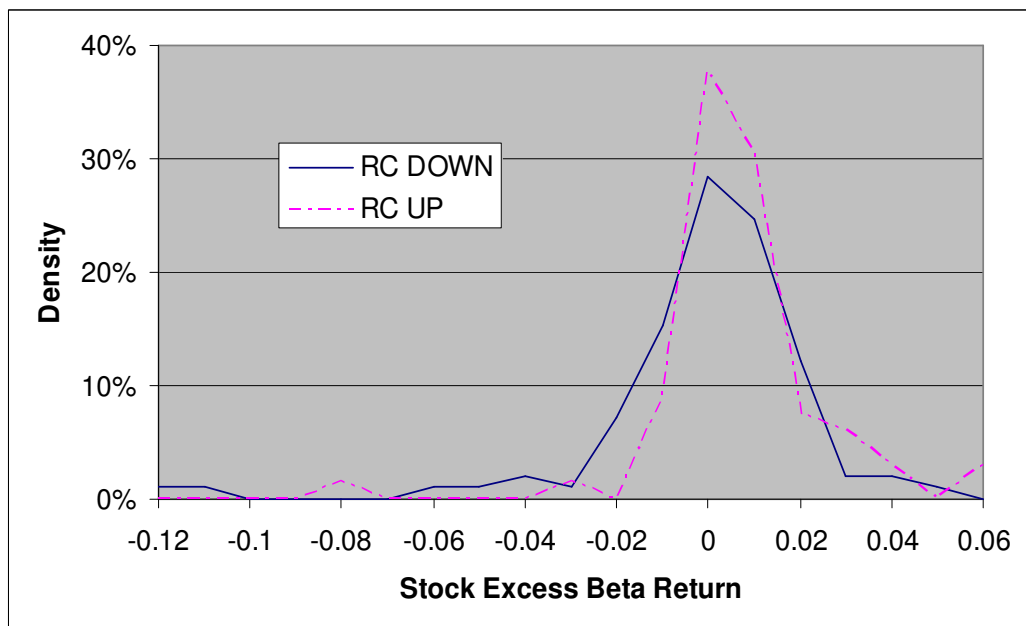


Figure 2.10. Density of Stock Excess Beta Returns Associated with Rating Change Announcements

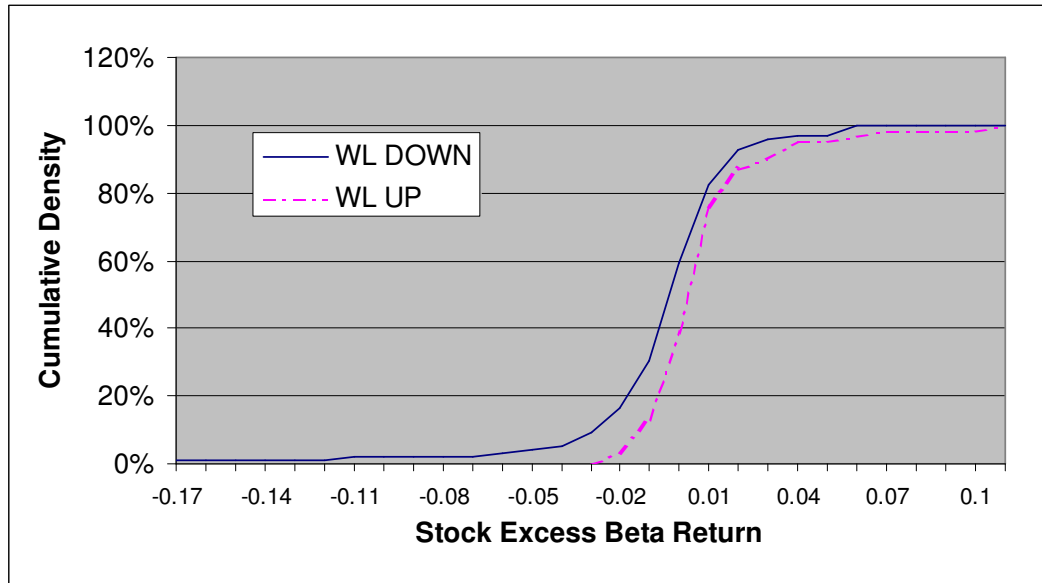


Figure 2.11. Cumulative Density of Stock Excess Beta Returns Associated with Watchlist Announcements

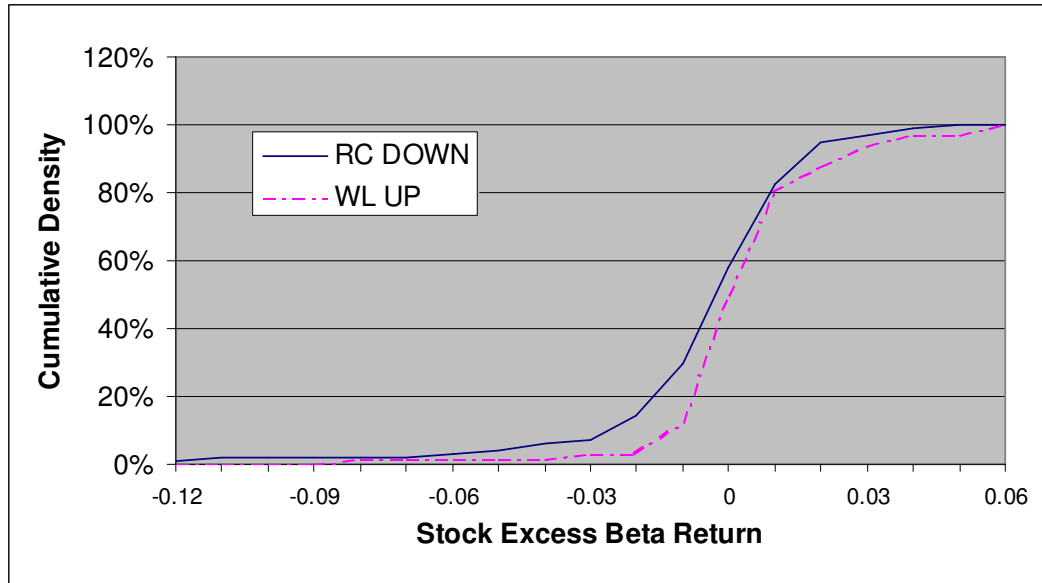


Figure 2.12. Cumulative Density of Stock Excess Beta Returns Associated with Rating Change Announcements

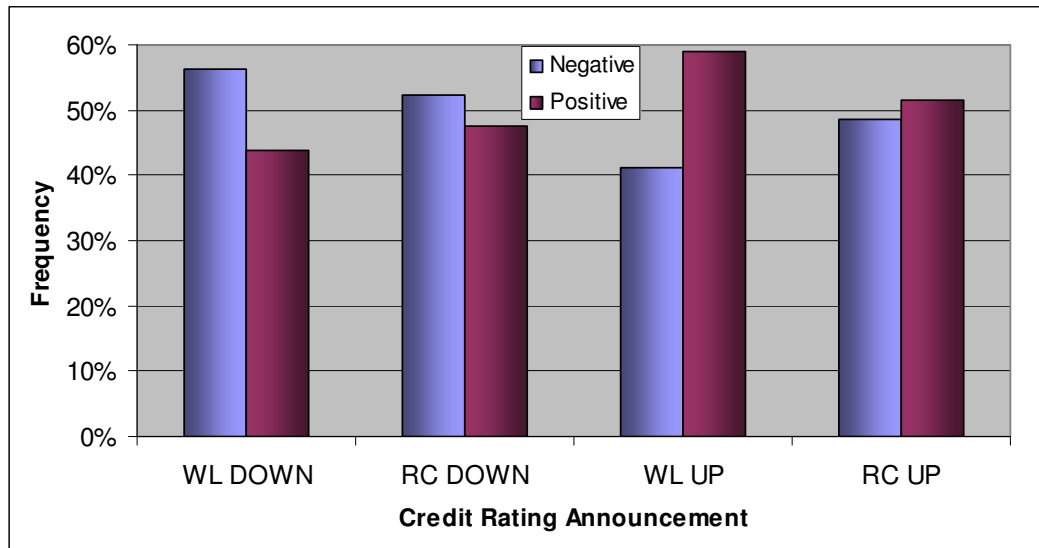


Figure 2.13. Frequency of Negative and Positive Stock Excess Returns Associated with Credit Rating Announcements

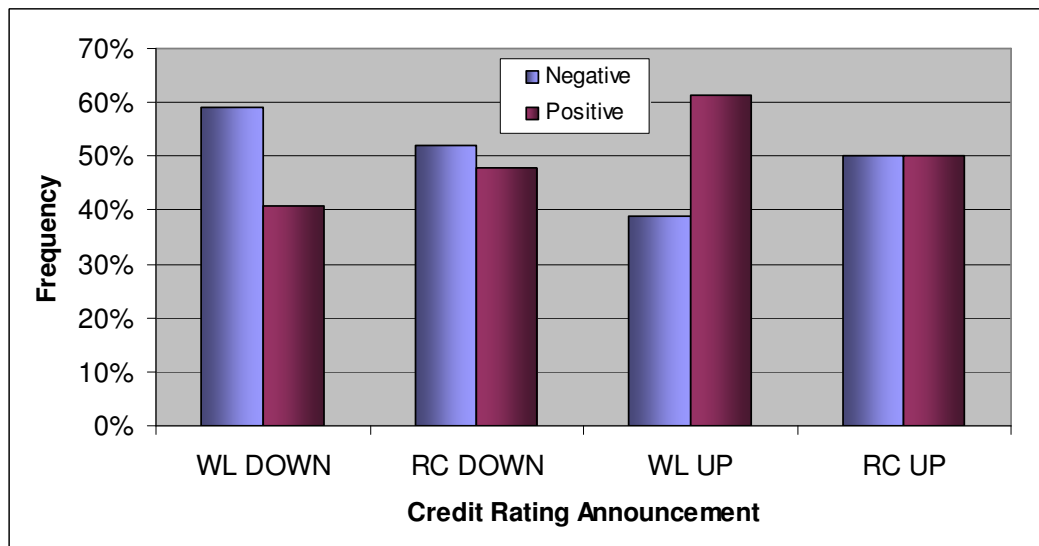


Figure 2.14. Frequency of Negative and Positive Stock Excess Beta Returns Associated with Credit Rating Announcements

2.4.3 Results of First Order Stochastic Dominance Tests

We assign a unique case number to each of the total 12 cases in our study as in table 2.17. For example, bond excess return with the entire sample associated with watchlist placements is case number 1. We test for the first order stochastic dominance by considering $k = 5$ and 10^{30} , and the significance levels of accepting H_{A2} in each case are reported in table 2.18. When $k = 5$, all cases indicate that upgrades are first-order stochastically dominant over downgrades at least at 20% significance levels, except case 11 which accepts H_{A1} at 5% significance level. The results are consistent with the cumulative density plots in that, except for case 11, the cumulative density curves associated with upgrades are always to right of the cumulative density curves corresponding to downgrades. For case 11, the cumulative density curve of rating upgrades in figure B.16 intersects with rating downgrades three times. When $k = 10$, only 5 cases accept H_{A2} at least at 5% significance level, while others cannot even at 20% significance level. Compared to other studies using thousands of observations, esp. Monte Carlo simulations, the difference between the results of $k = 5$ and $k = 10$ is expected to be the small sample size in the present paper. Hence, we can conclude that rating announcements with (possible) upgrades are stochastically dominant over (possible) downgrades by order 1. That is to say, investors in both bond and equity markets treat Moody's rating (possible) upgrading/downgrading announcements as valuable positive/negative signals.

Table 2.17. Description of Defined Cases' Numbers

			Watchlist placements	Rating changes
Bond	Excess return	Entire sample	1	3
		Straight-debt bonds	5	7
	Excess rating return	Entire sample	2	4
		Straight-debt bonds	6	8
Stock	Excess return		9	11
	Excess beta return		10	12

³⁰ Limited by the sample size, we prefer not to try large K values but 5 and 10.

Table 2.18. Significance Levels of First Order Stochastic Dominance Tests

Case No.	1	2	3	4	5	6	7	8	9	10	11	12
k=5	5%	1%	10%	5%	5%	5%	20%	20%	20%	1%	Note 2	10%
k=10	1%	1%	-	5%	-	1%	-	-	-	1%	-	-

Note 1: "-" represents that the significance level is greater than 20%.

Note 2: Case 11 accepts H_{A1} at 5% significance level.

2.4.4 Comparison of Bond and Equity Markets

In general, we find stronger evidence of reactions to credit rating announcements in the bond market, than in the equity market. Both bond excess returns and bond excess rating returns show significant evidence of market reactions to watchlist announcements for possible downgrades, watchlist announcements in general, rating downgrade announcements, and rating change announcements in general. Bond excess rating returns also report strong evidence of bond market reactions to watchlist announcements for possible upgrades and rating upgrade announcements. However, stock excess returns and excess beta returns only show significant evidence of equity market reactions to watchlist announcements for possible downgrades/upgrades, watchlist announcements in general, and rating change announcements in general. Compared to the bond market, the equity market provides weaker evidence of reactions to rating downgrade/upgrade announcements. In addition, the significance level of the evidence in the bond market is typically smaller than in the equity market.

However, none of the markets reports an average return significantly different from zero as a reaction to credit rating announcements by the t -test. That is to say, comparing to no rating announcements, the average returns associated with rating announcements are not statistically different. But if we compare the distribution of returns associated with rating upgrade announcements with the distribution of returns associated with rating downgrade announcements, they are statistically different by the first order stochastic dominance test. The different results come from the testing method itself. The t -test only employs two moments of the distribution (i.e., the mean and the variance), while stochastic dominance test utilize the entire distribution. Hence, we conclude that rating upgrade/downgrade announcement is a valid good/bad signal for the company in the market.

Wansley and Clauretje (1985) and Hand *et al.* (1992) find significant bond market reactions to watchlist placements only. In contrast, the present study finds strong evidence to both watchlist and rating change announcements. The literature on equity market reactions find significant evidence to rating downgrades but not to rating upgrades, while there are not many studies for watchlist placements. Our findings are consistent with the literature for rating upgrades. However, we do not find any strong evidence of reactions to rating downgrades. In addition, we find strong equity market reactions to watchlist placements.

Previous studies usually find more evidence of reactions in equity markets than in bond markets, by reporting significant average returns. However, we fail to reject *t*-tests that mean returns are not significantly different from zero. The possible reason for this is that our sample size is not large enough. On the other hand, our study reports more evidence of bond market reactions by other analyses, i.e. sign tests, Pearson's chi-square tests, Goodman and Kruskal's gamma statistics, and first order stochastic dominance tests, which have seldom been used before. Also, previous studies usually control for the risk-free rate in bond returns but we also control for the default risk premium. Bond excess rating returns in our sample show stronger and more consistent evidence than excess returns. However, researchers usually control for a stock's beta, market-to-book ratio and other financials; we are only able to control for beta. This could be a reason why we find less evidence in equity markets. The evidence of market reactions for stock excess returns and excess beta returns is similar, while that for excess beta returns is somewhat stronger. Hence, controlling for default risk premium is beneficial for bond market studies, while controlling for beta coefficients does not appear to make much of a difference for equity market studies.

2.5 Conclusion

This chapter examines bond and equity market reactions to Moody's credit rating announcements, namely, watchlist placement and actual rating changes following such placements. We employ three returns in bond markets, namely, bond gross returns, bond excess returns (controlling for risk-free rate), and bond excess rating returns (controlling for the default risk premium), and two returns in equity markets, which are stock excess returns based on a market model and stock excess beta returns based on a beta portfolio. The *t*-tests

of average returns do not find any significant evidence of market reactions to either announcement. However, other tests (i.e., sign tests, Pearson's chi-square tests, and Goodman and Kruskal's gamma statistics) report significant bond and equity market reactions to watchlist placement for possible downgrades/upgrades, watchlist placement general, and rating changes general. The bond market also shows a significant reaction to rating upgrade/downgrade announcements. The results suggest that we find stronger evidence of bond market reactions to credit rating announcements because we control for both the risk-free rate and the default risk premium. In addition, the returns associated with rating downgrades are first order stochastically dominated by the returns corresponding to rating upgrades. It shows that rating downgrades/upgrades are truly valuable information for investors and this conclusion is more reliable than it from the t -test, especially with a small sample size.

2.6 References

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CHAPTER 3. MATCHING IPO ISSUERS AND UNDERWRITERS AND EFFECT OF UNDERWRITER REPUTATION ON IPO UNDERPRICING

3.1 Introduction

An Initial Public Offering (IPO) is an effort made by a private firm to raise external capital in a public equity market. As there is asymmetric information between the issuing firm and the market, the former usually chooses an underwriter to help it sell the offered shares to the public. This begs an answer to the question of how an issuing firm chooses an underwriter. Do different types of issuing firms have any preference over specific underwriters? As it is difficult to gather information about each issuer's selection set of underwriters before an IPO, we can only show the matched evidence from observed offerings.

A related issue of interest regarding IPOs is the relation between an underwriter's reputation and an IPO's underpricing. Intuitively, high-reputation underwriters should be more knowledgeable in evaluating the offerings, so that they should be associated with smaller underpricings than low-reputation underwriters. Hence, we examine this hypothesis by looking at the entire sample and two types of subsamples.

The present paper has three primary objectives. First, the study examines the potential preference of issuing firms over underwriter reputation, with issuers grouped by the state of incorporations or the industry they belong to. Second, the analysis tries to find how an underwriter's characteristics are associated with its reputation. Third, the paper examines the effect of underwriter reputation on IPO underpricing.

3.1.1 Literature Review

The empirical literature on IPOs focuses on three major areas of inquiry. The first one investigates the reasons why firms go public. Theories trying to answer such a question include life-cycle theories (Zingales (1995), Chemmanur and Fulghieri (1999), and Maksimovic and Pichler (2001)) and market-timing theories (Lucas and McDonald (1990), and Choe, Masulis and Nanda (1993)). Empirically testing the determinants of the decision to

go public is difficult because only the firms actually going public are observed. However, using data from Italian firms, Pagano *et al.* (1998) apply a probit model to analyze the decision to go public by comparing the ex-ante characteristics of IPO firms and other private firms. They find that the two primary factors affecting the probability of going public are the average market-to-book ratio in the industry and the size of the company. Comparing the ex post characteristics of IPO firms and other private firms by nonparametric methods, they examine the consequences of the decision to go public on the company's investment and financials, especially the cost of bank credit and profitability after IPO. Analysing one industry in the U.S., Lerner (1994) confirms Pagano *et al.*'s finding (1998) that market-to-book ratio is an important determinant of the IPO decision.

The second focus of the IPO literature is the allocation of shares and IPO short-run and long-run performance. The allocation of shares examines how IPOs are allocated to investors and how their shares trade. Increasing attention on share allocation is related to IPO short-run underpricing and long-run underperformance, especially the relation between IPO underpricing and underwriter reputation. There is ample evidence that IPOs managed by prestigious banks are less likely to exhibit short-run underpricing than IPOs managed by less prestigious banks, and that prestigious banks tend to be associated with less-risky IPOs than their nonprestigious counterparts. Most previous empirical studies in this area have used OLS regression models, such as Logue (1973), Johnson and Miller (1988), Carter and Manaster (1990), Carter, Dark and Singh (1998), Habib and Ljungqvist (2001), Cooney, Singh, Carter and Dark (2001), Bradley, Cooney, Jordan and Singh (2002) and Loughran and Ritter (2004).

Logue (1973) shows that the average short-run underpricing measure associated with prestigious underwriters is 40% of that associated with nonprestigious underwriters during March 1965 and February 1969. Johnson and Miller (1988) find a negative relation between banker prestige and IPO underpricing during the 1981-1983 period; however, such relation disappears when initial returns are adjusted for risk. Carter and Manaster (1990) find a significantly negative coefficient on underwriter reputation in the regression of the price run-up from 1979 to 1983, which indicates that IPOs managed by prestigious banks should be associated with a smaller price run-up. Carter *et al.* (1998) report that the estimated

coefficients on three underwriter reputation measures³¹ in the regression of market-adjusted initial return are all significantly negative during the 1979 to 1991 period. Habib and Ljungqvist (2001) control for the issuer's endogenous choice of underwriters and report a negative³² relation between underpricing and underwriter reputation during 1991 through 1995. Cooney *et al.* (2001) examine whether there is a flipped relation between IPO initial return and underwriter reputation in the 1990s. They report such a significantly negative relation in the 1980s and an insignificantly positive relation in the 1990s. In addition, they show that such inverse relation is consistent only for those IPOs priced within the filing range in both subperiods. However, Bradley *et al.* (2002) show that high-reputation underwriters are associated with smaller (larger) underpricing in the 1980s (during 1991 through 1998), while no significant relation is found during the internet bubble. Loughran and Ritter (2004) argue that IPO's underpricing has changed over time. High-reputation underwriters are associated with greater underpricing in the 1990s (i.e. the internet bubble years), than in the 1980s, which is consistent with the results from OLS and two-stage procedures that control for the endogeneity of the issuer's selection of a lead underwriter.

The third focus of the IPO literature concerns the development of suitable measures of underwriter reputation. Logue (1973) is among the first to develop a measure of underwriter reputation. Carter and Manaster (1990) use underwriters' relative placements in the stock offering announcement to rank their reputation. As the Carter-Manaster (CM) method requires a substantial amount of work to check the impact of each tombstone announcement on every underwriter reputation ranking, Johnson and Miller (1988) and Megginson and Weiss (1991) use modifications of the CM method. The Johnson-Miller (JM) method sorts underwriters into four categories according to several measurements, whereas the Megginson-Weiss (MW) method takes the relative market share as a proxy for the underwriter reputation. Carter *et al.* (1998) report that in the context of short-run and long-run IPO performance, the CM measure is the most significant underwriter reputation index among the three measures CM, JM, and MW. Recently, Carter and Dark (2007) introduced

³¹ For each regression equation, a different reputation measure is included but all other independent variables are the same.

³² When they directly apply an OLS regression on underpricing without controlling for that endogeneity, the estimated coefficient of underwriter reputation rank is positive, which is counterintuitive.

an adjusted CM method, which is obtained by adjusting the CM measure by the average offer price of IPOs that an underwriter has managed during each 5-year period.

3.1.2 Issuer's Choice of Underwriter

Interestingly, the literature has paid relatively little attention to the issuing firm's choice of underwriters. Johnson and Miller (1988), Carter and Manaster (1990) and Fernando Gatchev and Spindt (2005) are among those few who have investigated this issue. Johnson and Miller (1988) find that prestigious banks are associated with less risky IPOs than nonprestigious banks. Carter and Manaster (1990) find a significantly lower average aftermarket return for IPOs associated with the prestigious underwriter group, compared to the nonprestigious underwriter group. Both empirical results support the hypothesis that higher underwriter reputation is associated with the marketing of lower risk IPOs. In contrast with the above two studies, Fernando *et al.* (2005) start from a theoretical standpoint. They set up a model assuming that issuers and underwriters associate by mutual choice, and underwriter ability and issuer quality are complementary. They derive a condition under which issuers and underwriters will have a positive assortative matching, such that underwriter ability and issuer quality have a positive correlation. Using OLS regression, they find that reputable underwriters are associated with firms that are less risky and larger in size. However, they include IPO proceeds as an explanatory variable into the regression, which is ex-post information. It is under debate whether it is appropriate to include ex-post information as a regressor.

In the present study we assume that the issuer chooses from a set of possible underwriters, as a one-sided selection. It may be argued that underwriters can choose to participate in the offering or not, which means they may have influence on the matched evidence. Since we are only interested in examining how issuer's characteristics are associated with underwriter reputation, we assume that issuers are rational and they can correctly predict whether high-reputation underwriters will reject them. In other words, the present paper analyzes how issuers form their beliefs about which level of underwriter reputation to go with. Since we only observe issuers' actual choices of underwriters, we can only examine issuing firms' preferences over underwriters in the context of the matched

evidence. However, we only use ex-ante information in order to mimic the real selection environment. Different from the methods used in the literature, we apply the Generalized Linear Model (GLM) with fixed and mixed effects to examine whether an issuer's choice of a lead underwriter is affected by its characteristics, or whether there are state- or industry-specific effects.

Then we examine how the market ranks underwriters. As the CM measure is derived from the relative placement of underwriters in the tombstone announcement, there is no direct explanation of how underwriters are placed in order. This brings the question of whether we can explicitly find a relationship between an underwriter's characteristics and its reputation measure.

3.1.3 Underwriter Reputation and IPO Underpricing

Lastly, we examine the effect of underwriter reputation on IPO short-run underpricing. The main problem to analyze this issue is that we observe the outcome where each IPO is associated with a specific underwriter, but we cannot observe the counterfactual. That is to say, if an issuer chooses a high-reputation underwriter, we cannot observe the underpricing that would have resulted from choosing a low-reputation underwriter. Because we can observe only one underpricing for each issuer, some degree of speculation is needed to find a counterpart for calculating the difference in underpricing if the issuer changed the choice of underwriter to a different reputation level. In addition, direct comparison of IPO underpricings associated with high-reputation and low-reputation underwriters in a non-experimental setting is contaminated by the process of issuers selecting underwriters, which needs to be controlled for.

Previous studies typically use OLS regressions of IPO underpricing with underwriter reputation as a dummy variable, ignoring the unobserved counterfactual problem. They test whether underwriter reputation can help explain the variation of the associated IPO underpricing, and arrive at conclusions based on the sign of the estimated regression coefficient on underwriter reputation. Nonparametric analyses are also sometimes employed, by performing *t*-test of the mean underpricing. Some other studies control for the endogeneity of the issuer's selection of the lead underwriter by a two-stage OLS regression

model. However, the empirical results are mixed. Most of the earlier studies show a significant negative relation between IPO underpricing and underwriter reputation. However, more recent studies find a flipped relation in 1990s. [See Logue (1973), Johnson and Miller (1988), Carter and Manaster (1990), Carter, Dark and Singh (1998), Habib and Ljungqvist (2001), Cooney *et al.* (2001), Bradley *et al.* (2002), and Loughran and Ritter (2004).]

In contrast to the literature, we consider the unobserved counterfactual problem and the underwriter selection process, by matching issuers who choose high-reputation underwriters with those who choose low-reputation underwriters. We find issuers matching as close as possible so that we can use the matched IPO underpricings to estimate the unobserved counterfactual underpricings. This method is often called estimating treatment effect, and the treatment and the effect in our case are the high reputation of an underwriter and the associated IPO underpricing, respectively.

Early studies applying this method used plain matches, where the treatment group is matched with the control group directly by their characteristics. This procedure is helpful when there are only a few observed variables, e.g., categorical variables, but not when the number of variables is large, as in the case of continuous variables. In order to overcome the dimensionality problem, the propensity score matching method has been utilized more recently. Propensity score matching matches observations by the estimated conditional probability of them receiving/choosing the treatment given their observed characteristics. Rosenbaum and Rubin (1983) prove that the propensity score is sufficient to remove the bias due to the unobserved counterfactual problem. In our case, we match issuers by the estimated conditional probability of them choosing high-reputation underwriters based on the observed characteristics of issuers and IPOs before the offerings. There are several matching methods, such as nearest neighbor matching, nearest K neighbors matching, caliper matching, stratification matching, and kernel matching. Here we employ the most popular two, namely, nearest neighbor matching and caliper matching. In order to examine whether IPO underpricing is sensitive to other characteristics, such as time periods³³ or location of the

³³ This idea is motivated by Bradley *et al.* (2002) and Loughran and Ritter (2004).

offer price to the filed price range in the prospectus³⁴, we stratify the entire sample into different subsamples and analyze the treatment effects separately.

The rest of this chapter is organized as follows. Section 3.2 introduces the model specification and methodology, and section 3.3 describes the data. Section 3.4 presents the empirical results and section 3.5 concludes.

3.2 Model Specification and Methodology

As mentioned in section 3.1.2, we employ GLM with fixed and mixed effects to match issuers and underwriters by their respective ex-ante characteristics. In addition, an OLS regression is applied to examine the relation between underwriter reputation measures and underwriters' characteristics. The final objective discussed in section 3.1.3, i.e., the treatment effect of underwriter reputation on IPO underpricing, is examined by propensity score matching methods.

3.2.1 Generalized Linear Model

If data are collected in clusters, e.g., the issuer's state and industry, the assumption that y_i is independently distributed in the natural exponential family will be violated. In order to examine the inter-cluster effect, we introduce a random effect into GLM. However, we need to find out whether the random effects we are interested in are large enough to impact our model selection between GLM with fixed effects and GLM with mixed effects. Hence, we match issuers and underwriters first by GLM with fixed effects and then by GLM with mixed effects.

Let $y_i = 1$ if an issuer chooses a high-reputation underwriter and $y_i = 0$ if an issuer chooses a low-reputation underwriter. In GLM, $E(\cdot)$ denotes the expectation operator, x_{ij} is the ex-ante characteristics of issuers and IPOs, β_j is the coefficient of the fixed effect, α_i is the random effect.

³⁴ Cooney *et al.* (2001) and Bradley *et al.* (2002) examined this topic.

3.2.1.1 GLM with Fixed Effects

A generalized linear model with fixed effects for binary data has three components, a random component, a systematic component, and a link function. The random component y_i has a distribution in the natural exponential family, such that we can define the expectation of y_i as $E[y_i] = \pi_i$. The systematic component η_i consists of a linear combination in x_i , such that $\eta_i = \sum_j x_{ij} \beta_j$. Finally the link function $g(\cdot)$ builds the connection between the systematic and the random component, such that $g[\pi_i] = \eta_i$.

In our case, y_i is a binary variable assumed to follow a binomial distribution. Thus, we employ a logit link to restrict the estimated probability in the range of $[0, 1]$, which is better than the identity link (i.e. $g(\pi_i) = \pi$), such that:

$$\log \frac{\pi_i}{1 - \pi_i} = \eta_i = \sum_j x_{ij} \beta_j .$$

Following Maximum Likelihood Estimation, the estimation equation is obtained as follows:

$$\frac{\partial L}{\partial \beta_j} = \sum_i n_i * x_{ij} * (y_i - \pi_i) = 0 .$$

As π_i is a function of β_j , we get estimates of β_j by solving the estimation equation above.

3.2.1.2 GLM with Mixed Effects

Similar to GLM with fixed effects, a generalized linear model with mixed effects for binary data also has three components. The GLM with mixed effects has $E[y_i | \alpha_i] = \pi_i$, $\eta_i = \alpha_i + \sum_j x_{ij} \beta_j$ and $g[\pi_i] = \eta_i$, with the random term α_i being the difference between the mixed-effect and the fixed-effect models. We assume that $\alpha_i \sim N(0, \delta^2)$, which indicates that we are only interested in the standard deviation of the random effect. The random effects we focus on are the issuer's state and industry, respectively.

Following our application of the GLM with fixed effects, for the mixed-effect model we also employ a logit link:

$$E(y_i) = E(\pi_i) = E[g^{-1}(\eta_i)] = \frac{\text{Exp}(\sum_j x_{ij} \beta_j) * E[\text{Exp}(\alpha_i)]}{1 + \text{Exp}(\sum_j x_{ij} \beta_j) * E[\text{Exp}(\alpha_i)]}.$$

Estimates for both fixed effects β_j and random effects α_i can be computed by means of Penalized Quasi-Likelihood estimation.

3.2.2 OLS Regression

To examine the relation between underwriter reputations and underwriter's characteristics, we employ the OLS regression method as follows

$$Y^* = X^* \beta + \varepsilon, \text{ and } \varepsilon \sim N(0, \delta^2),$$

where Y^* is the underwriter reputation measure (CMOP), and X^* is the vector containing underwriter's characteristics. Instead of the binary choice variable y_i , in this OLS regression we use the continuous underwriter reputation measure CMOP as the dependent variable. As the CMOP measure is adjusted by the average offer price of IPOs that an underwriter has managed during the 5-year period which includes the year of the offering, an underwriter's IPOs performance is included in the dependent variable. Hence, we limit independent variables to underwriters' characteristics.

3.2.3 Estimating Treatment Effect by Propensity Score Matching

3.2.3.1 Estimating Treatment Effect

Let U_1 and U_0 be the IPO underpricing with a high-reputation underwriter and with a low-reputation underwriter, respectively. We define IPO underpricing as:

$$U = (\text{Close price of the first trading day} - \text{Offer price}) / \text{Offer price}.$$

The treatment here is the high reputation of an underwriter that an issuer selects for its offering. The so-called control group consists of the issuers that select low-reputation underwriters. The propensity score $P(X)$ is the estimated conditional probability of issuers choosing high-reputation underwriters.

Typically, there are three treatment effects considered in the literature, namely, the Average Treatment Effect (ATE), the Average Treatment Effect on the Treated (ATT), and

the Marginal Treatment Effect (MTE). As our interest is to find that how much underpricing is related to underwriter reputation if an issuer chooses a high-reputation underwriter, in our study we focus on ATT. The ATT is defined as follows:

$$ATT = E(U_1 - U_0 | X, Y = 1),$$

and the bias is:

$$\begin{aligned} Bias(ATT) &= [E(U_1 | X, Y = 1) - E(U_0 | X, Y = 0)] - E(U_1 - U_0 | X, Y = 1) \\ &= E(U_0 | X, Y = 1) - E(U_0 | X, Y = 0). \end{aligned}$$

ATT is the mean difference between the observed and the matched outcomes for the treated. The bias of ATT is the mean difference between the matched outcome for the treated and the observed outcomes for the control.

Rosenbaum and Rubin (1983) show in Theorem 4 that if the treatment assignment is strongly ignorable and the propensity score is a balancing score, the estimated ATT is unbiased, i.e. $Bias(ATT) = 0$. The strongly ignorable treatment assignment indicates that even though the treatment effect might be correlated with the treatment assignment, once we control for the units' characteristics they are not correlated. This is to say,

$$E(U_1 | X, Y = 1) = E(U_1 | X, Y = 0) = E(U_1 | X),$$

and

$$E(U_0 | X, Y = 1) = E(U_0 | X, Y = 0) = E(U_0 | X).$$

Rosenbaum and Rubin (1983) prove in Theorem 3 that if the treatment assignment is strongly ignorable given the units' characteristics, it will be also strongly ignorable given any balancing propensity score based on the units' characteristics.

Under the assumption of one-sided selection stated in section 3.1.2, our case satisfies the above condition because each issuer has a chance to choose from high-reputation underwriters and low-reputation underwriters before the offering. Based on their characteristics, they might select to send proposals to underwriters with reputation in one level only or both. Finally, they select one lead underwriter, based on their endogenous decision. Hence, if we can observe enough information about issuers and IPOs, we can get a good estimation of the selection process. Even though the propensity score function is unknown in a nonrandomized case, people can estimate it from the observed information. In

this paper, the choice of treatment is assumed to be determined in the fashion of a standard GLM with fixed effects and a logit link, which is the same model as the one already presented in section 3.2.1. However, the linear component η_i will depend on the best-fit model developed later in section 3.4.1.

A balancing propensity score is a function of the observed information regarding units, such that the conditional distribution of the observed information of units based on the propensity score is the same for the treated group as for the control group. This is more concerned for a nonrandomized case where it is more likely for the treated and control units to have significantly different characteristics, which could make the direct comparison of the treatment effect less useful. The notation for this condition is:

$$X \perp Y \mid P(X),$$

where \perp means independence and \mid means conditional on. We need to test the balancing of the best-fit logit model reported in section 3.4.1 before estimating the treatment effect.

If the strong ignorable treatment assignment and the balancing propensity score are both satisfied in our sample, the estimation of treatment effect will generate an unbiased estimate of the average treatment effect on the treated. We already explain that our case satisfies the former condition such that we only need to test and choose a balancing propensity score to get an unbiased ATT estimate.

3.2.3.2 Propensity Score Matching Estimators

There are several methods for propensity score matching and the estimator takes the generalized form for ATT:

$$ATT = E(U_1 - U_0 \mid X, Y = 1) = \frac{1}{n_i} \sum_i [U_{1i} - \hat{U}_{0i}],$$

with

$$U_{1i} = \sum_j \hat{W}(i, j) \cdot U_{0j},$$

where $\hat{W}(i, j)$ is the weight that depends upon the distance between the propensity scores for i and j , and is different for different estimation methods. For convenience of calculation, we

employ the nearest matching method. For a more precise estimation, we employ the caliper matching method.

The nearest matching method matches the conditional probability of an issuer choosing a high-reputation underwriter in the treated group with the closest such probability in the control group. It ensures that the distance of the propensity scores between the treated and the matched is smallest; however, it does not place restrictions on how large the distance has to be. It is defined as follows:

$$\hat{W}(i, j) = \begin{cases} 1, & j = \arg \min | \hat{P}_i(X) - \hat{P}_j(X) | \\ 0, & \textit{otherwise} \end{cases},$$

where the weight is 1 for the matched propensity score and 0 otherwise.

The caliper matching method matches the conditional probability of an issuer choosing a high-reputation underwriter in the treated group with such probabilities in the control group that are at a smaller distance than a specified radius. This method ensures that we use only good matches and as many as there are available, which increases the precision of the estimation at the cost of increasing bias. It is defined as follows:

$$\hat{W}(i, j) = \begin{cases} \frac{1}{n_i}, & | \hat{P}_i(X) - \hat{P}_j(X) | < c \\ 0, & \textit{otherwise} \end{cases},$$

where n_i denotes the number of caliper matches in the control group for unit i , and c denotes the specified radius. The weights are equally distributed among the caliper matches.

3.3 Data

3.3.1 Data Description

The initial sample of IPOs is collected from the Thomson Financial SDC database³⁵ with all U.S. domestic IPOs for the years 1981 through 2000. After removing unit offerings, closed-end funds, REITS, limited partnerships, and stocks with offering prices of less than \$2, the sample has 5,077 IPOs left. The data include the issuing firm's name, offering date,

³⁵ We obtain the data from Professor Richard Carter, who obtained the data originally from the subscribed database, Thomson Financial SDC.

offer price, highest and lowest filed price, number of shares offered, total shares after offering, lead underwriter's name, underwriting fee, exchange market, SIC code, and issuer's state.

The issuing firm's financial statement variables, such as total sales, net income, cash flows and total assets in the year prior to the IPO, are obtained from the Standard and Poor's Compustat database³⁶. Because there is often insufficient time to accumulate annual data prior to the IPO and data from some firms were either purged from or never included in the Compustat database, we only have financial statement data for a limited number of firms. Wherever partial year data are reported, we annualize them to facilitate comparisons.

After removing IPOs without issuer's financial statement variables, the final sample consists of 3,201 offerings. The average size of these 3,201 offerings is \$61.33 million. The largest size is \$1,425 million and the smallest size is \$1.5 million.

Underwriter headquarter location is hand-collected from various issues of the Security Year Book. Underwriter's total capital and number of institutional sales force are also collected from the Security Year Book³⁷. The final sample for the OLS regression consists of 77 underwriters from 1980 to 1996.

3.3.2 The Underwriter Reputation Variable

The CM measure is calculated from the tombstone announcement, which is a listing of pending public security offerings. This announcement shows the offer price and the investment banks in the underwriting syndicate from the lead to the co-lead. The position/order of an investment bank in the announcement reflects its reputation. Usually, the most prestigious underwriters are listed first, followed by the second most prestigious banks, and finally the least prestigious underwriters are listed. The CM measure is determined by underwriters' relative positions in these tombstone announcements. The CM measure ranges from zero to nine, with a higher value indicating a higher reputation. Underwriters with CM measure nine were never dominated in the tombstone announcements, whereas underwriters with CM measure zero never ranked above any other underwriters.

³⁶ We get the data from Professor Richard Carter and he gets it originally from the subscribed database, S&P's Compustat.

³⁷ We get underwriter's total capital and the number of institutional sales force from Professor Carter, who gathered the information from the Security Year Book.

Loughran and Ritter (2004) point out that a potential flaw of the CM measure is that penny-stock³⁸ underwriters might never be assigned low CM values, as they are never allowed to participate in a syndicate of prestigious underwriters. This problem is systematically and objectively accounted for in Carter and Dark (2007) by the CMOP measure, which is calculated as:

$$CMOP = CM * (\text{Average offer price of underwriters' IPOs}) / 100.$$

Because the CMOP measure decreases the ranking of the penny stock underwriters through their low average offer prices, we use the CMOP measure of underwriter reputation in this paper.

The CMOP measures in our sample range from a minimum of 0.02 to a maximum of 1.70 (see summary in table 3.1). So we use the median CMOP measure 1.11 as the threshold to classify underwriter reputation as high or low. If the CMOP measure of an underwriter is greater than 1.11, it is classified as a high reputation. If the CMOP measure of an underwriter is less than or equal to 1.11, it is classified as a low reputation. We denote the variable "UW" to represent reputation, as follows:

$$UW = \begin{cases} 1, & \text{if } CMOP > 1.11 \\ 0, & \text{if } CMOP \leq 1.11 \end{cases}.$$

3.3.3 Other Variables

Other variables included in the model (see summary in table 3.1) are issuer's age (AGE), issuer's assets (AST), expected offer size (EOS), expected offer price (EOP), issuer's leverage ratio (LE), issuer's Standard Industry Code (SIC), state where the issuer is headquartered (ST), underwriter's total capital (CAP), underwriter's headquarter location (HQ), size of underwriter's institutional sales force (INST) and IPO's underpricing (U). These variables are measured as follows.

³⁸ Penny-stock underwriters are underwriters associated with IPOs which have low offer prices, usually less than five dollars, and are not traded on NASDAQ or listed on a stock exchange. Under federal securities laws, a penny stock is defined generally as: an equity security that is not listed on NASDAQ or a national securities exchange and either (a) has a price per share that is less than \$5 or (b) whose issuer has net tangible assets that are less than \$2 million, if the issuer has been in continuous operation for at least three years; or a market capitalization less than \$5 million, if the issuer has been in continuous operation for less than three years; or whose average revenues are less than \$6 million for the last three years. See Section 3(a)(51) of the Securities Exchange Act of 1934, 15 U.S.C. 78c(a)(51), and Rule 3a51-1, 17 C.F.R. 240.3a51-1.

AGE is the number of years the issuer has been in the industry a year prior to the IPO. AGE is a proxy for issuer's reputation in the industry. Alternatively, AGE can be interpreted as an indicator of difficulties in evaluating the issuer.

AST is total assets of an issuer a year prior to IPO, in millions of dollars.

CAP is the underwriter's total capital at the year of the offering, in billions of dollars. It is defined as the sum of equity and liabilities.

EOP is a proxy for expected offer price of an IPO, in dollars. It is the mid-point of the highest and the lowest filed price written in the contract.

EOS is a proxy for expected offer size of an IPO, in millions of dollars. It is EOP times the expected offering shares written in the contract.

HQ is a dummy variable of underwriter headquarter location. We define HQ=1 if underwriters have headquarters in New York, otherwise HQ=0.

INST is the number of people in the underwriter's institutional sales force that the investment bank has during each five-year period that includes the offering year. The institutional sales force is not owned by the investment bank, but contracted by it to engage in the sales for the investment bank.

LE is the issuer's leverage ratio defined as total liabilities over total assets. It represents the risk of the issuing firm before IPO.

SIC is the issuing firm's Standard Industry Code. There are 5 categories. 'A' represents Manufacturing, 'B' represents Utility, 'C' represents Wholesale and Retail Trade, 'D' represents Finance, Insurance, and Real Estate, and 'E' represents Services.

ST is the state in which the issuing firm has its headquarter. There are 5 categories. 'A' represents New York, 'B' represents California, 'C' represents Illinois, 'D' represents New Jersey, and 'E' represents other states.

VC is a dummy variable indicating whether there is venture capital investment in an issuing firm before an IPO. VC=1 if there is venture capital, otherwise VC=0.

U is the IPO's short-run underpricing, which is calculated as $U = (\text{Close price of the first trading day} - \text{Offer price}) / \text{Offer price}$.

For estimation purposes, we use the natural logarithm of AGE, AST, EOP, EOS, and LE in our model as LN(AGE), LN(AST), LN(EOP), LN(EOS), and LN(LE). The major

reason is to adjust variable skewness by normalizing. Also, most of the literature utilizes the natural logarithm transformation.

Table 3.1. Data Summary

<i>Continuous Variables</i>	Mean	Median	STD	Min	Max	Obs.
Issuer's age (AGE)	12.91	7	18.44	1	161	3201
Issuer's total asset (AST)	220.57	62.58	636.11	1.01	8591.80	3201
Underwriter reputation measure (CMOP)	1.07	1.11	0.36	0.02	1.70	3201
Expected offer size (EOS)	59.24	33.00	98.66	1.50	1500.00	3201
Expected offer price (EOP)	12.56	12.00	3.84	2.00	33.00	3201
Issuer's leverage ratio (LE)	1.99	0.50	17.31	0.01	919.14	3201
IPO's underpricing (U)	24.21%	8.91%	50.56%	-34.38%	697.50%	3201
Underwriter's institutional sales force (INST)	398.67	250	411.23	54	2000	77
Underwriter's total capital (CAP)	5.53	1.24	12.31	0.03	56.61	77

<i>Dummy Variables</i>	0	1	Obs.
Underwriter's headquarter location (HQ)	41	36	77
Issuer's selection of underwriter reputation (y_i)	1552	1649	3201
Venture Capital backing (VC)	1833	1368	3201

<i>Categorical Variables</i>	Manufacturing	Utility	Trade	Finance	Service	Others	Obs.
Issuer's industry (SIC)	1210	240	398	199	1044	110	3201
	New York	California	Illinois	New Jersey	Others	Obs.	
Issuer's state (ST)	220	864	104	104	1909	3201	

3.4 Empirical Results

3.4.1 Issuer's Selection of Underwriter

3.4.1.1 GLM with Fixed Effects

The dependent variable is y_i , a binary variable denoting whether an issuing firm chooses a high-reputation underwriter ($y_i = 1$) or not ($y_i = 0$). The explanatory variables are LN(AGE), LN(AST), LN(EOS), LN(LE), and LN(EOP)³⁹. As all individual Variance Inflation Factors (VIFs) are less than 4 and the average VIF is 2.15, there is no indication of collinearity problems in the linear regression.⁴⁰ We double check the correlation between EOS and EOP, because EOS is generated by EOP times the expected offering shares, which may involve a collinearity problem. Since the correlation between EOS and EOP is only 51%⁴¹, combined with the result from VIFs, we are confident to include both EOS and EOP as explanatory variables. The intuition for including both of them is that EOS represents the expected total value of the offering, which is a mass problem, whereas EOP represents the expected offer price, which is a quality problem. It is not necessarily that an offering with a larger size has a larger offer price. Hence, EOS and EOP need to be considered at the same time.

We use the forward selection method to fit the model, starting from a null specification with the scope of all 2-way interactions. The best-fit model is

$$\log \frac{\pi_i}{1 - \pi_i} = \beta_0 + \beta_1 * LN(AGE) + \beta_2 * LN(AST) + \beta_3 * LN(EOS) + \beta_4 * [LN(EOS)]^2 + \beta_5 * LN(LEV) + \beta_6 * LN(EOP) + \beta_7 * VC + \varepsilon_i$$

The estimation results are reported in table 3.2.

³⁹ As we fit the sample into a mixed model and introduce random effects by issuer's state or Standard Industry Code, we cannot include variables ST or SIC into the fixed effects.

⁴⁰ When the individual VIF is greater than 10 or the average VIF exceeds 6, the regression model needs inspection on either individual variables or the whole set of variables for collinearity problems.

⁴¹ When performing a simple test for collinearity, typically the correlation between the two variables is used directly. When the correlation is larger than 0.9, we would further inspect the two variables for collinearity problems.

Table 3.2. Results from GLM with Fixed Effects

	Estimates	Std. Error
Intercept	-14.00	1.00 ^{***}
LN(AGE)	-0.14	0.05 ^{***}
LN(AST)	0.37	0.07 ^{***}
LN(EOS)	4.30	0.46 ^{***}
[LN(EOS)] ²	-0.39	0.06 ^{***}
LN(LEV)	-0.12	0.04 ^{***}
LN(EOP)	1.00	0.24 ^{***}
VC	0.18	0.09 ^{**}
Null deviance	4434.6 on 3200 df	
Residual deviance	3002.5 on 3193 df	
AIC	3018.5	

1. Signif. codes: 0.1% '***', 1% '**', 5% '*'.

All of the coefficient estimates in the best-fit model are significant at the 1% level or higher. The best fit model indicates that issuing firms with fewer years in the industry, more assets, a larger expected offer size, a smaller leverage ratio, a higher expected offer price, or having venture capital backing, tend to choose high-reputation underwriters.

As the issuer's age is a proxy for issuer's own reputation in its industry, it is intuitive for an issuer to take its own reputation as a complement of underwriter reputation when selling the shares. Another argument is that if an issuer stays longer in the industry, there will be more public information in the market to facilitate evaluating the offering by underwriters and investors. However, it will be harder to look into all of the complex corporate conditions developed over the years (such as structure and culture). From our model, the estimated coefficient (-0.14) shows that the overall marginal effect of AGE on the choice of underwriter reputation is substitutionary. This indicates that a firm with more years in the industry has better reputation and does not need the high reputation of an underwriter for marketing purposes. Also, our result supports the hypothesis that historical information of the issuing firms reduces the need for the evaluation knowledge of high-reputation underwriters.

When an issuer has more assets, a larger expected offer size⁴², or a higher expected offer price, it faces the mass problem of selling a large amount equity to the market, and a quality problem of selling each share at a high price. To avoid the mass problem, issuers need underwriters with a large sales force. To solve the quality problem, issuers need underwriters with better knowledge for evaluation purpose and more reliable ways of signaling. The positive coefficients (0.37 for LN(AST), 4.30 for LN(EOS), and 1.00 for LN(EOP)) indicate that issuers expect high-reputation underwriters to help them solve mass and quality problems. This raises the question of how underwriter reputation matches with underwriter's own characteristics, which is investigated in section 3.4.2.

If an issuer has a larger leverage ratio a year prior to the IPO, it will tend to choose a low reputation underwriter. Because leverage ratio is a proxy for the risk of the offering, a risky issuer may expect its offering to disqualify for the quality requirement from high-reputation underwriters of a relatively steady aftermarket performance. Another argument focuses on the underwriter's ability to identify the potential risk of the offering. Titmand and Truemen (1986) show that prestigious underwriters are good at identifying the risk level of the offering and they charge a higher fee for riskier IPOs. So it is beneficial only for low risk issuers (e.g., with low leverage ratio) to choose prestigious underwriters. Carter and Manaster (1990) confirm the above idea by matching underwriters and issuers, and conclude that issuers tend to fit underwriter reputation with the risk level of their offerings. Our result is consistent with their argument, by showing a negative relation between the risk proxy for offerings (LN(LEV)) and the associated underwriter reputation.

The coefficient on VC is 0.18, indicating that an issuer tends to choose a high-reputation underwriter if there is venture capital investment in the issuing firm before the IPO. Usually venture capitalists have relationships with high-reputation underwriters through previous business. Then, when a venture capitalist has a seat in the executive team of an issuing firm, it would recommend continuing the business with the high-reputation underwriter that it knows already.

⁴²As the size of the coefficient on LN(EOS) is much larger than it on [LN(EOS)]², we only consider LN(EOS) at this stage and will consider the square term later in this section.

Besides linear terms, the best-fit model includes the square term $[\text{LN}(\text{EOS})]^2$ as an explanatory variable. The coefficient on $\text{LN}(\text{EOS})$ is positive and the coefficient on $[\text{LN}(\text{EOS})]^2$ is negative, which means that the positive marginal effect of IPO's expected offer size is decreasing. By using the following formula

$$\frac{\partial E(y_i | x_i)}{\partial \text{EOS}} = \frac{\text{Exp}(X\beta)}{(1 + \text{Exp}(X\beta))^2} \cdot \frac{\beta_3 + 2\beta_4 \text{LN}(\text{EOS})}{\text{EOS}},$$

we calculate the individual marginal effect of EOS for each observation. When expected offer size is larger than 247.85 million dollars, the marginal effect of EOS is negative and otherwise positive. Table 3.3 shows that 96.44% for our sample expected offer size has a positive marginal effect on the probability of selecting a high-quality underwriter. This is because 96.44% of the expected offering sizes in our sample are smaller than 247.85 million dollars.

Table 3.3. Frequency and Cumulative Percentage of the Marginal Effect of EOS in GLM with Fixed Effects

Interval	Frequency	Cumulative Percentage
-0.0002	0	0.00%
-0.0001	94	2.94%
0	20	3.56%
0.001	426	16.87%
0.005	665	37.64%
0.010	557	55.05%
0.015	608	74.04%
0.020	607	93.00%
0.025	201	99.28%
0.030	20	99.91%
0.035	3	100.00%

Figure 3.1 shows an up-side-down U-shape for the marginal effect of EOS, as expected. The largest marginal effect is 0.0348, attained when expected offer size is 12.4

million dollars⁴³. This means that when IPO's expected offer size is 12.4 million dollars and other variables are the same, the conditional probability of the issuer choosing a high-reputation underwriter will on average increase by 3.48%, if expected offer size increases by 1 million dollars.

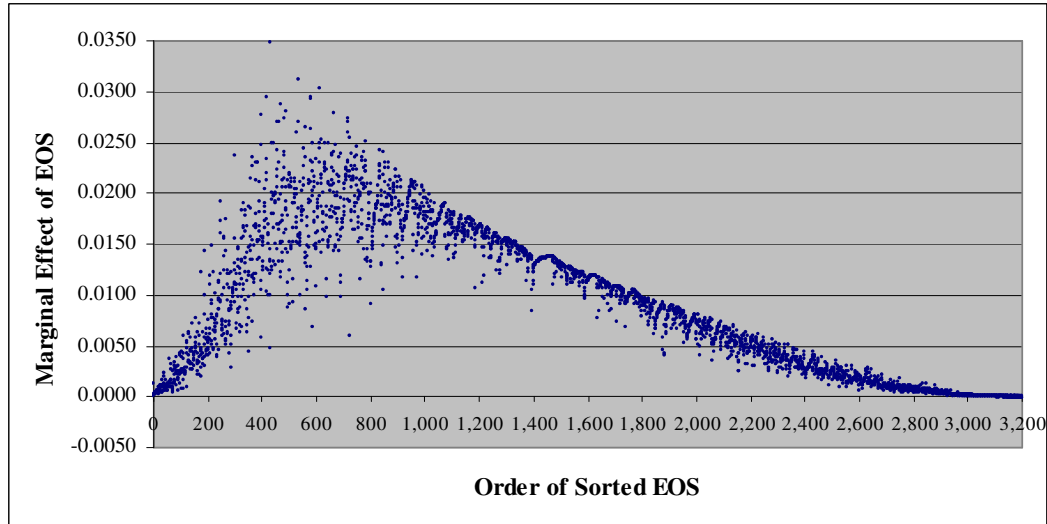


Figure 3.1. Histogram of Marginal Effect of Expected Offer Size for the Entire Sample in GLM with Fixed Effects

We also calculate the marginal effects of other explanatory variables and summarize them in table 3.4, using the following formulas:

$$\frac{\partial E(y_i | x_i)}{\partial x_i} = \frac{\text{Exp}(X\beta)}{(1 + \text{Exp}(X\beta))^2} \cdot \frac{\beta_i}{x_i}, \text{ for variables with logarithm;}$$

$$\frac{\partial E(y_i | x_i)}{\partial x_i} = \frac{\text{Exp}(X\beta)}{(1 + \text{Exp}(X\beta))^2} \cdot \beta_i, \text{ for variables without logarithm.}$$

The sign of the estimated coefficient for each variable is consistent with the sign of its marginal effect, except for IPO's expected offer size which has been discussed already. The marginal effects show that if an issuer has one more million dollars of assets, expects an offer price one dollar higher, expects an offer size one million dollars larger, or has venture capital backing, the probability of it choosing a high-reputation underwriter will on average increase

⁴³ Please note that the formula for calculating marginal effects for a logit model is dependent on all the variables, which is different from the case of an OLS model.

by 0.12%, 1.30%, 0.91%, and 2.79%, respectively. In contrast, if an issuer increases its leverage ratio by 1, or stays in the industry one year longer, such probability will on average decrease by 7.73% and 0.47%, respectively.

Table 3.4. Marginal Effects of Variables from GLM with Fixed Effects

Variable	Estimated Coefficient	Marginal Effect
Issuer's age	-0.14	-0.0047
Issuer's total asset	0.37	0.0012
IPO's expected offer price	1.00	0.0130
IPO's expected offer size	4.30 on LN(EOS) -0.39 on [LN(EOS)] ²	0.0091
Issuer's leverage ratio	-0.12	-0.0773
Venture capital backing	0.18	0.0279

The mosaic plots⁴⁴ presented in figures 3.2 and 3.3 show that GLM with fixed effects has a good fit for estimating issuers' preference over underwriter reputation. Comparing the mosaic plots for the original sample and for GLM with fixed effects, the width and sub-division of each rectangle are very similar. However, there are some problems about density estimates for all of the states and industries, because the sub-division of rectangles of all categories in figures 3.2 and 3.3 are different. Comparisons of figures 3.2A and 3.2B (3.3A and 3.3B) shows that the best-fit model always predicts a higher probability of choosing a high-reputation underwriter for issuers in all states (industries). In addition, the odds ratio estimate for New York and Illinois State is imprecise, because the relative position of the sub-division of rectangles of categories A and B in figures 3.2 and 3.3 are different. These problems leave room for GLM with mixed effects to improve the fit. We also show the residual boxplots⁴⁵ in figure 3.4 and 3.5⁴⁶. In figure 3.4, the notch of E does not overlap with

⁴⁴ Mosaic plots are used to visualize a contingency table, say of X and Y. Mosaic plots are hierarchical displays, such that the width of the vertical bars are according to the marginal distribution of X and each of these rectangles is sub-divided horizontally according to the conditional distribution of Y given X.

⁴⁵ The Box-and-Whisker plot of residuals helps us to explore residuals and draw informal conclusions. The box shows the first quartile, the median and the third quartile by horizontal lines. The width of the box indicates the marginal distribution of specified variables. The notch of the box gives roughly a 95% confidence interval for the median. Any residual which lies more than 1.5*Interquartile Range (IQR, is the difference between the third quartile and the first quartile) lower than the first quartile or 1.5*IQR higher than the third quartile is considered an outlier by an open and closed dot, and is separated by a horizontal line.

notches of A and B, which indicates the median of category E is statistically different from the median of A or B. A, B, E have many observations (i.e. the width of the box is relatively large), which shows that the majority of the residuals have different medians in each category. Figure 3.5 is similar in that the notches of A or C do not overlap with the notches of B or E, and A, B, C, E have many observations. All of the above indicates that there are some state- or industry-related properties left in the residuals.

3.4.1.2 GLM with Mixed Effects

3.4.1.2.1 Random Effect of Industry

Estimation results for GLM with mixed effects are reported in table 3.5. The fixed effects here are very similar to the results of GLM with fixed effects reported earlier in table 3.2, as expected. The standard deviation of the random effect introduced by the issuer's industry is about 23.8% (i.e., $0.315/(0.315+1.007)$) of the standard deviation of the residual that is left from the fixed effects in section 3.4.1.1. This indicates that issuer's industry is highly effective in explaining the unexplained variation of issuer's selection from the fixed effect model. Comparing the values for each industry, we find that issuers in Service (Utility) industry are the most (more) likely to choose high-reputation underwriters. Issuers in industries other than Manufacturing, Utility, Trade, Finance, and Service are more likely to choose low-reputation underwriters. All of the above shows that issuers have industry-related preferences over underwriter reputation.

3.4.1.2.2 Random Effect of State

When we introduce the random effect by issuers' state, we get the results reported in table 3.6. Compared to table 3.2, the coefficient estimates for the fixed effects are quite similar as expected.

⁴⁶ We include both a complete and a smaller (focus on region (-1, 1)) residual plot.

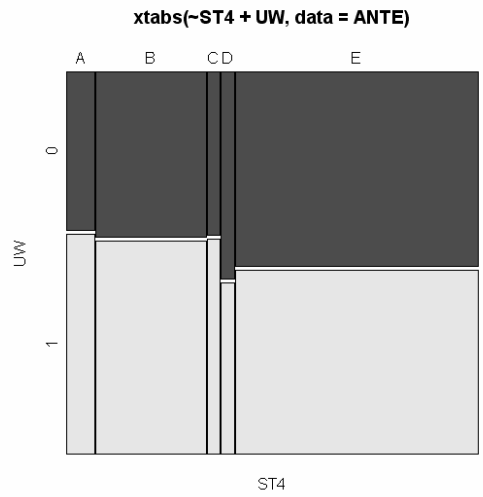


Figure 3.2A. Mosaic Plot over State for Original Sample

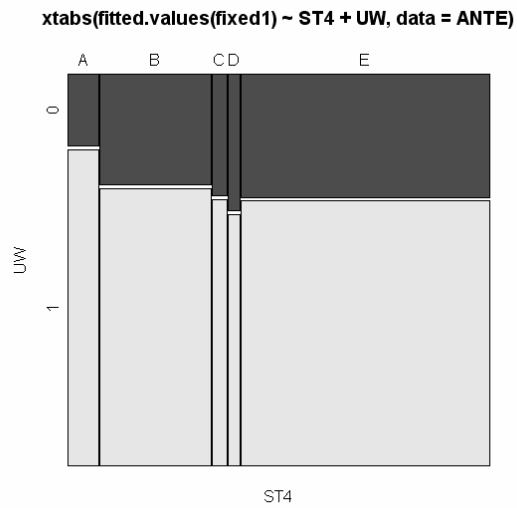


Figure 3.2B. Mosaic Plot over State for GLM with Fixed Effects

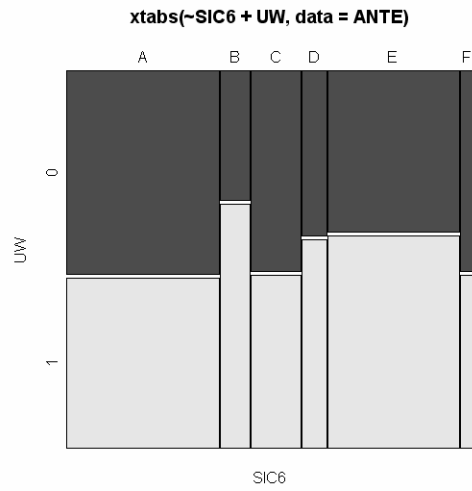


Figure 3.3A. Mosaic Plot over Industry for Original Sample

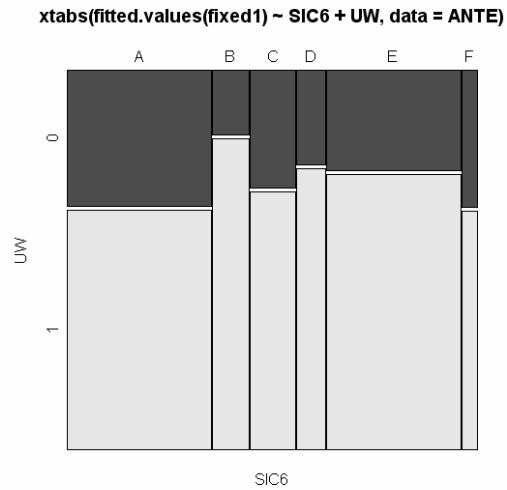


Figure 3.3B. Mosaic Plot over Industry for GLM with Fixed Effects

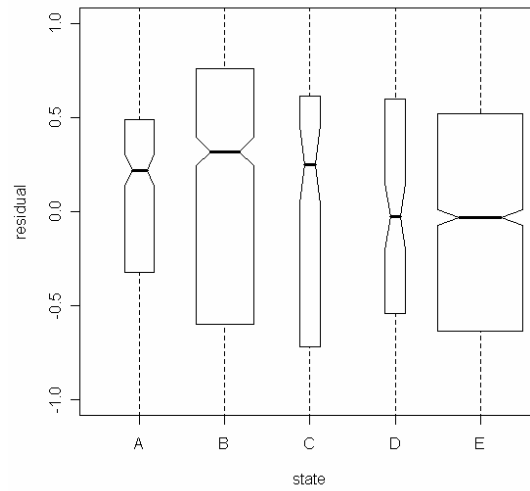
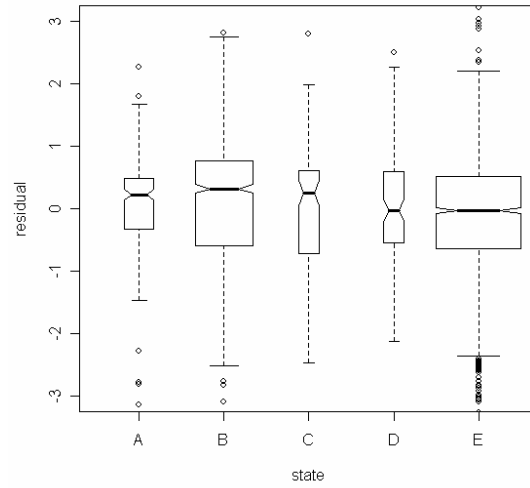


Figure 3.4. Residual Plots over State for GLM with Fixed Effects

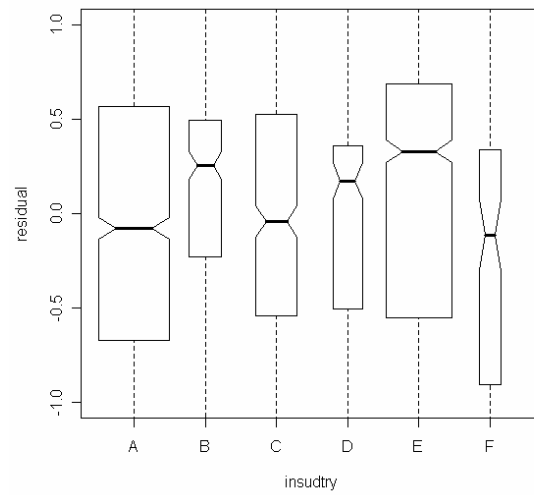
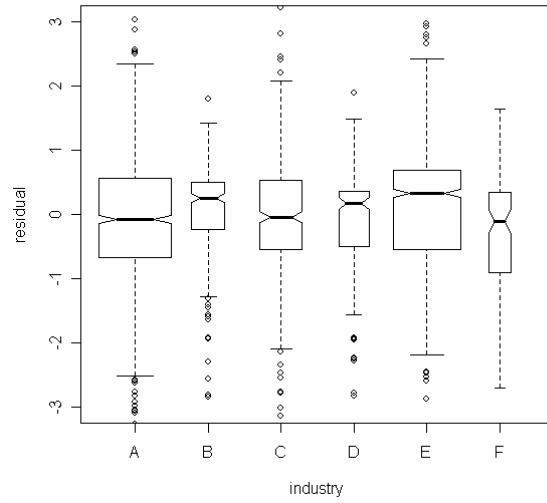


Figure 3.5. Residual Plots over Industry for GLM with Fixed Effects

Table 3.5. Results for GLM with Mixed Effects when Random Effect is by Industry

Fixed Effect:		
	Estimates	Std. Error
Intercept	-14.21	1.03***
LN(AGE)	-0.13	0.05***
LN(AST)	0.41	0.07***
LN(EOS)	4.14	0.48***
[LN(EOS)] ²	-0.37	0.06***
LN(LEV)	-0.11	0.04***
LN(MP)	1.11	0.24***
VC	0.18	0.09**

1. Signif. codes: 0.1% '***', 1% '**', 5% '*'.

Random Effect:		
	Intercept	Residual
Std Dev	0.315	1.007
Value for SIC	Intercept	
Manufacturing	-0.049	
Utility	0.217	
Trade	0.096	
Finance	-0.161	
Service	0.389	
Others	-0.492	

The standard deviation of the random term (i.e., the intercept) is 17.5% (i.e. $0.213/(0.213+1.007)$) of the total residual, which shows that issuer's state can explain 17.5% of the unexplained variation left by the fixed effects. This indicates that the random effect associated with state is significant and the mixed effect model is a good fit. Issuers in the state of California are most likely to choose high-reputation underwriters. In contrast, issuers in states other than New York, California, Illinois and New Jersey, are least likely to choose high-reputation underwriters. All of the above shows that issuers have state-related preferences over underwriter reputation.

Table 3.6. Results for GLM with Mixed Effects when Random Effect is by State

Fixed Effect:		
	Estimates	Std. Error
Intercept	-14.36	1.03***
LN(AGE)	-0.13	0.05***
LN(AST)	0.36	0.07***
LN(EOS)	4.28	0.47***
[LN(EOS)] ²	-0.39	0.06***
LN(LEV)	-0.09	0.04***
LN(MP)	1.19	0.24***
VC	0.17	0.09**

1. Signif. codes: 0.1% '***', 1% '**', 5% '*'.

Random Effect:		
	Intercept	Residual
Std Dev	0.213	1.007
Value for ST		
New York	0.088	
California	0.271	
Illinois	-0.074	
New Jersey	-0.051	
Others	-0.234	

3.4.1.3 Comparison of Fixed- and Mixed-Effects Model

In order to compare the fixed- and mixed-effects models, we first use a forward selection method to fit our sample into a fixed-effects model. Then, we add a random variable into the model, which results in very similar estimates of the fixed-effect component in the mixed-effects model. So we have a similar standard deviation of residuals from the fixed-effects model and from the fixed-effect component in the mixed-effects model. Based on these results, we show how much the random effect can help explain the variation of y_i in addition to the fixed effects. Since the mixed-effects model by industry (state) can explain 17.5% (23.8%) of the unexplained variation left by the fixed-effects model, it strongly suggests that the mixed-effects model is a better fit for our sample.

3.4.2 Market Understanding of Underwriter Reputation

To find the relationship between underwriter reputation and its own characteristics, we use an OLS regression model with CAP, INST and HQ as independent variables as follows:

$$CMOP_i = \alpha_1 + \alpha_2 CAP_i + \alpha_3 INST_i + \alpha_4 HQ_i + \varepsilon_i.$$

The estimation results in table 3.7 show that all the coefficient estimates are statistically significant at 5% level or higher, except for INST. The positive coefficient 0.00001 on CAP indicates that the marginal effect of underwriter's total capital on underwriter reputation is positive. If an underwriter has \$100 billion more capital while keeping INST and HQ the same, its reputation measure will increase 0.001. Underwriter's headquarter location has a significantly positive correlation with its reputation measure as well. If two underwriters have the same institutional sales force but one has headquarters in New York and the other one has headquarters outside New York, the reputation measure for the former underwriter will be 0.24 greater than for the latter. The regression results show that HQ has a very large impact on CMOP, while CAP has a little effect.

A possible reason why an underwriter's headquarter location has a larger impact on reputation than its total capital is that having headquarters in New York is a strong positive signal of an underwriter's ability, and there may be more industry relation/connection in New York. It could also be that the model specification puts the underwriter's headquarter location into the spotlight. However, the R-square is 0.386, which is empirically large and suggests that lacking of information is not that important for this sample.

Table 3.7. Results for OLS regression of Underwriter Reputation

	Estimates	Std. Error
Intercept	0.909	0.037***
CAP	0.00001	0.000005*
INST	0.00006	0.00009
HQ	0.237	0.054***
R-square	0.386	
Prob>F	0.000	

1. Signif. codes: 0.1% '***', 1% '**', 5% '*'.

3.4.3 Underwriter Reputation and IPO Underpricing

3.4.3.1 Balancing Test for the Entire Sample

Since the random effect of issuer's industry in the mixed-effects model can explain more of the remaining variation (23.8%) than the model with random effect of issuer's state (17.5%), we add issuer's industry as dummy variables⁴⁷ into the logit model for the purpose of estimating propensity scores. The remaining part of the logit model is the same as the GLM with fixed effects reported in section 3.4.1.1. Taking it as an original model⁴⁸, the test of balancing property shows that variable LN(EOP) is not balanced in two blocks (see appendix C.1 for a sample test result). After dropping LN(EOP), the adjusted model satisfying the balancing property is as follows:

$$\begin{aligned} \log \frac{\pi_i}{1 - \pi_i} = & \beta_0 + \beta_1 * LN(AGE) + \beta_2 * LN(AST) + \beta_3 * LN(EOS) \\ & + \beta_4 * [LN(EOS)]^2 + \beta_5 * LN(LEV) + \beta_6 * VC + \beta_7 * I_A + \beta_8 * I_B , \\ & + \beta_9 * I_C + \beta_{10} * I_D + \beta_{11} * I_E + \varepsilon_i \end{aligned}$$

where I_A denotes a dummy variable of issuer's industry for category A – Manufacturing. Dummy variables I_B , I_C , I_D , and I_E are individually defined for other industries.

The distribution of the estimated propensity scores is reported in figure 3.6 and table 3.8. Because we define underwriter reputation by the sample median, the treated group (1649 units) and the control group (1552 units) are about the same size. Figure 3.6 is consistent with our expectation that there are a large number of small propensity scores in the control group and a large number of big values in the treated group. Table 3.8 shows that there are 352 treated units in the range [0.9, 1) and only 20 control units, which introduces the potential problem of overusing these 20 controls. As a result, we expect caliper matching to yield more precise estimates than nearest matching. That is true because caliper matching can restrict the distance between the matched and the treated by a radius, whereas nearest matching finds the closest match no matter how large the distance is. However, caliper

⁴⁷ Because there are six categories in issuers' industry codes in our sample, we add five dummy variables corresponding to categories A, B, C, D, and E.

⁴⁸ The balancing tests for other subsamples start with the same original model specified here.

matching has to sacrifice the number of treated that can be matched. The situation is similar for the range $[0.8, 0.9)$, but the matching problem is not obvious for other ranges. On the other hand, in the range $(0, 0.1)$, there are many more control units than the treated and the difference between the two matching methods should be negligible. The situation is similar to other small value ranges under 0.5.

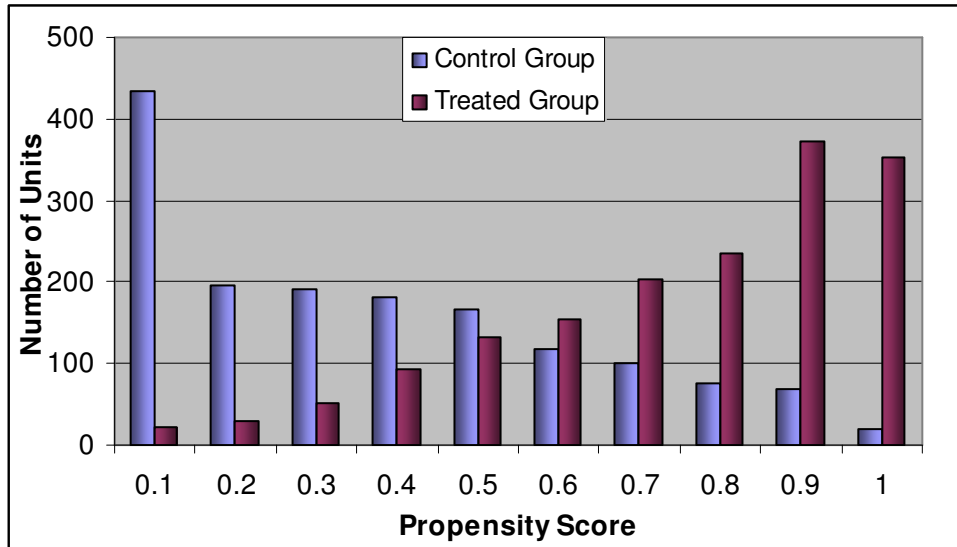


Figure 3.6. Histogram of Propensity Scores for the Control and the Treated Group

Table 3.8. Distribution of the Estimated Propensity Scores

Inferior of Block of Propensity Score	Control Group	Treated Group	Total
0	325	10	335
0.05	110	12	122
0.1	196	30	226
0.2	190	51	241
0.3	181	94	275
0.4	167	133	300
0.5	117	155	272
0.6	101	204	305
0.7	77	236	313
0.8	68	372	440
0.9	20	352	372
Total	1552	1649	3201

3.4.3.2 The Entire Sample

After adjusting the model to satisfy the balancing property, we employ the nearest matching and caliper matching methods as follows, and we set the OLS regression result as a comparison.

3.4.3.2.1 Nearest Matching Method

To increase the precision of the estimation, we apply nearest matching without replacement. In figure 3.7, the matched propensity score is very close to the treated by eye examination. Table 3.9 provides that the average difference of the propensity scores between the treated and the matched is only -0.0041% and the median is 0%. Even though the minimum value is -1.371% and the maximum value is 0.521%, the standard deviation is only 0.141%. Figure 3.8 shows the individual propensity score difference between the treated and the matched, and most of the data are in the range of (-0.02%, 0.02%). These results suggest that nearest matching is sufficiently good for our entire sample.

Since the propensity score estimates are balancing and the matched propensity scores are sufficiently close, the treatment effect estimated is unbiased (see results summary in table 3.10). The average treatment effect on the treated is 0.180, which indicates that for an issuer who chose a high-reputation underwriter, its IPO's underpricing on average tends to be 18.0% larger than if it would have chosen a low-reputation underwriter. There are 1649 treated units that have been matched by 527 control units. The ATT is significantly different from zero by *t*-test (with *t*-statistic 7.138) as the standard error is only 0.025.

3.4.3.2.2 Caliper Matching Method

We set two radiuses, $r=0.001$ and $r=0.0005$, and we also use matching without replacement. In figures 3.9 and 3.11, the matched propensity scores are very close to the treated units. Table 3.9 reports that when $r=0.001$ ($r=0.0005$), the average difference of the propensity scores between the treated and the matched is only -0.0011% (0.0003%) and the median is -0.001% (0.0010%). The maximum and minimum values are bounded by the radius, and when $r=0.001$ ($r=0.0005$) the standard deviation is only 0.044%, (0.0256%).

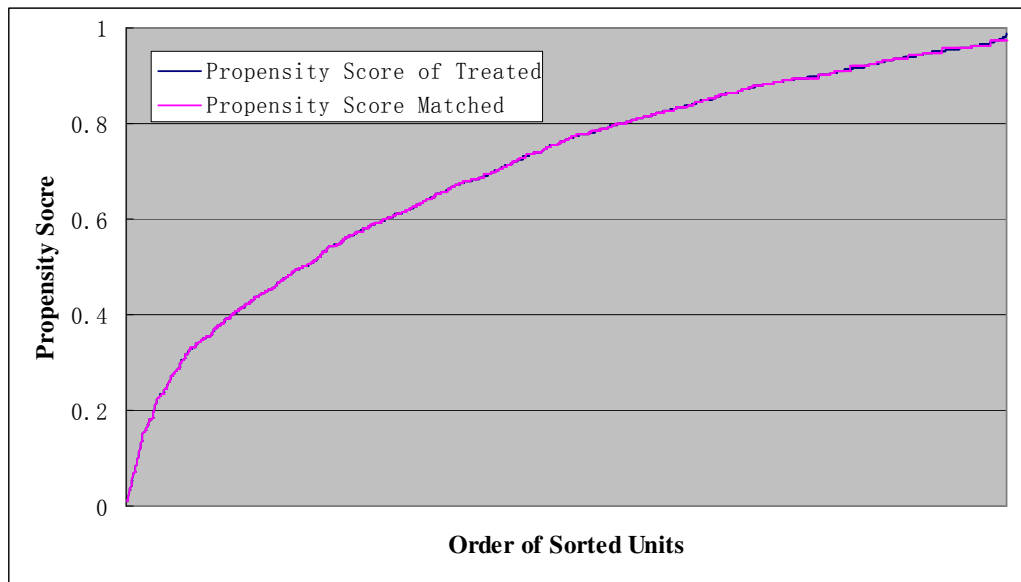


Figure 3.7. Comparison of Propensity Scores between the Treated and the Matched for the Entire Sample by Nearest Matching Method

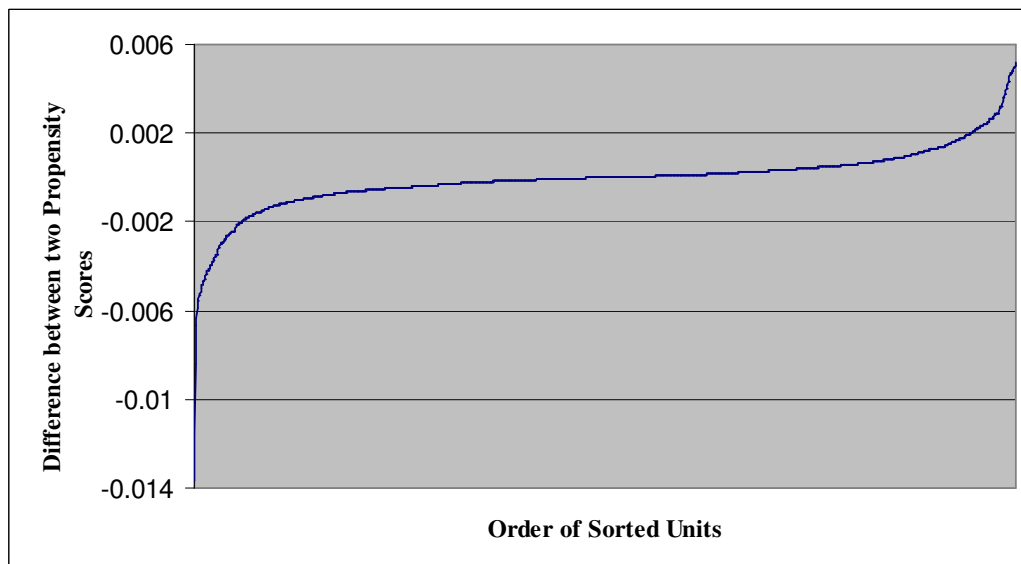


Figure 3.8. Difference of Propensity Scores between the Treated and the Matched for the Entire Sample by Nearest Matching Method

Figures 3.10 and 3.12 show the individual difference of the propensity score between the treated and the matched. Most of the data are in the range of (-0.05%, 0.05%) and (-

0.03%, 0.03%), respectively. These all indicate that the quality of caliper matching for the entire sample is very high.

The estimated treatment effect is unbiased (see table 3.10), because the propensity score estimates are balancing and are sufficiently similar between the treated and the matched. For the larger (smaller) radius, i.e., $r=0.001$ ($r=0.0005$), the ATT is 0.161 (0.130), which indicates that for an issuer who chose a high-reputation underwriter, its IPO's underpricing tends to be 16.1% (13.0%) larger on average than if it would have chosen a low-reputation underwriter. There are 1221 (900) treated units that have been matched by 1008 (766) control units for the larger (smaller) radius. The standard error of the larger (smaller) radius is 0.021 (0.022), which yields a t -statistic of 7.829 (5.970). Hence, the ATT is significantly different from zero by t -test.

Table 3.9. Summary Statistics for the Difference of the Propensity Scores between the Treated and the Matched for the Entire sample

	Mean	Std. Dev.	Median	Min.	Max.
Nearest Matching	-0.0041%	0.1409%	0%	-1.3705%	0.5210%
Caliper Matching ($r=0.001$)	-0.0011%	0.0435%	-0.0010%	-0.0990%	0.0990%
Caliper Matching ($r=0.0005$)	0.0003%	0.0256%	0.0010%	-0.0500%	0.0500%

Table 3.10. Results of Estimated Treatment Effect for the Entire sample

	No. of Treated ¹	No. of Controls ²	ATT	Std. Err.	t -statistic
Nearest Matching	1649	527	0.180	0.025	7.138
Caliper Matching ($r=0.001$)	1221	1008	0.161	0.021	7.829
Caliper Matching ($r=0.0005$)	900	776	0.130	0.022	5.970

¹No. of Treated is the number of treated units that has been matched.

²No. of Controls is the number of control units that has been used as a match to a treated unit.



Figure 3.9. Comparison of Propensity Scores between the Treated and the Matched for the Entire Sample by Caliper Matching Method ($r=0.001$)

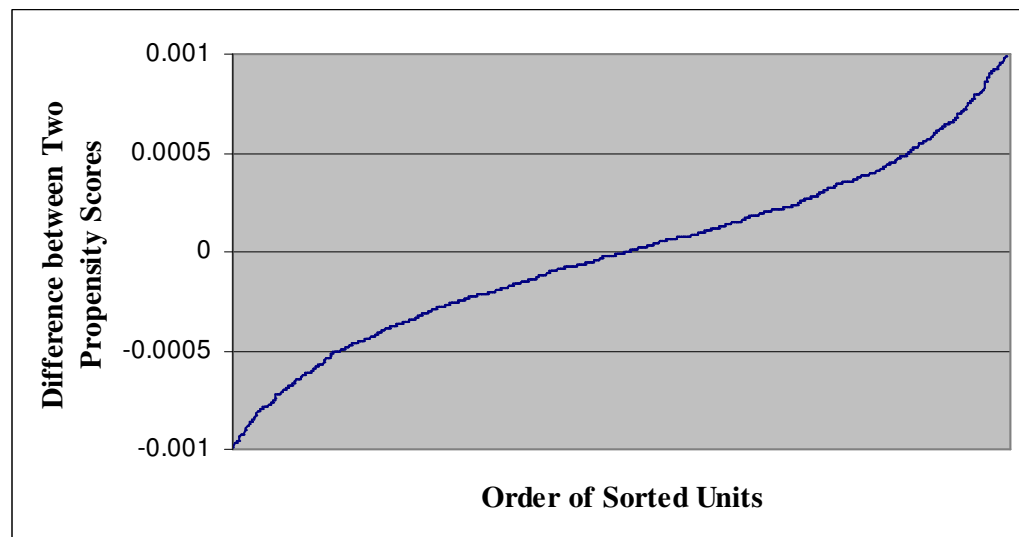


Figure 3.10. Difference of Propensity Scores between the Treated and the Matched for the Entire Sample by Caliper Matching Method ($r=0.001$)

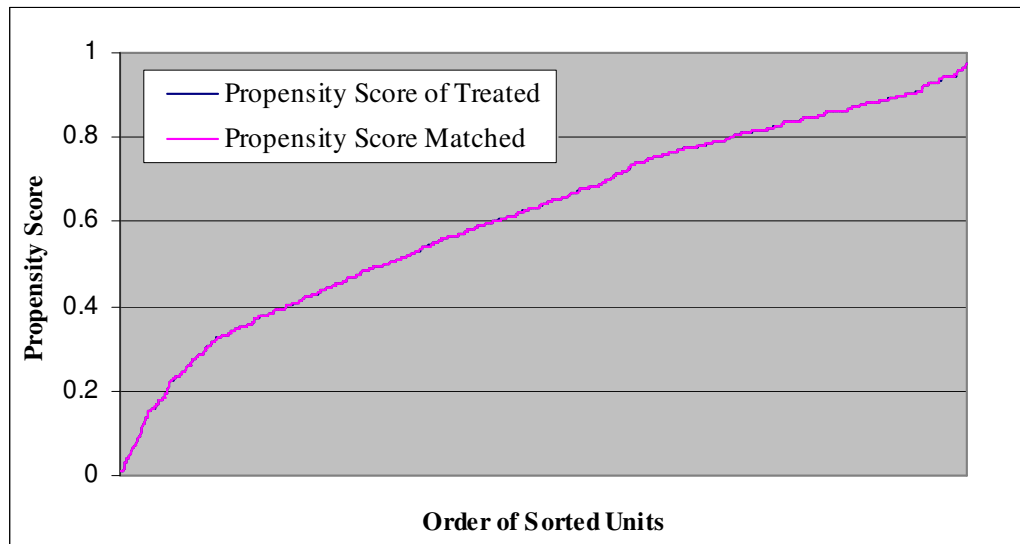


Figure 3.11. Comparison of Propensity Scores between the Treated and the Matched for the Entire Sample by Caliper Matching Method ($r=0.0005$)

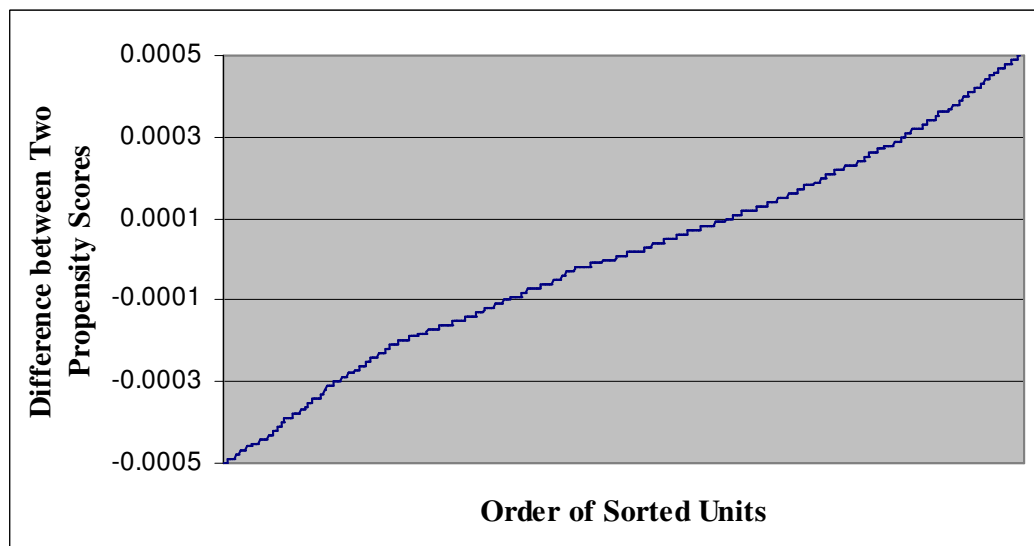


Figure 3.12. Difference of Propensity Scores between the Treated and the Matched for the Entire Sample by Caliper Matching Method ($r=0.0005$)

3.4.3.2.3 Comparison

As the treatment effect estimation method and the OLS regression model are both based on observed characteristics, it is argued that the results of the OLS regression should fall into the 95% confidence interval of the results of the treatment effect estimation. We run the OLS regression of IPO underpricing including underwriter reputation as an explanatory dummy variable and other variables, as follows:

$$\begin{aligned}
 U_i = & \beta_0 + \beta_1 * LN(AGE) + \beta_2 * LN(AST) + \beta_3 * LN(EOS) \\
 & + \beta_4 * [LN(EOS)]^2 + \beta_5 * LN(LEV) + \beta_6 * VC + \beta_7 * I_A + \beta_8 * I_B . \\
 & + \beta_9 * I_C + \beta_{10} * I_D + \beta_{11} * I_E + \beta_{12} * LN(MP) + \beta_{13} * y_i + \varepsilon_i
 \end{aligned}$$

The estimated coefficient on underwriter reputation (y_i) is 0.1514 with a standard error 0.0203 and t -statistic 7.46.⁴⁹ It shows that the high reputation of an underwriter on average increases the associated IPO underpricing by 15.14%, which applies not only to the treated but to the entire sample. 15.14% falls into the 95% confidence intervals of all three ATTs estimated by propensity score matching in table 3.10. However, nearest matching and caliper matching with radius 0.001 both report larger treatment effects than OLS regression.

From the standpoint of propensity score matching, the precision of the estimate decreases from caliper matching with radius 0.0005, to caliper matching with radius 0.001, to nearest matching. However, the difference is small such that nearest matching is still very popular due to ease of implementation. From the standpoint of the estimated ATT, the number of treated that has been matched decreases as the precision of propensity score matching increases. Both caliper matching methods use more control units than nearest matching and all of the three ATT estimates are significantly positive. The ATT estimated by nearest matching has the largest size and the one by caliper matching with radius 0.0005 has the smallest. Even though a radius 0.0005 provides a more precise matching, it has a smaller number of treated that has been matched, which loses more information than when using radius 0.001. Radius 0.001 has fewer treated that have been matched compared to nearest

⁴⁹ Since we are only interested in the relation between underwriter reputation and IPO underpricing, we will not report other estimates.

matching, but it uses more control units, which utilizes more information from the sample. Hence, caliper matching with radius 0.001 is a preferred method for our sample.

Since most of the literature does not cover the internet bubble period, its finding of a negative relation during 1981 through 1998 is not comparable to our result of a positive relation during 1981 through 2000. This is one of the motivations for further analyzing the relation in different subperiods, as done in the following section.

3.4.3.3 Subsamples by Subperiods

We stratify the sample into three subperiods, 1980-1990, 1991-1998, and 1999-2000, such that we can test whether the treatment effect is consistent over different periods. Because the subperiod sample sizes are much smaller and the best method that fits our sample is caliper matching with radius 0.001, we employ that method only for the remaining analysis.

There are no matching problems for the first two subperiods, except for 1999-2000 (see table 3.11). There are no issuers selecting low-reputation underwriters during 1999-2000 that can be control units, which is due to two main reasons. First, during the internet bubble period issuers were most likely to prefer high-reputation underwriters. Second, there are 718 IPO cases during 1999-2000 in the original data, but only 16.6% of which are handled by low-reputation underwriters (esp. 119 cases). Because we do not have financial information about issuers who select low-reputation underwriters during 1999-2000, 525 IPO cases handled by high-reputation underwriters are left after data cleaning. To solve this problem, we use the entire 1,552 control units during 1981-1998 as a substitute for the controls during 1999-2000.

Table 3.11. Sample Description of Y_i for the Subperiod Subsamples

Subperiod	$Y_i=1$	$Y_i=0$	Total Units
1981-1990	100	583	683
1991-1998	1,024	969	1,993
1999-2000	525	0	525

We do the balancing test for each subperiod starting from the original model reported in section 3.4.3.1. The subperiods 1991-1998 and 1999-2000 are balanced, and after dropping LN(AST) the subperiod 1981-1990 is balanced as well. Table 3.12 shows a descriptive summary of the matched scores, and caliper matching with radius 0.001 works well for different subperiods (see figures in appendix C.2.1-C.2.6). The means of the difference between the treated and the matched scores are -0.011%, 0.002% and -0.003% for the three subperiods, respectively. The standard deviations are similar, all around 0.05%.

Table 3.12. Summary Statistics for the Difference of the Propensity Scores between the Treated and the Matched for the Subperiod Subsamples

Subperiod	Mean	Std. Dev.	Median	Min.	Max.
1981-1990	-0.0111%	0.0457%	-0.0088%	-0.0970%	0.0900%
1991-1998	0.0017%	0.0469%	0.0030%	-0.1000%	0.0980%
1999-2000	-0.0031%	0.0507%	-0.0030%	-0.0990%	0.0990%

The treatment effect estimated for 1980-1990 is positive, which means that for an issuer who chose a high-reputation underwriter during 1980-1990, its IPO's underpricing is 3.0% larger than if it would have chosen a low-reputation underwriter (see table 3.13). However, the estimate is not statistically significant and the number of matched treated units is very small, i.e., 42. Results are very similar for the insignificant ATT = -1.2% corresponding to 1991-1998.

Since the control units for 1999-2000 are from 1981-1998, the estimated positive relation shows that compared to IPOs with low-reputation underwriters during 1981-1998, an issuer who chose a high-reputation underwriter during 1999-2000 has a 45.2% larger underpricing on average than if it would have chosen a low-reputation underwriter. The t -statistic is 7.417 with 236 treated that have been matched, so the one-sided p -value is less than 0.001%.

Hence, we find no significant relation between underwriter reputation and IPO underpricing during 1981-1990 and 1991-1998, whereas during 1999-2000 the relation is positive and statistically (as well as economically) significant. In addition, we carry further analysis over subperiod 1981-1998, and the estimated ATT = 0.2% is insignificantly positive

with t -statistic 0.193, which is consistent with the findings above. Our conclusion is different from most of the literature which supports a significantly negative relation before the internet bubble by OLS regressions. Bradley *et al.* (2002) find that high-reputation underwriters are associated with smaller (larger) IPO underpricing in the 1980s (during 1991 through 1998) and no significant relation during the internet bubble, which are all different from our findings. Loughran and Ritter (2004) report no such significant relation in the 1980s and a significant positive relation during the internet bubble, which are consistent with our results, except that they also find a positive relation during 1991-1998. The main reason is that we employ different estimation methods, due to the use of different measures of underwriter reputation, i.e. a binary variable in the present paper and a continuous variable in the literature. Since we consider the unobserved counterfactual problem, our treatment effect estimates are more appropriate.

It is clear that the major factor driving the positive relation of the entire sample is IPOs during the internet bubble. Since information frictions are more severe with high-tech IPOs, it is harder for underwriters to evaluate those IPOs. Also, issuers pay more attention to analyst coverage when they choose an underwriter, because an underwriter's ability to precisely forecast a firm's future profitability is realized to be more important than its ability to evaluate current assets. Choosing a high-reputation underwriter can gain more attention from the media for marketing purposes, as well. Those are some of the possible reasons why issuers during the internet bubble tended to choose high-reputation underwriters. Hence, we consider such positive relation as an industry effect as well, besides an underwriter's reputation effect.

We further test whether the industry effect we propose above is statistically significant. Using the same treatment effect estimation method with propensity score matching (i.e. caliper matching with radius 0.001), we define the treated units as issuers who select high-reputation underwriters during 1999-2000 and the 'control'⁵⁰ units as issuers who select high-reputation underwriters during 1981-1998 for the purpose of testing the effect of issuers' industry on IPO underpricing. The estimated ATT is 35.0% with a standard error

⁵⁰ The definition of control units in this paragraph is different from the rest of the paper and only this paragraph has a different definition. Hence, we use 'control' with single quotation marks to differentiate it with the rest of the paper.

0.047 and the t -statistic 7.45, calculated from 416 treated units matched by 751 ‘control’ units. This significantly positive ATT shows that during internet bubbles issuers who choose high-reputation underwriters has a 35.0% larger underpricing than those who choose high-reputation underwriters during 1981 to 1998. The obtained significantly positive industry effect on IPO underpricing confirms that issuers’ industry plays an important role during the internet bubble.

Being motivated by the antecedent explanation in the literature for negative/positive relations, our explanation for no significant relation before the internet bubble is that even though a high-reputation underwriter has larger analyst coverage, it can effectively offset a part of the higher cost by charging a higher fee structure. A low-reputation underwriter, on the other hand, has to charge a smaller fee structure to attract clients, but, the cost of its smaller analyst coverage is less expensive. Hence, no underwriters need to assess a significantly higher/lower level of underpricing as an implicit way of making profit. Therefore, before the internet bubble underwriters can maintain similar levels of underpricing regardless of their reputation.

Table 3.13. Results of Estimated Treatment Effect for the Subperiod Subsamples

Subperiod	No. of Treated ¹	No. of Controls ²	ATT	Std. Err.	t
1981-1990	42	110	0.030	0.048	0.627
1991-1998	661	644	-0.012	0.014	-0.863
1999-2000	236	466	0.452	0.061	7.417

¹No. of Treated is the number of treated units that has been matched.

²No. of Controls is the number of control units that has been used as a match to a treated unit.

3.4.3.4 Subsamples by Offer Price and the Filed Price Range

We stratify the sample into three groups by the location of the offer price in the filing range reported in the prospectus. If the offer price is higher (lower) than the highest (lowest) price filed in the prospectus, we define it as “Above Range” (“Below Range”). If the offer price is written in the range of the filed price in the prospectus, we define it as “Within Range”. We test whether the relation between underwriter reputation and IPO underpricing is consistent over different price ranges. For the same reason explained in section 3.4.3.3, we employ only caliper matching with radius 0.001. The sample description in table 3.14 shows

that the sample units are well distributed over the treated and the control for the three Price-Range subsamples. 42% of those 595 Above Range IPOs with $Y_i=1$ were offered during the internet bubble, i.e., 249 offerings, which means that the internet bubble period plays an important (but not dominant) role in Above Range subsample.

Table 3.14. Sample Description of Y_i for the Price-Range Subsamples

Price-Range	$Y_i=1$	$Y_i=0$	Total Units
Above Range	595	255	850
Within Range	702	885	1,587
Below Range	352	411	763

We test the balancing property for each subsample starting from the original model in section 3.4.3.1 and all three subsamples that are already balanced. Table 3.15 reports a descriptive summary for the matched propensity scores, suggesting that caliper matching with radius 0.001 works well for different Price-Ranges (also see figures in appendix C.2.7-C.2.12). The means of the propensity score differences between the treated and the matched are -0.004%, 0.002% and -0.002% for the three subsamples, respectively. The standard deviation for Within Range is smaller than for the other two, mainly because the Within Range subsample has more units to facilitate the matching.

Table 3.15. Summary Statistics for the Difference of the Propensity Scores between the Treated and the Matched for the Price-Range Subsamples

Price-Range	Mean	Std. Dev.	Median	Min.	Max.
Above Range	-0.0035%	0.0555%	-0.0090%	-0.1000%	0.0990%
Within Range	0.0024%	0.0030%	0.0499%	-0.0990%	0.0970%
Below Range	0.0020%	0.0518%	0.0020%	-0.0970%	0.0990%

The treatment effect estimated for Above Range subsample is 0.424, which means that when the offer price is above the filing range, the IPO underpricing for an issuer who chose a high-reputation underwriter is 42.4% larger than if it would have chosen a low-reputation underwriter (see table 3.16). This estimate is highly statistically significant with t -statistic 5.407 and 212 treated units that have been matched. However, for Within Range the

relation is insignificantly positive, because the ATT is only 0.6%, with t -statistic 0.387 and 369 treated units that have been matched. Below Range subsample shows a positive relation as well, and it is borderline significant with one-sided p -value 6.86%. The Below Range estimate indicates that when the offer price is below the filing range, the IPO underpricing for an issuer who chose a high-reputation underwriter is on average 2.0% larger than if it would have chosen a low-reputation underwriter. Hence, we find a significantly positive underpricing for Above Range and Below Range, and no significant underpricing for Within Range.

An explanation for these results is that during road shows, underwriters may discover investors' interests over the offerings and might later adjust the original filed price according to the outcome of the road show. So, if investors have shown stronger interest than expected to purchase the IPO shares, underwriters may be short of share supplies and one way to solve the problem is to increase the offer price. For the Above Range subsample, the estimated ATT is positive, which means that usually high-reputation underwriters can get hot issues but they do not necessarily understand exactly how hot those offerings are, even after the road show. In addition, the large value of ATT for Above Range offerings, i.e., 42.4%, indicates that high-reputation underwriters are very conservative (or risk averse) when increasing the offer price to reflect the high market demand. On the other hand, the small but significantly positive ATT for Below Range offerings indicates that high-reputation underwriters are risk averse, such that they lower the offer price more than what they should when the market demand is lower than expected. The insignificant ATT for Within Range is also consistent with the intuition that when investors show interest as expected, high-reputation underwriters are most likely to choose a suitable offer price within the filed price range in the prospectus.

Cooney *et al.* (2001) report a negative relation between IPO's initial return and underwriter reputation for Within Range IPOs, for the 1980s and 1991-1998. They find no such significant relation for Below Range IPOs for the 1980s or 1991-1998, or for Above Range IPOs in the 1980s, whereas a positive relation only for Above Range IPOs in the period 1991-1998. Bradley *et al.* (2002) find that Above Range (Within Range) IPOs during 1981 through 2000 generally have the largest (median) underpricings among the three. Considering the sample size issue, we do not further stratify the sample by subperiods in each

price range. Also, in each subsample we include the internet bubble period and it is likely to increase the ATT which is indicated by the results in section 3.4.3.3. Hence, our finding in this section is different from Cooney *et al.*'s (2001) but they are still consistent. Our results for Above Range and Below Range IPOs are consistent with Bradley *et al.*'s (2002), except for Within Range IPOs.

Table 3.16. Results of Estimated Treatment Effect for the Price-Range Subsamples

Price-Range	No. of Treated ¹	No. of Controls ²	ATT	Std. Err.	t-statistic
Above Range	212	126	0.424	0.078	5.407
Within Range	369	355	0.006	0.016	0.387
Below Range	151	138	0.020	0.013	1.494

¹No. of Treated is the number of treated units that has been matched.

²No. of Controls is the number of control units that has been used as a match to a treated unit.

3.5 Conclusion

The present study matches IPO issuing firms with underwriters to examine an issuing firm's preference over underwriter reputation. We employ two Generalized Linear Models (GLMs), with fixed and mixed effects. Our sample consists of 3,201 IPOs issued between 1981 and 2000.

From the GLM with fixed effects, we find that expected offer size and expected offer price of the IPO, age of the issuer, leverage ratio of the issuer, assets of the issuer, and venture capital backing are important aspects when an issuer decides to choose an underwriter. The marginal effect of expected offer size has an up side down U-shape. From the GLM with random effect, we find that there are significant preferences associated with issuer's industry and state. Issuers in the state of California are more likely to choose high-reputation underwriters. Issuers in the Service industry are most likely to choose high-reputation underwriters and issuers in the Utility industry are also more likely to choose high-reputation underwriters.

We also find that underwriter's headquarter location is significantly associated with its reputation. Total underwriter capital has a statistically significant impact in reputation, while the size of institutional sales force does not.

Using treatment effect estimation by propensity score matching, we find a significantly positive relation between underwriter reputation and IPO underpricing for issuers who chose high-reputation underwriters for the entire sample. However, when we stratify the sample by subperiods, we find no such significant relation for 1981-1990 or 1991-1998, but a significantly positive relation during internet bubble 1999-2000. This suggests that such positive relation is both an issuer's industry effect and an underwriter's reputation effect. When we stratify the sample by the location of offer price in the filing range reported in the prospectus, we find that high-reputation underwriters are more risk averse than low-reputation underwriters, such that they are more reluctant (willing) to increase (reduce) the offer price when the market demand is higher (lower) than expected. Hence, there is a significantly positive average treatment effect on treated for Above Range and Below Range, and the ATT for Above Range is much higher than for Below Range.

3.6 References

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APPENDIX A. FOR CHAPTER 1

A.1 Assumption Justification

The reason for assuming that issuers do not know their initial types is that otherwise there are no equilibria where bad issuers go through the CRA. However, historical ratings data strongly suggests that bad issuers seek CRA ratings. For example, we collect all the initial issuer ratings from Fitch Ratings, Inc. from 1/1/2004 through 6/20/2007 in table A.1. There are 5,515 initial issuer ratings in our sample, 77.4% of which are investment grades and 22.6% of which are speculative grades. Fitch Ratings, Inc. defines investment grade as BBB or above and speculative grade as BBB- or below. As 22.6% of initial issuer ratings during that period are speculative grades, it shows strong evidence that not only good issuers go to CRA but also bad issuers do.

Second, we prove that if issuers know their initial types, there are no equilibria where initial bad issuers will go through the CRA. Note that there are only two initial types (initial good and initial bad) and issuers know their initial types, such that initial good issuers have incentive to go through the CRA to signal their qualities to the market and get higher prices. However, if initial bad issuers go through the CRA, they will pay the CRA to signal their bad quality to the market and finally get lower prices. Thus, if initial bad issuers do not go through the CRA but initial good issuers do, initial bad issuers can signal their quality to the market without paying the CRA by showing no ratings. When initial good issuers go to the CRA, initial bad issuers are better off by not going through the CRA. Because doing so reduces rating expenses and results in the same bond price. Therefore, investors will anticipate that all initial good issuers will have ratings h and no rating means initial bad quality. In the other case when initial good issuers choose not to go through the CRA, there is no reason for initial bad issuers to go through the CRA either. Hence, the only possible issuers that may go through the CRA in the equilibria with the relaxed assumption are initial good issuers, and initial bad issuers will never go through the CRA. This is inconsistent with the empirical evidence we show above. However, in section 1.4.2.2 Equilibrium Condition, the equilibrium strategies derived from the current assumption are consistent with the empirical evidence.

Table A.1. Rating Grades Example

Rating	Proportion	Count
AAA	1.2%	68
AA+	0.7%	40
AA	3.2%	177
AA-	5.8%	321
A+	32.5%	1793
A	9.6%	529
A-	8.6%	472
BBB+	8.8%	487
BBB	7.2%	396
BBB-	6.2%	344
BB+	2.4%	135
BB	2.5%	138
BB-	2.6%	146
B+	2.8%	152
B	2.5%	136
B-	2.1%	116
CCC+	0.6%	33
CCC	0.4%	20
CCC-	0.0%	1
CC	0.1%	3
C	0.1%	3
DDD	0.0%	1
DD	0.0%	1
Total	100.0%	5512

In the real world, why do bad issuers go through the CRA? A discussion with rating analysts in Fitch Rating, Inc. reveals three major reasons. First, underwriters usually require a rating for the ease of marketing. Second, many investors, e.g. institutional investors, cannot hold bonds without ratings. Third, the rating system has more than 25 grades, which can provide relative advantage to bad issuers compared to even worse issuers. Because we do not want to include underwriters in our model, we do not want to limit investor's behavior, and we make the simplified assumption that there are only two rating grades in our model, people may frown on the assumption that issuers do not know their initial types. However, considering the equilibria derived from the relaxed assumption, the empirical evidence supports our current assumption instead of the relaxed one.

A.2 Proof for Bond Prices

Under both cases, $P_{3h}^a = P_{3h}^{na} = F^S = 1$ and $P_{3l}^a = P_{3l}^{na} = F^F = \gamma$.

A.2.1 Go Through the CRA and Take Action

We want to compare those prices and find the price change.

$$\begin{aligned}
 P_{2h}^a &= \{[(1-\theta)(1-\alpha)\eta+\theta]/[(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)]\} F^S \\
 &\quad + \{[(1-\theta)\alpha(1-\eta)]/[(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)]\} F^F \\
 &= (\eta-\eta\alpha-\eta\theta+\eta\theta\alpha+\theta+\alpha\gamma-\alpha\gamma\eta-\alpha\gamma\theta+\alpha\gamma\eta\theta)/(\eta-2\eta\alpha-\eta\theta+2\eta\theta\alpha+\theta+\alpha-\theta\alpha), \\
 P_{2w}^a &= \{[(1-\alpha)(1-\eta)]/[(1-\alpha)(1-\eta)+\alpha\eta]\} F^S + \{(\alpha\eta)/[(1-\alpha)(1-\eta)+\alpha\eta]\} F^F \\
 &= (1-\eta-\alpha+\eta\alpha+\alpha\gamma\eta)/(-\eta+2\eta\alpha+1-\alpha), \\
 P_{1h}^a &= [(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)] P_{2h}^a + (1-\theta)(1-\alpha)(1-\eta) P_{3h}^a + (1-\theta)\alpha\eta P_{3l}^a \\
 &= \alpha\gamma-\alpha\gamma\theta+1-\alpha+\theta\alpha,
 \end{aligned}$$

where P_{ij}^a means the bond price is for issuers with rating j at $t=i$ when initially good issuers take action.

As P_{2h}^a and P_{2w}^a are both weighted average of F^S and F^F and $F^S > F^F$, we only need to compare the conditional weights on F^S .

$$\begin{aligned}
 &[(1-\theta)(1-\alpha)\eta+\theta]/[(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)] - [(1-\alpha)(1-\eta)]/[(1-\alpha)(1-\eta)+\alpha\eta] \\
 &= \alpha[(1-\alpha+\theta\alpha)(2\eta-1)+\theta(1-\eta)]/\{[\eta(1-\theta)+\alpha+\eta(1-\theta)(1-2\alpha)][(1-\eta)(1-\alpha)+\alpha\eta]\} > 0
 \end{aligned}$$

Thus, we know $1 > P_{2h}^a > P_{2w}^a > \gamma$.

Now we compare P_{1h}^a and P_{2w}^a :

$$P_{1h}^a - P_{2w}^a = \alpha\{(1-\alpha)[(1-\gamma)(2\eta-1)+\gamma\eta\theta]+\theta[(1-\alpha)(1-\eta)+\alpha\eta]\}/[(1-\eta)(1-\alpha)+\alpha\eta] > 0$$

Then we substitute P_{2h}^a , P_{3h}^a and P_{3l}^a to P_{1h}^a that

$$P_{1h}^a = [1-(1-\theta)\alpha] F^S + (1-\theta)\alpha F^F,$$

and then we compare P_{1h}^a and P_{2h}^a by the weights on F^F

$$\begin{aligned}
 &(1-\theta)\alpha - \{[(1-\theta)\alpha(1-\eta)]/[(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)]\} \\
 &= (1-\theta)\alpha\{[(2\eta-1)(1+\alpha\theta-\alpha)+\theta(1-\eta)]/[(1-\theta)(1-\alpha)\eta+\theta+(1-\theta)\alpha(1-\eta)]\} > 0.
 \end{aligned}$$

Thus, we get $P_{1h}^a < P_{2h}^a$.

Hence the price comparison result is $P_{3h}^a > P_{2h}^a > P_{1h}^a > P_{2w}^a > P_{3l}^a$.

A.2.2 Go Through the CRA and Take No Action

The prices are as follows,

$$\begin{aligned} P_{2h}^{na} &= \{[(1-\alpha)\eta]/[(1-\alpha)\eta+\alpha(1-\eta)]\} F^s + \{[\alpha(1-\eta)]/[(1-\alpha)\eta+\alpha(1-\eta)]\} F^r \\ &= (-\eta+\alpha\eta-\alpha\gamma+\alpha\gamma\eta)/(-\eta+2\alpha\eta-\alpha), \end{aligned}$$

$$\begin{aligned} P_{2w}^{na} &= \{[(1-\alpha)(1-\eta)]/[(1-\alpha)(1-\eta)+\alpha\eta]\} F^s + \{(\alpha\eta)/[(1-\alpha)(1-\eta)+\alpha\eta]\} F^r \\ &= (1-\eta-\alpha+\alpha\eta+\alpha\gamma\eta)/(1-\eta-\alpha+2\alpha\eta), \end{aligned}$$

$$\begin{aligned} P_{1h}^{na} &= \alpha[\eta P_{3l}^{na} + (1-\eta) P_{2h}^{na}] + (1-\alpha)[\eta P_{2h}^{na} + (1-\eta) P_{3h}^{na}] \\ &= 1-\alpha+\alpha\gamma, \end{aligned}$$

where P_{ij}^{na} means the bond price is for issuers with rating j at $t=i$ when initially good issuers take no action.

As P_{2h}^{na} and P_{2w}^{na} are both weighted average of F^s and F^r and $F^s > F^r$, we only need to compare the conditional weights on F^s .

$$\begin{aligned} &[(1-\alpha)\eta]/[(1-\alpha)\eta+\alpha(1-\eta)] - [(1-\alpha)(1-\eta)]/[(1-\alpha)(1-\eta)+\alpha\eta] \\ &= [\alpha(1-\alpha+\theta\alpha)(2\eta-1)+\theta(1-\eta)]/[\{\eta(1-\theta)+\alpha+\eta(1-\theta)(1-2\alpha)\}[(1-\eta)(1-\alpha)+\alpha\eta]] > 0 \end{aligned}$$

Thus, we know $1 > P_{2h}^{na} > P_{2w}^{na} > \gamma$.

Now we substitute P_{2h}^{na} , P_{3h}^{na} and P_{3l}^{na} to P_{1h}^{na} that $P_{1h}^{na} = (1-\alpha) F^s + \alpha F^r$. Then we compare P_{1h}^{na} and P_{2w}^{na} by their weights on F^r :

$$\alpha - \{(\alpha\eta)/[(1-\alpha)(1-\eta)+\alpha\eta]\} = -\{[(2\eta-1)(1-\alpha)\alpha]/[(1-\eta)(1-\alpha)+\alpha\eta]\} < 0$$

Thus, we get $P_{1h}^{na} > P_{2w}^{na}$.

And then we compare P_{1h}^{na} and P_{2h}^{na} by the weights on F^r :

$$\alpha - \{[\alpha(1-\eta)]/[(1-\alpha)\eta+\alpha(1-\eta)]\} = [(2\eta-1)(1-\alpha)\alpha]/[\eta(1-\alpha)+\alpha(1-\eta)] > 0$$

Thus, we get $P_{1h}^{na} < P_{2h}^{na}$.

Hence the price comparison result is $P_{3h}^{na} > P_{2h}^{na} > P_{1h}^{na} > P_{2w}^{na} > P_{3l}^{na}$.

A.3 Proof for Subgame Equilibrium

We solve this model by Pure Strategy Nash Equilibrium, which means we only consider the case that game participants with same information will take same strategies.

A.3.1 Private Cost of Action

A.3.1.1 Condition for Costly Action

We assume that if issuers do not go through the CRA, they will not take action as the cost of taking action is very high. In order to define the costly action, we compare the expected utility of taking action (i.e., $E(U_{nr}^a)$) and taking no action (i.e., $E(U_{nr}^{na})$) while no ratings. Thus

$$E(U_{nr}^a) = [1-\beta\theta-\beta(1-\theta)(1-\alpha)]\gamma(R_p P_1^a - 1) + [\beta\theta + \beta(1-\theta)(1-\alpha)](R_p P_1^a - 1),$$

where $P_1^a = \beta(1-\alpha) + \gamma(1-\beta) + \alpha\beta\gamma + \theta\alpha\beta(1-\gamma)$; and

$$E(U_{nr}^{na}) = [1-\beta(1-\alpha)]\gamma(R_p P_1^{na} - 1) + \beta(1-\alpha)(R_p P_1^{na} - 1),$$

where $P_1^{na} = \beta(1-\alpha) + \gamma(1-\beta) + \gamma\beta\alpha$.

The solution to $E(U_{nr,na}) > E(U_{nr}^a)$ is

$$C_a > \underline{C}_a = C_{a1} = \beta\alpha\theta(\gamma-1)(2\alpha\beta R_p - 2\gamma R_p - 2\beta R_p + 2\beta\gamma R_p - \theta\alpha\beta R_p - 2\alpha\beta\gamma R_p + \theta\alpha\beta\gamma R_p + 1).$$

Therefore, we assume $C_a > \underline{C}_a$ is always true in the present setup.

A.3.1.2 Subgame Equilibrium Condition

$$U_a - U_{na} = (g(\eta, \theta)) / (-\eta + 2\alpha\eta - \alpha),$$

where $g(\eta, \theta) = \theta R_p \eta^2 + 2\theta R_p \alpha\gamma\eta - 2\theta R_p \eta^2\gamma\alpha - \theta R_p \eta - \theta R_p \alpha\eta^2 - 2\theta R_p \alpha^2\gamma\eta + 2\theta R_p \eta^2\gamma\alpha^2 - \theta R_p \alpha + \theta R_p \alpha^2\eta + \theta R_p \alpha\gamma^2\eta + \theta R_p \alpha^2\gamma^2 - 2\theta R_p \alpha^2\gamma^2\eta - \gamma\theta + \alpha\gamma\eta\theta + \theta R_p \alpha\eta + C_a\eta - 2 C_a\alpha\eta + C_a\alpha$.

As $-\eta + 2\alpha\eta - \alpha = (1-\alpha)\eta + \alpha(1-\eta) < 0$, basically we want to know the sign of the numerator $g(\eta, \theta)$. The solution of $g(\eta, \theta) = 0$ is

$$\theta = \theta_1,$$

where $\theta_1 = C_a (-\eta + 2\alpha\eta - \alpha) / (2R_p \alpha\gamma\eta - R_p \alpha\eta^2 - 2R_p \alpha^2\gamma\eta + 2R_p \eta^2\gamma\alpha^2 - \gamma + R_p \eta^2 - R_p \alpha + R_p \alpha^2\eta + R_p \alpha\gamma^2\eta + R_p \alpha^2\gamma^2 - 2R_p \alpha^2\gamma^2\eta + \alpha\gamma\eta + R_p \alpha\eta - 2R_p \eta^2\gamma\alpha - R_p \eta)$.

We assume that when the action is always successful, good issuers will take action for sure. This means $g(\eta, 1) < 0$, so we get

$$C_a < C_{a2},$$

where $C_{a2} = (-2R_p \alpha\gamma\eta + R_p \alpha\eta^2 + 2R_p \alpha^2\gamma\eta - 2R_p \alpha^2\gamma\eta^2 + R_p \alpha - R_p \alpha^2\eta - R_p \alpha\gamma^2\eta - R_p \alpha^2\gamma^2 + 2R_p \alpha^2\gamma^2\eta - R_p \eta^2 + \gamma - \alpha\gamma\eta - R_p \alpha\eta + 2R_p \gamma\eta^2\alpha + R_p \eta) / (\eta - 2\alpha\eta + \alpha)$.

We also assume that when the action is always unsuccessful, there is no action at all. This means $g(\eta, 0) > 0$, so we get $C_a > 0$.

From those two assumptions, we can get that if $0 < C_a < C_{a2}$, then $0 < \theta_1 < 1$ is true.

A.3.1.3 Restriction for C_a

Hence, when $\underline{C}_a < C_a < \bar{C}_a$ is true, if $\theta < \bar{\theta}_a$, $g(\eta, \theta) > 0 \rightarrow$ No issuer takes action; if $\theta > \bar{\theta}_a$, $g(\eta, \theta) < 0 \rightarrow$ Issuer takes action; where $\bar{\theta}_a = \theta_1$, $\underline{C}_a = C_{a1}$ and $\bar{C}_a = C_{a2}$.

A.3.2 Property of the Threshold $\bar{\theta}_a$

We take first partial derivative of $\bar{\theta}_a$ w.r.t η that

$$\partial \bar{\theta}_a / \partial \eta = C_a R_p f(\eta) / (-\gamma + 2R_p \alpha\gamma\eta - R_p \alpha\eta^2 - 2R_p \alpha^2\gamma\eta + 2R_p \eta^2\gamma\alpha^2 + R_p \eta^2 - R_p \alpha + R_p \alpha^2\eta + R_p \alpha\gamma^2\eta + R_p \alpha^2\gamma^2 - 2R_p \alpha^2\gamma^2\eta + \alpha\gamma\eta + R_p \alpha\eta - 2R_p \eta^2\gamma\alpha - R_p \eta)^2,$$

where $f(\eta) = (-\alpha^2 + \alpha - 2\alpha^2\gamma + 2\gamma\alpha^3)\eta^2 + (2\alpha + 4\alpha\gamma - 4\alpha^2\gamma - 2)\eta - \alpha^3\gamma^2 - 2\alpha\gamma + 2\alpha^2\gamma + 1 - \alpha\gamma^2 - \alpha + 2\alpha^2\gamma^2$.

Thus, we want to know the sign of the numerator $f(\eta)$. The solution to $f(\eta) = 0$ is η_1 and η_2 , where

$$\eta_1 = \frac{1}{\alpha} + \frac{1}{\alpha} \frac{(1 - \alpha\gamma)\sqrt{1 - \alpha}}{\sqrt{1 - 2\alpha\gamma}}$$

and

$$\eta_2 = \frac{1}{\alpha} - \frac{1}{\alpha} \frac{(1 - \alpha\gamma)\sqrt{1 - \alpha}}{\sqrt{1 - 2\alpha\gamma}}.$$

As $2\alpha^2\gamma - \alpha < 0$ and $1/\alpha > 2$, we get $\eta_1 > 1$.

As the solution to $\frac{(1-\alpha\gamma)\sqrt{1-\alpha}}{\sqrt{1-2\alpha\gamma}} = 1$ (which is $(\alpha^3 - \alpha^2)\gamma^2 - 2\alpha^2\gamma + \alpha = 0$) is $\gamma_1 = \frac{1}{\sqrt{\alpha}(\sqrt{\alpha} - 1)} < 0$ and $\gamma_2 = \frac{1}{\sqrt{\alpha}(\sqrt{\alpha} + 1)} > 1$, and the parabola is open to the bottom ($\alpha^3 - \alpha^2 < 0$),

so for any $\gamma \in (0, 1)$ we have $\frac{(1-\alpha\gamma)\sqrt{1-\alpha}}{\sqrt{1-2\alpha\gamma}} > 1$. Then we have $\eta_2 < 0$.

As the parabola of $f(\eta) = 0$ is open to the top ($-\alpha^2 + \alpha - 2\alpha^2\gamma + 2\gamma\alpha^3 = \alpha(1-\alpha)(1-2\alpha\gamma) > 0$), we get for any $(\eta_2 < 0) < \eta < 1 (< \eta_1)$, $f(\eta) < 0$ is always true.

Hence, we get $\partial \bar{\theta}_a / \partial \eta < 0$, which means the higher the ability of the CRA to put an issuer on watchlist is, the smaller is the threshold of θ needed to make initially good issuers take action.

A.4 Proof for Equilibrium

There exist three strategies for issuers. One is not going through the CRA. The second one is going through the CRA and taking no action if it is initially good. The third one is going through the CRA and taking action if it is initially good. We already get utilities of those three strategies in section 1.5.2 and by comparing them we can get the equilibrium condition.

A.4.1 Equilibrium Condition for $E(U_a) > E(U_{nr})$

The expected utility of choosing the CRA and taking action if it is initially good, is larger than the expected utility of not choosing the CRA, that is $E(U_a) > E(U_{nr})$.

$$-k(\eta) = A_1\eta^2 + B_1\eta + C_1 > 0$$

where $A_1 = 2\beta\theta R_p \alpha\gamma - \beta\theta R_p - 2R_p\gamma\beta\alpha - \beta R_p\alpha + 2\beta R_p\alpha^2\gamma + \beta\theta R_p\alpha + \beta R_p - 2\beta\theta R_p\alpha^2\gamma$, $B_1 = -\beta\theta R_p\alpha\gamma^2 - 2R_p\gamma\beta^2\alpha + 4\beta^2\alpha^2 R_p\gamma - 2\beta^2\alpha^2 R_p\gamma^2 - 4\beta R_p\alpha^2\gamma - 2\beta^2\alpha^3 R_p\gamma - \beta\alpha - \beta R_p + C_r\alpha + \beta\alpha^2 + \gamma\beta\alpha + R_p\beta^2\alpha + \beta\theta R_p + \beta R_p\alpha^2 + \beta C_a\alpha - \gamma\beta\alpha^2 + \beta^2\alpha^3 R_p - 2\beta^2\alpha^2 R_p R_p + R_p\gamma^2\beta^2\alpha - \beta\theta R_p\alpha - \beta\theta R_p\alpha^2 - \beta\theta\alpha\gamma + \beta^2\alpha^3 R_p\gamma^2 + 4R_p\gamma\beta\alpha + 2\beta\theta R_p\alpha^2\gamma^2 - 2\beta\theta R_p\alpha\gamma + 2\beta\theta R_p\alpha^2\gamma$, $C_1 = 2R_p\gamma\beta\alpha - 2R_p\gamma^2\beta\alpha -$

$$4 R_p \gamma \beta^2 \alpha + 2 R_p \gamma^2 \beta^2 \alpha + 2 \beta^2 \alpha^2 R_p \gamma + \beta \theta R_p \alpha + \beta R_p \alpha^2 \gamma^2 + \gamma \beta \alpha + \beta - \beta \alpha - \gamma \beta - R_p \beta^2 - C_r - R_p \gamma^2 \beta^2 - \beta^2 \alpha^2 R_p - 2 \nu \gamma \beta + R_p \gamma^2 \beta + 2 R_p \gamma \beta^2 + 2 R_p \beta^2 \alpha - \beta^2 \alpha^2 R_p \gamma^2 - \beta C_a + \beta R_p - \beta R_p \alpha + \beta \theta \gamma - \beta \theta R_p \alpha^2 \gamma^2.$$

The solution to $k(\eta)=0$ is

$$\eta_{3,4} = \frac{-B_1 \pm \sqrt{B_1^2 - 4A_1C_1}}{2A_1}.$$

As $A_1 = \beta R_p (1-\alpha)(1-\theta)(1-\alpha\gamma) > 0$, this parabola is open to the top.

$$k(1) > 0 \text{ is true under condition } C_r < C_{r1}, \text{ where } C_{r1} = -\beta^2 R_p \alpha^2 \gamma^2 - \beta^2 \alpha^2 R_p + 2\beta^2 \alpha^2 R_p \gamma + 2\beta^2 R_p \alpha + \alpha \beta \gamma + 2\beta^2 R_p \gamma^2 \alpha - 4\beta^2 R_p \gamma \alpha + 2 R_p \gamma \beta \alpha - \alpha \beta + \beta \theta R_p \alpha - \beta R_p \alpha - R_p \gamma^2 \beta \alpha - \beta \theta R_p \alpha \gamma^2 + 2\beta^2 R_p \gamma - \beta C_a - \beta^2 R_p - \beta^2 R_p \gamma^2 + \theta \beta \gamma - \beta \gamma + \beta - 2 R_p \gamma \beta + \beta R_p + R_p \gamma^2 \beta.$$

$$k(0) < 0 \text{ is true under condition } C_r > C_{r2}, \text{ where } C_{r2} = 2 R_p \gamma^2 \beta^2 \alpha + R_p \gamma^2 \beta - R_p \gamma^2 \beta^2 - \beta \alpha + \beta R_p - R_p \beta^2 - \gamma \beta + \beta + \gamma \beta \alpha - \beta^2 \alpha^2 R_p + \beta \theta \gamma - 2 R_p \gamma^2 \beta \alpha - 4 R_p \gamma \beta^2 \alpha - 2 R_p \gamma \beta + 2\beta^2 \alpha^2 R_p \gamma - \beta^2 \alpha^2 R_p \gamma^2 - \beta C_a + \beta R_p \alpha^2 \gamma^2 + 2 R_p \gamma \beta^2 + 2 R_p \beta^2 \alpha - \beta R_p \alpha + \beta \theta R_p \alpha - \beta \theta R_p \alpha^2 \gamma^2 + 2 R_p \gamma \beta \alpha.$$

Now we compare those two conditions.

$$C_{r1} - C_{r2} = R_p \gamma^2 \beta^2 \alpha (1-\alpha)(1-\theta) > 0 \rightarrow C_{r1} > C_{r2}.$$

Thus, if $C_{r1} > C_r > C_{r2}$ is satisfied, one of the solutions to $k(\eta)=0$ is inside unit interval, say $1 > \eta_3 > 0 > \eta_4$.

If $C_r > C_{r1}$, we get $k(1) < 0$ and $k(0) < 0$ which means issuers will never go through the CRA.

Hence if $\eta > \eta_a$ and $\underline{C}_r^a < C_r < \bar{C}_r^a$, we get $k(\eta) > 0 \rightarrow E(U_a) > E(U_{nr})$ that issuers will go through the CRA and take action, where $\underline{C}_r^a = C_{r1}$, $\bar{C}_r^a = C_{r2}$ and $\eta_a = \eta_3$.

Also we want to know the relationship between \underline{C}_r^a and β .

$$\partial \underline{C}_r^a / \partial \beta = 2 R_p (-\gamma^2 + 2\alpha^2 \gamma - 1 + 2\gamma - \alpha^2 \gamma^2 - 4\gamma \alpha + 2\gamma^2 \alpha - \alpha^2 + 2\alpha) \beta - 2 R_p \gamma + R_p \gamma^2 - \gamma - \alpha + R_p - \theta R_p \alpha^2 \gamma^2 + \theta \gamma + 1 + \gamma \alpha + R_p \alpha^2 \gamma^2 - 2 R_p \gamma^2 \alpha - C_a + \theta R_p \alpha + 2 R_p \gamma \alpha - R_p \alpha.$$

As the solution to $\partial \underline{C}_r^a / \partial \beta = 0$ is $\beta = \beta_1$, where $\beta_1 = (-2 R_p \gamma + R_p \gamma^2 - \gamma \alpha + R_p - \theta R_p \alpha^2 \gamma^2 + \theta \gamma + \gamma \alpha + 1 + R_p \alpha^2 \gamma^2 - 2 R_p \gamma^2 \alpha - C_a + \theta R_p \alpha + 2 R_p \gamma \alpha - R_p \alpha) / (2(-R_p \gamma^2 + 2\alpha^2 R_p \gamma - R_p + 2 R_p \gamma - R_p \alpha^2 \gamma^2 - 4 R_p \gamma \alpha + 2 R_p \gamma^2 \alpha - \alpha^2 R_p + 2 R_p \alpha))$.

As $\beta_1 > 1$ is always true, $\beta (< 1) < \beta_1$ is also always true. Thus, we know $\partial \underline{C}_r^a / \partial \beta > 0$, which means when issuers have larger probability to be initially good, the lower bound of \underline{C}_r^a required for this strategy is higher.

A.4.2 Equilibrium Condition for $E(U_{na}) > E(U_{nr})$

The expected utility of choosing the CRA and taking no action, is larger than the expected utility of not choosing the CRA, that is $E(U_a) > E(U_{nr})$.

$$\leftarrow q(\eta) = A_2 \eta^2 + B_2 \eta + C_2 > 0$$

where, $A_2 = \beta R_p - \beta R_p \alpha + 2\beta R_p \alpha^2 \gamma - 2 R_p \gamma \beta \alpha$, $B_2 = -\beta \alpha + C_r \alpha + R_p \beta^2 \alpha + \beta R_p \alpha^2 + \gamma \beta \alpha - \gamma \beta \alpha^2 - \beta R_p - 2\beta^2 \alpha^2 R_p + \beta^2 \alpha^3 R_p + 4\beta^2 \alpha^2 R_p \gamma - 4\beta R_p \alpha^2 \gamma + \beta \alpha^2 + 4 R_p \gamma \beta \alpha + \beta^2 \alpha^3 R_p \gamma^2 + R_p \gamma^2 \beta^2 \alpha - 2\beta^2 \alpha^2 R_p \gamma^2 - 2 R_p \gamma \beta^2 \alpha - 2\beta^2 \alpha^3 R_p \gamma$, $C_2 = 2 R_p \gamma \beta \alpha - 2 R_p \gamma^2 \beta \alpha - 4 R_p \gamma \beta^2 \alpha + 2 R_p \gamma^2 \beta^2 \alpha + 2\beta^2 \alpha^2 R_p \gamma + \beta R_p \alpha^2 \gamma^2 + \gamma \beta \alpha + \beta - \beta \alpha - \gamma \beta - R_p \beta^2 - C_r - R_p \gamma^2 \beta^2 - \beta^2 \alpha^2 R_p - 2 R_p \gamma \beta + R_p \gamma^2 \beta + 2 R_p \gamma \beta^2 + 2 R_p \beta^2 \alpha - \beta^2 \alpha^2 R_p \gamma^2 + \beta R_p - \beta R_p \alpha$.

The solution to $q(\eta) = 0$ is

$$\eta_{5,6} = \frac{-B_2 \pm \sqrt{B_2^2 - 4A_2 C_2}}{2A_2} \text{ and } \eta_5 > \eta_6.$$

As $A_2 = \beta R_p (1 - \alpha)(1 - 2\alpha\gamma) > 0$ (by assumption $\alpha < 0.5$), this parabola is open to the top.

$q(1) < 0$ is true under condition $C_r > C_{r3}$, where $C_{r3} = \beta + R_p \beta - \alpha \beta - \beta \gamma - R_p \alpha \beta - 2 R_p \beta \gamma + \alpha \beta \gamma + 2 R_p \alpha \beta \gamma + 2 R_p \alpha \beta^2 + R_p \beta \gamma^2 + 2 R_p \beta^2 \gamma - \beta^2 R_p - R_p \alpha \beta \gamma^2 - 4 R_p \alpha \beta^2 \gamma - R_p \beta^2 \gamma^2 + 2 R_p \alpha \beta^2 \gamma^2 + 2 R_p \alpha^2 \beta^2 \gamma - \alpha^2 \beta^2 R_p - R_p \alpha^2 \beta^2 \gamma^2$.

$q(0) > 0$ is true under condition $C_r < C_{r4}$, where $C_{r4} = 2R_p \gamma \beta \alpha - 2R_p \gamma^2 \beta \alpha - 4R_p \gamma \beta^2 \alpha + 2R_p \gamma^2 \beta^2 \alpha + 2\beta^2 \alpha^2 R_p \gamma + \beta R_p \alpha^2 \gamma^2 + \gamma \beta \alpha + \beta - \beta \alpha - \gamma \beta - R_p \beta^2 - R_p \gamma^2 \beta^2 - \beta^2 \alpha^2 R_p - 2R_p \gamma \beta + R_p \gamma^2 \beta + 2R_p \gamma \beta^2 + 2R_p \beta^2 \alpha - \beta^2 \alpha^2 R_p \gamma^2 + \beta R_p - \beta R_p \alpha$.

Also we get $C_{r4} > C_{r3}$ so that $C_{r3} < C_r < C_{r4}$ is true under assumption. Thus, under condition $\eta < \eta_6$, issuers will go through the CRA and take action.

Hence if $\underline{C}_r^{na} < C_r < \overline{C}_r^{na}$ and $\eta < \eta_{na}$, issuers will go through the CRA and take no action, where $\overline{C}_r^{na} = C_{r4}$, $\underline{C}_r^{na} = C_{r3}$ and $\eta_{na} = \eta_6$.

A.4.3 Summary

When action cost or rating cost is too high, no issuer will go through the CRA. When rating cost is too low, issuers will always go through the CRA. As those are straightforward, action cost and rating cost are in their median ranges under our assumptions. Thus, we only report the result in their median ranges, as follows.

1) If $\theta > \overline{\theta}_a$, $\eta > \eta_a$ and $\underline{C}_r^a < C_r < \overline{C}_r^a$, $E(U_a) > E(U_{nr})$ and $E(U_a) > E(U_{na})$ are true.

Thus, issuers will go through the CRA and initial good will take action.

2) If $\theta < \overline{\theta}_a$, $\underline{C}_r^{na} < C_r < \overline{C}_r^{na}$ and $\eta < \eta_{na}$ is true, $E(U_{na}) > E(U_{nr})$ and $E(U_{na}) > E(U_a)$ are true. Thus, issuers will go through the CRA and initial good will take no action.

3) Otherwise, $E(U_{nr}) > E(U_a)$ and $E(U_{nr}) > E(U_{na})$ are true. Thus, issuers will not go through the CRA.

A.5 Proof for Social Welfare Analysis

A.5.1 CRA without Monitoring Role

A.5.1.1 Go Through the CRA

If there is CRA but no watchlist, investor has no signal for shock happenings. They will make pricing decision based on market average quality that $\Pr(t_2 = G | r_1 = h) = 1 - \alpha$. Thus, the price is $P_{1h}^{nw} = \alpha F^F + (1 - \alpha) F^S = \alpha \gamma + 1 - \alpha$, $P_{1l}^{nw} = \gamma$ and the social welfare is

$$SW_r^{nw} = \beta(1-\alpha)(R_p P_{1h}^{nw} - 1) + (1-\beta)\gamma(R_p P_{1l}^{nw} - 1) + \beta\alpha\gamma(R_p P_{1h}^{nw} - 1) - C_r,$$

where the superscript means no watchlist and the subscript means issuers go through CRA (that there are ratings in the market).

A.5.1.2 Not Go Through the CRA

If there is no rating and no watchlist, investor has no signal at all. They will make pricing decision based on market average quality that $\Pr(t_2=G)=\beta(1-\alpha)$. Thus, the price $P^{nw} = [1-\beta(1-\alpha)] F^r + \beta(1-\alpha) F^s = \gamma - \gamma\beta + \beta\alpha\gamma + \beta - \beta\alpha$. Thus, the social welfare is

$$SW_{nr}^{nw} = \beta(1-\alpha)(R_p P^{nw} - 1) + [1-\beta(1-\alpha)]\gamma(R_p P^{nw} - 1),$$

where the subscript means issuers do not go through CRA (that there are no ratings in the market).

A.5.2 CRA with Monitoring Role

When there is asymmetric information and CRA exists, the social welfare depends on issuer's equilibrium strategy. As break-even for both investors and CRA, we do not need to consider investors and CRA in social welfare. Under both cases when issuers go through CRA, $P_{3h}^a = P_{3h}^{na} = F^s = 1$ and $P_{3l}^a = P_{3l}^{na} = F^r = \gamma$.

A.5.2.1 Not Go Through the CRA

It is exactly the same as the case of issuers choosing not go through CRA when there is CRA but no watchlist. Thus $SW_{nr}^w = SW_{nr}^{nw}$.

A.5.2.2 Go Through the CRA and Take No Action

There are four possibilities for initially good issuers: shock and on watchlist and downgrade (with probability $\alpha\eta$), shock and not on watchlist (with $\alpha(1-\eta)$), no shock and on watchlist and affirm initial rating (with $(1-\alpha)(1-\eta)$), and no shock and not on watchlist (with $(1-\alpha)\eta$). Thus, the social welfare is

$$SW_r^{w,na} = (1-\beta+\beta\alpha\eta)\gamma(R_p \gamma - 1) + \beta(1-\alpha)\eta(R_p P_{2h}^{na} - 1)$$

$$+\beta\alpha(1-\eta)\gamma(R_p P_{2h}^{na}-1)+\beta(1-\alpha)(1-\eta)(R_p-1)-C_r,$$

where $P_{2h}^{na} = (-\eta + \alpha\eta - \alpha\gamma + \alpha\gamma\eta) / (-\eta + 2\alpha\eta - \alpha)$ (refer to section 1.4.1.2), the superscript means there are watchlist and issuers take no action.

A.5.2.3 Go Through the CRA and Take Action

When issuers take action, compared to the strategy of ‘No action’ here is one more possibility, which is successful action and then no shock nor watchlist. Thus, the social welfare is

$$\begin{aligned} SW_r^{w,a} = & [1-\beta+\beta(1-\theta)\alpha\eta]\gamma(R_p\gamma-1)+[\beta\theta+\beta(1-\theta)(1-\alpha)\eta](R_p P_{2h}^a-1) \\ & +\beta(1-\theta)\alpha(1-\eta)\gamma(R_p P_{2h}^a-1)+\beta(1-\theta)(1-\alpha)(1-\eta)(R_p-1)-C_r-C_a, \end{aligned}$$

where $P_{2h}^a = (\eta - \eta\alpha - \eta\theta + \eta\theta\alpha + \theta + \alpha\gamma - \alpha\gamma\eta - \alpha\gamma\theta + \alpha\gamma\eta\theta) / (\eta - 2\eta\alpha - \eta\theta + 2\eta\theta\alpha + \theta + \alpha - \theta\alpha)$ (refer to section 1.4.1.1), the superscript means there are watchlist and issuers take action.

A.5.3 Compare

A.5.3.1 Inter-setup Analysis

When issuers take no action, the difference of social welfare between the two setups is

$$SW_r^{w,na} - SW_r^{nw} = [(\beta R_p \alpha) / (\eta - 2\eta\alpha + \alpha)] g,$$

where $g = (\gamma^2 + 1 - \alpha - \alpha\gamma^2 - 2\gamma + 2\alpha\gamma)\eta^2 - 2\alpha\gamma + \alpha\gamma^2 + \alpha - \alpha^2\gamma^2 - \alpha^2 + 2\alpha^2\gamma + (4\alpha\gamma - 4\alpha^2\gamma + 2\alpha^2\gamma^2 + 2\alpha^2 - 2\alpha - 2\alpha\gamma^2)\eta$.

As $\eta - 2\eta\alpha + \alpha > 0$ and $g > 0$ is always true as long as $\eta > 0$, we get that $\eta > 0 \rightarrow SW_r^{w,na} - SW_r^{nw} > 0$. Thus when issuers choose go through CRA but take no action, no matter how good/bad CRA is at monitoring, social welfare will be increased as long as CRA has the monitoring role.

A.5.3.2 Intra-setup Analysis

$SW_r^{w,a} - SW_r^{w,na}$ is complicated that we cannot get intuitive condition. Thus we consider issuer’s strategy directly in section 1.6.

However, we do a value trial. When there is watchlist and we set $\theta=1/2$, $\alpha=0.1$, $\gamma=0.67$, $\beta=0.5$, $R=2$, $C_r=0.15$, we get $SW_r^{w,a} - SW_r^{w,na} > 0$. It indicates that social welfare will be increased if issuers go through CRA and take action, instead of go through CRA but take no action, when CRA has the monitoring role.

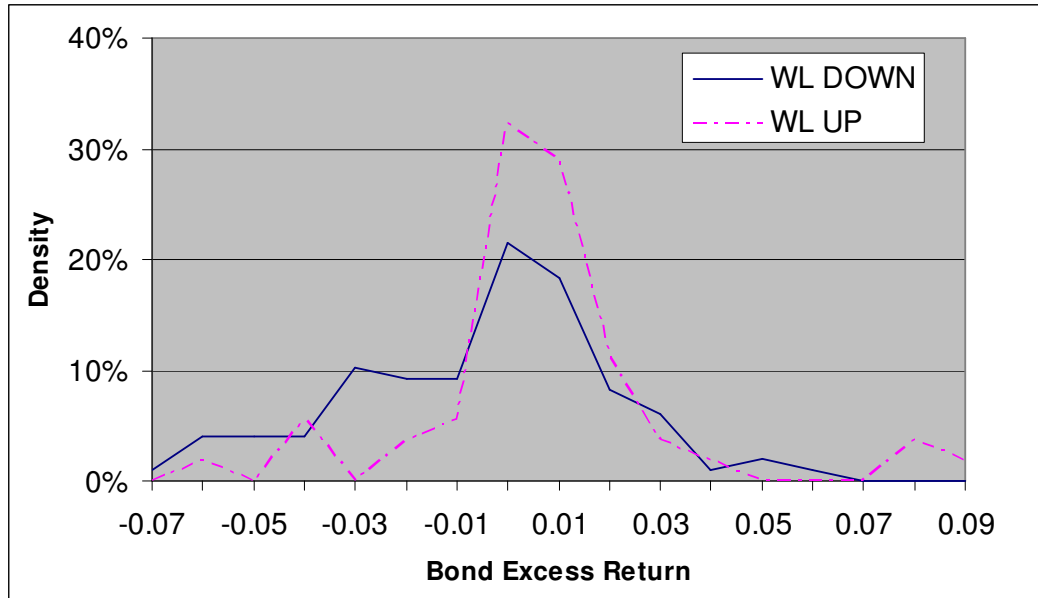
APPENDIX B. FOR CHAPTER 2

Figure B.1. Density of Bond Excess Returns of the Entire Sample Associated with Watchlist Announcements

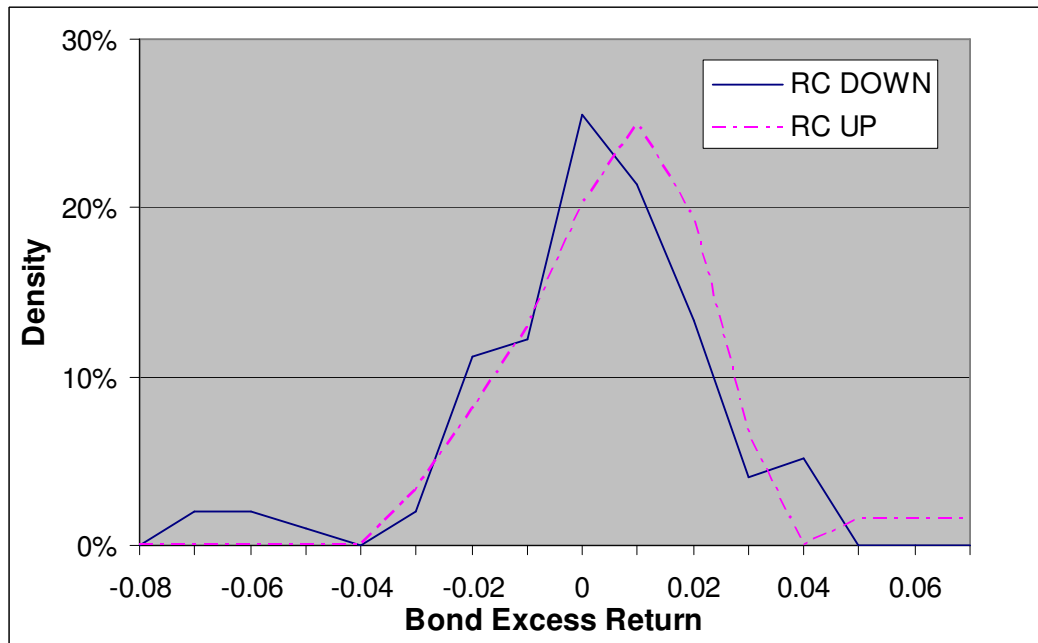


Figure B.2. Density of Bond Excess Returns of the Entire Sample Associated with Rating Changes Announcements

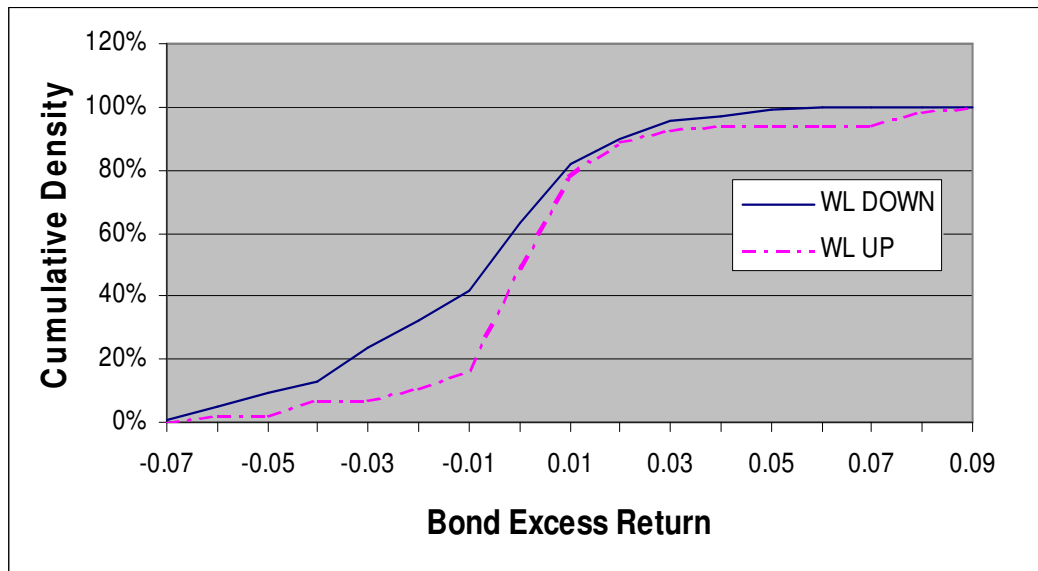


Figure B.3. Cumulative Density of Bond Excess Returns of the Entire Sample Associated with Watchlist Announcements

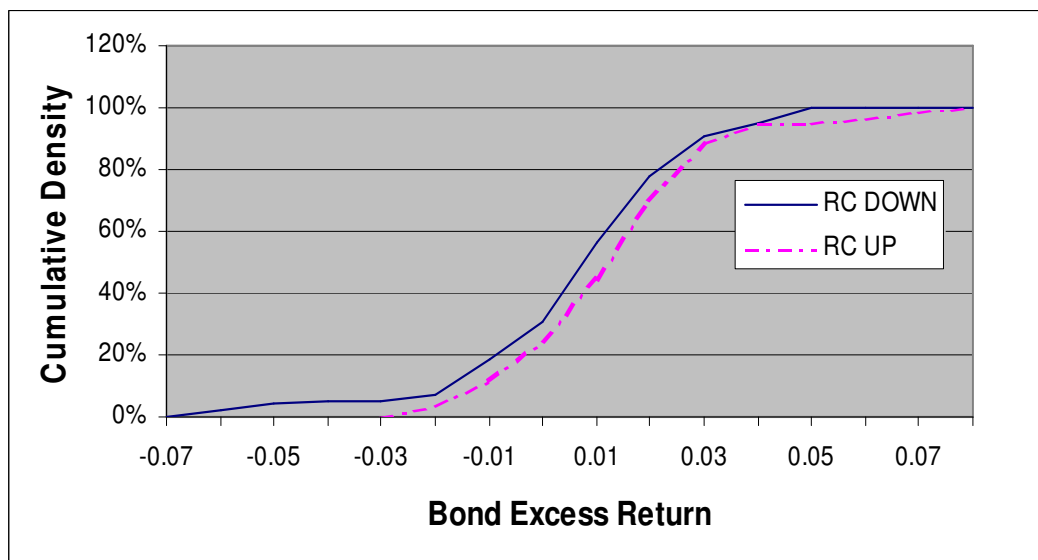


Figure B.4. Cumulative Density of Bond Excess Returns of the Entire Sample Associated with Rating Changes Announcements

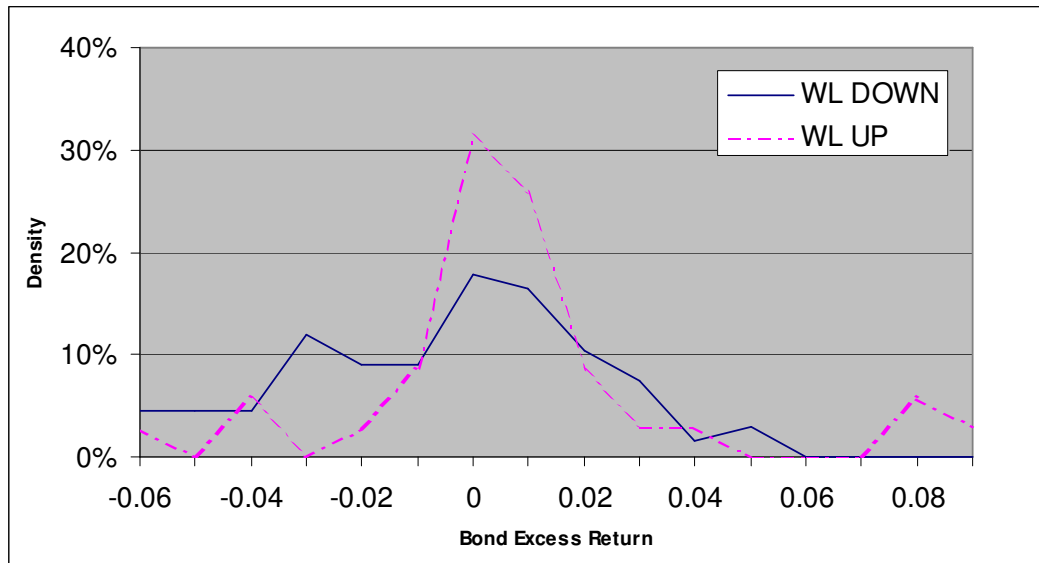


Figure B.5. Density of Bond Excess Returns of Straight-debt Bonds Associated with Watchlist Announcements

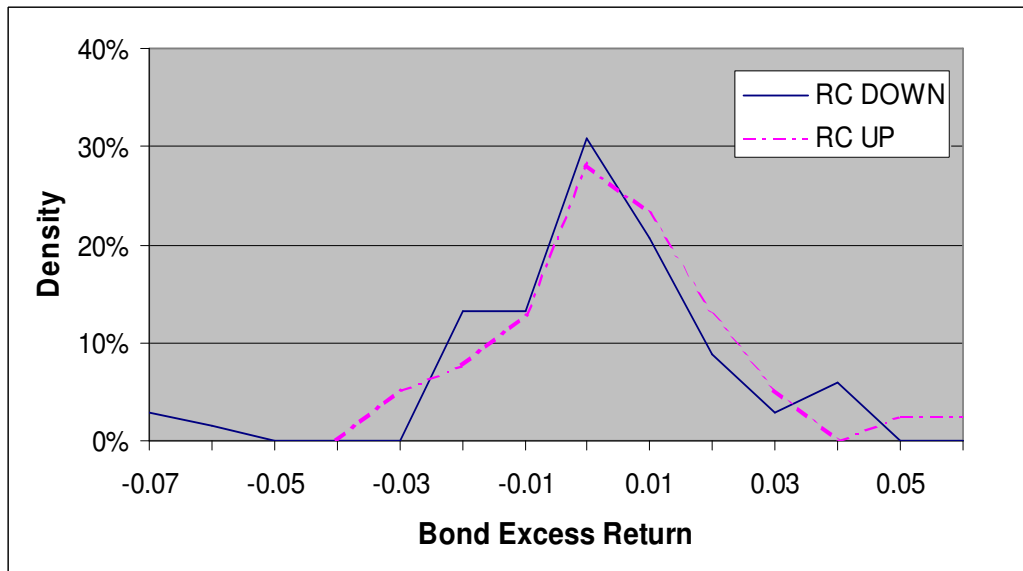


Figure B.6. Density of Bond Excess Returns of Straight-debt Bonds Associated with Rating Changes Announcements

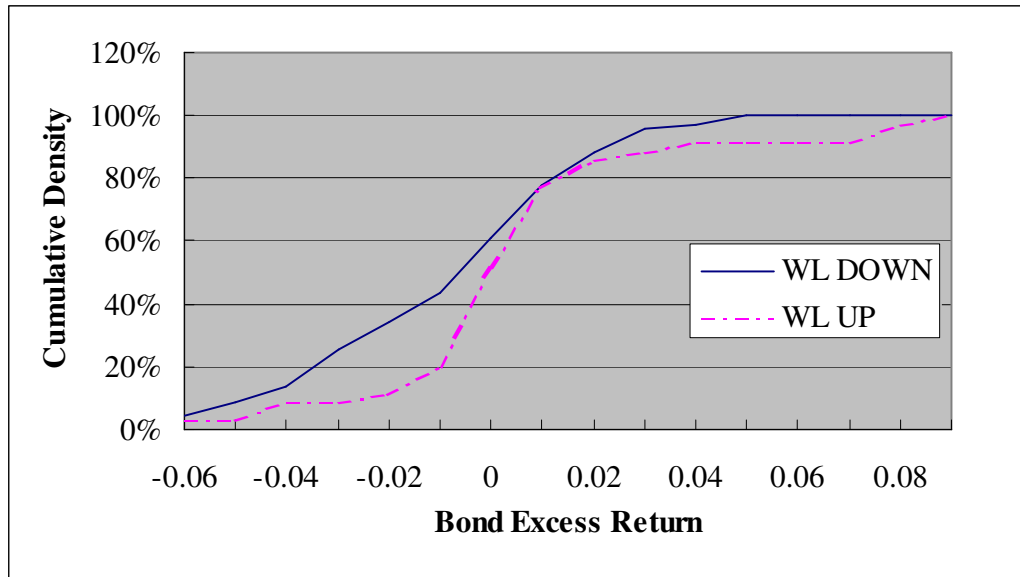


Figure B.7. Cumulative Density of Bond Excess Returns of Straight-debt Bonds Associated with Watchlist Announcements

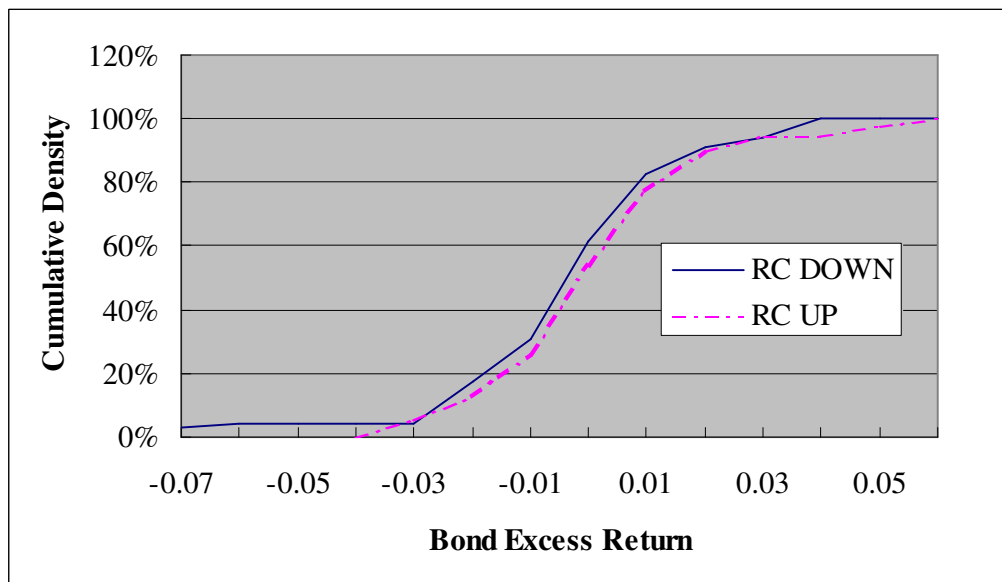


Figure B.8. Cumulative Density of Bond Excess Returns of Straight-debt Bonds Associated with Rating Changes Announcements

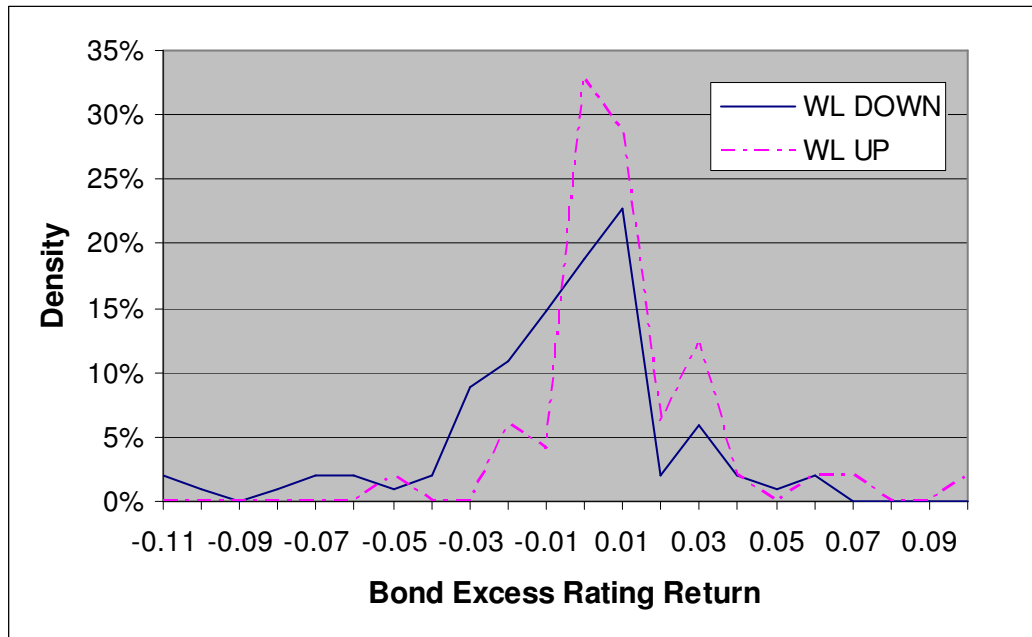


Figure B.9. Density of Bond Excess Rating Returns of the Entire Sample Associated with Watchlist Announcements

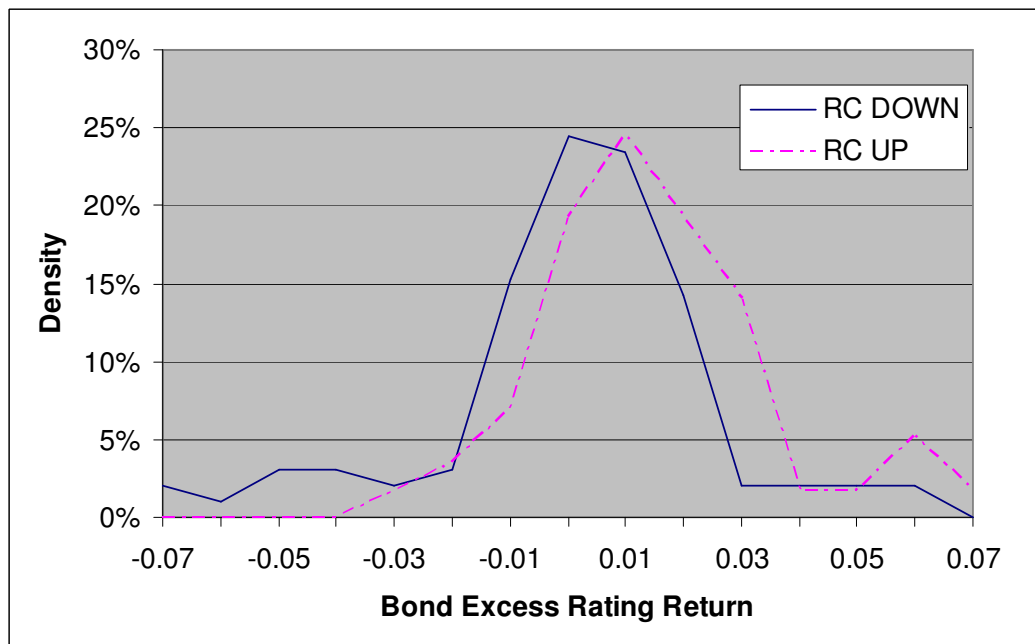


Figure B.10. Density of Bond Excess Rating Returns of the Entire Sample Associated with Rating Changes Announcements

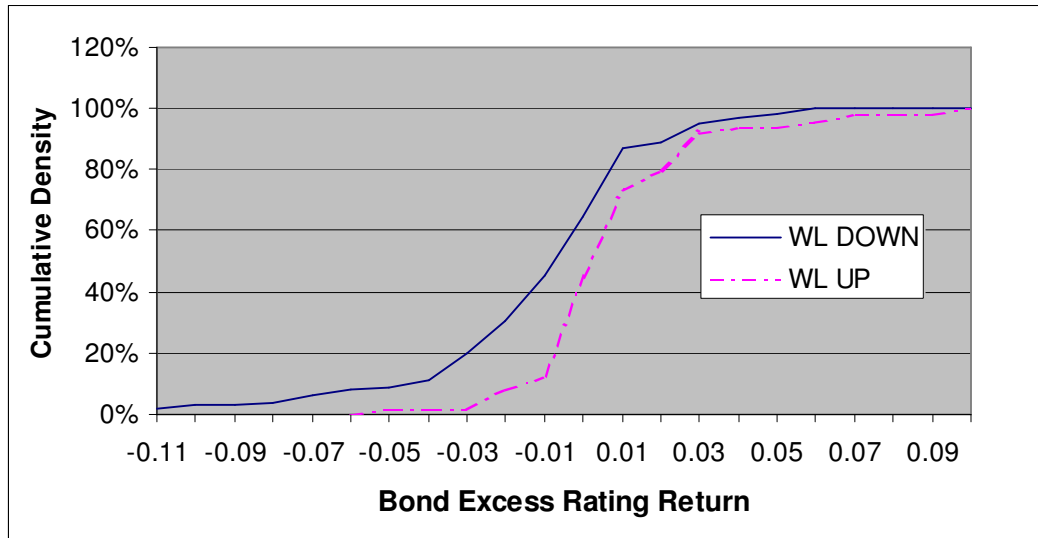


Figure B.11. Cumulative Density of Bond Excess Rating Returns of the Entire Sample Associated with Watchlist Announcements

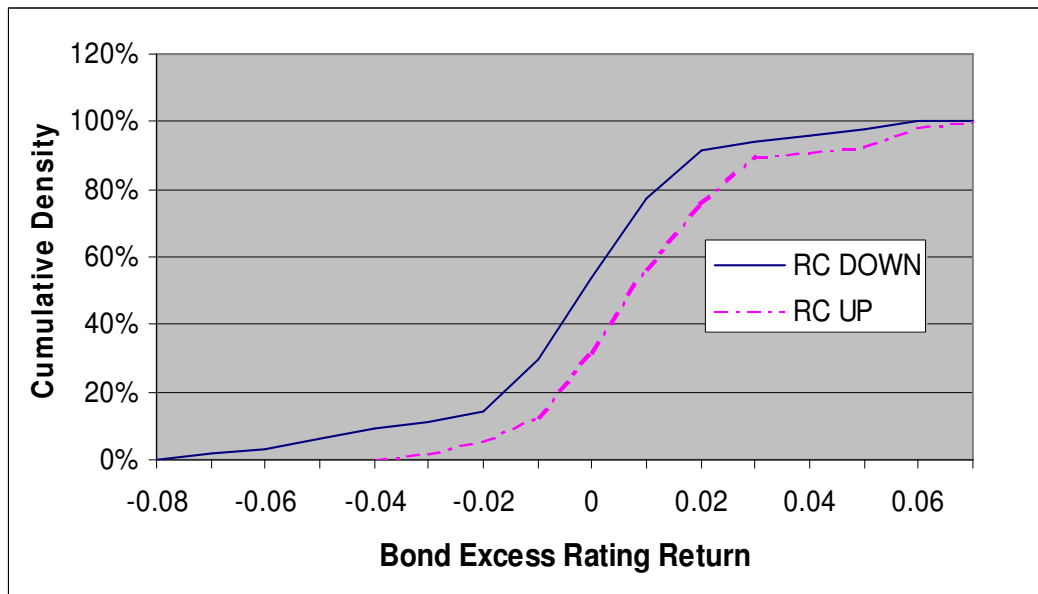


Figure B.12. Cumulative Density of Bond Excess Rating Returns of the Entire Sample Associated with Rating Changes Announcements

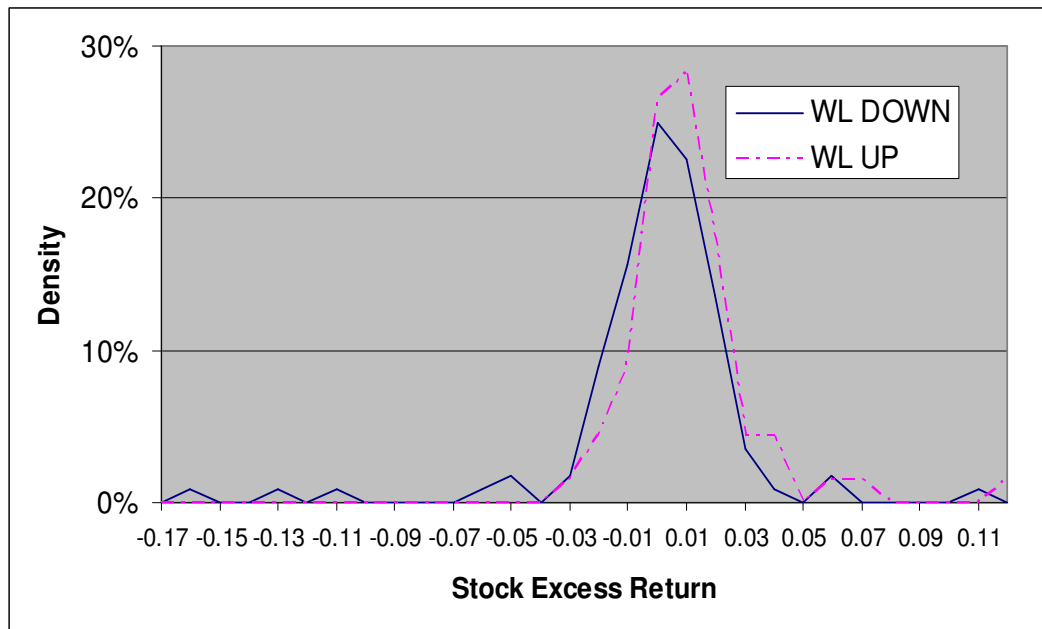


Figure B.13. Density of Stock Excess Returns Associated with Watchlist Announcements

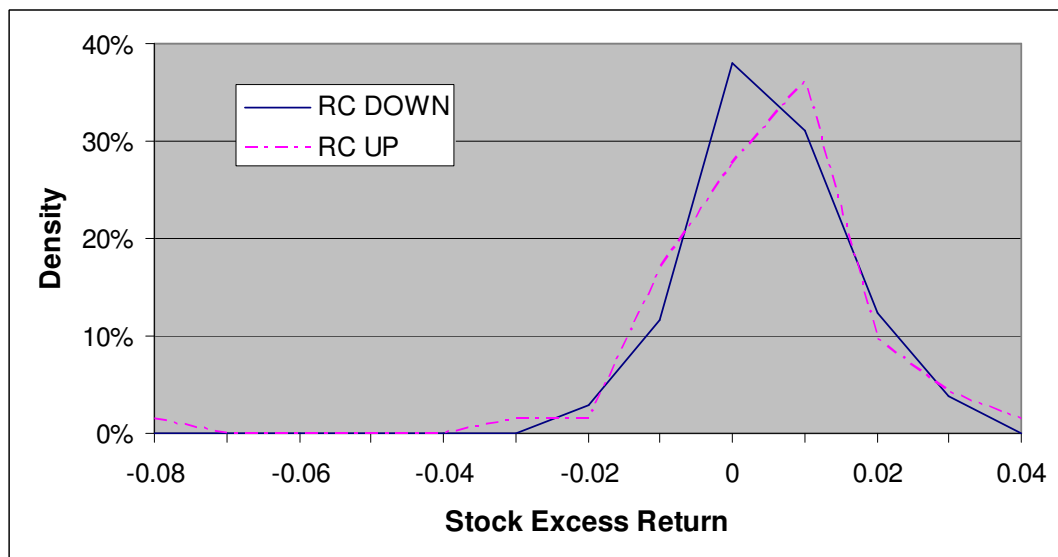


Figure B.14. Density of Stock Excess Returns Associated with Rating Changes Announcements

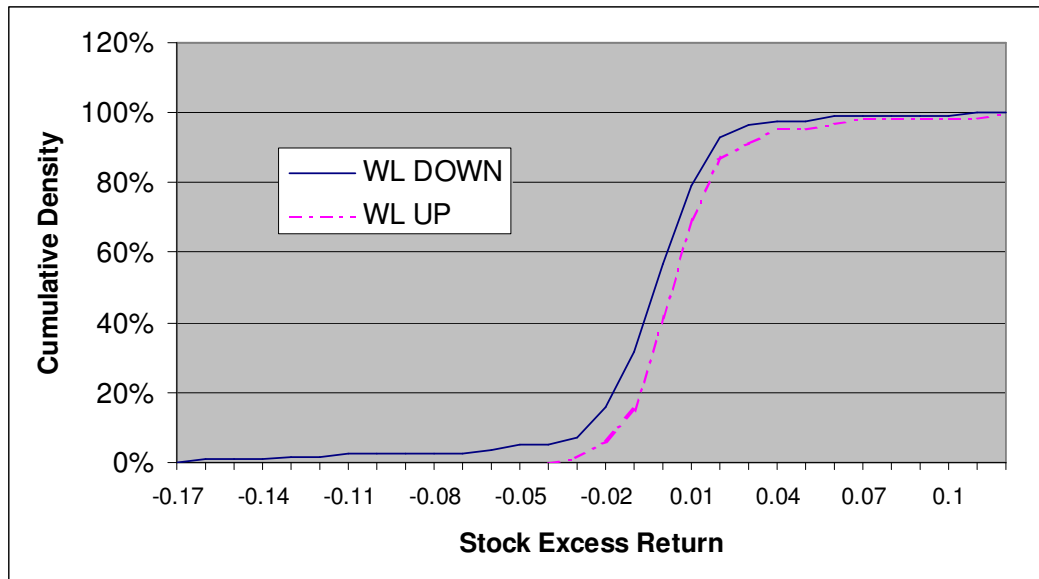


Figure B.15. Cumulative Density of Stock Excess Returns Associated with Watchlist Announcements

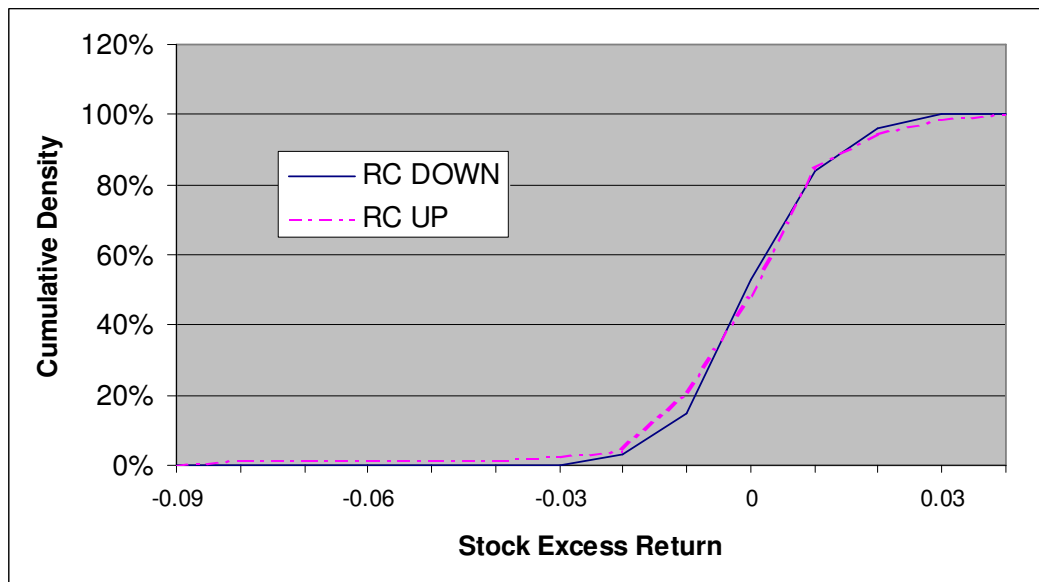


Figure B.16. Cumulative Density of Stock Excess Returns Associated with Rating Changes Announcement

C.2 Figures for Subsamples

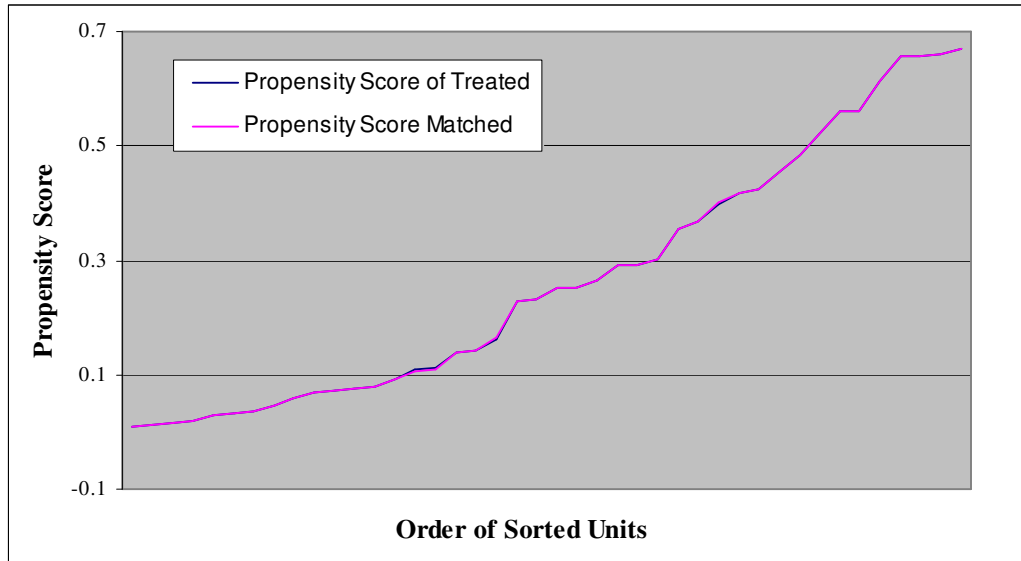


Figure C.2.1. Comparison of Propensity Scores for Subperiod 1981-1990

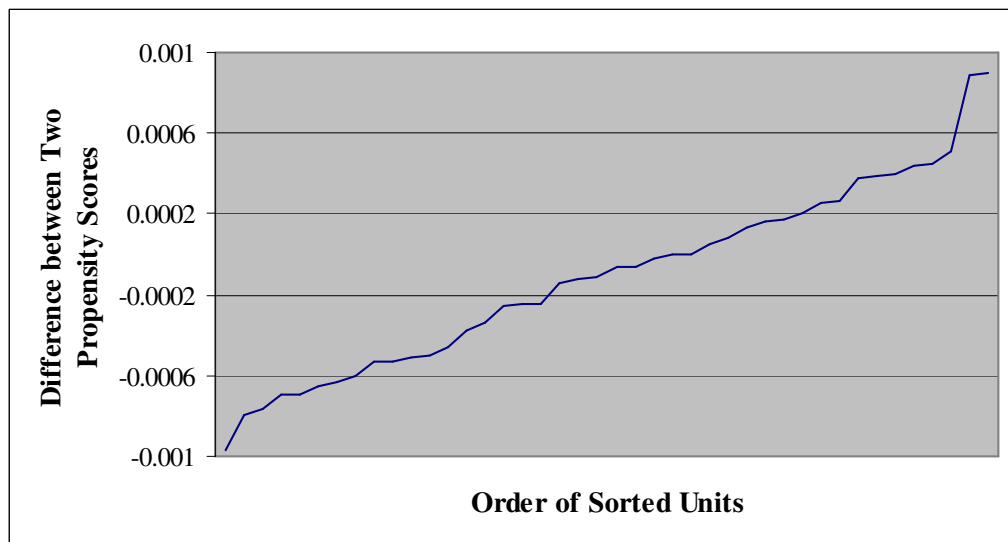


Figure C.2.2. Difference of Propensity Scores between the Treated and the Matched for Subperiod 1981-1990

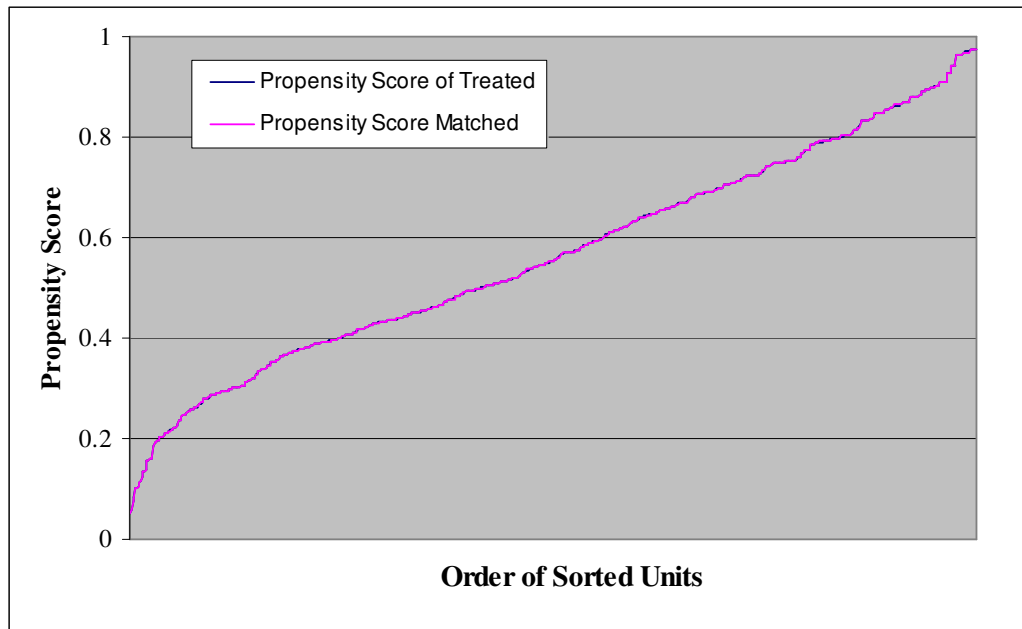


Figure C.2.3. Comparison of Propensity Scores for Subperiod 1991-1998

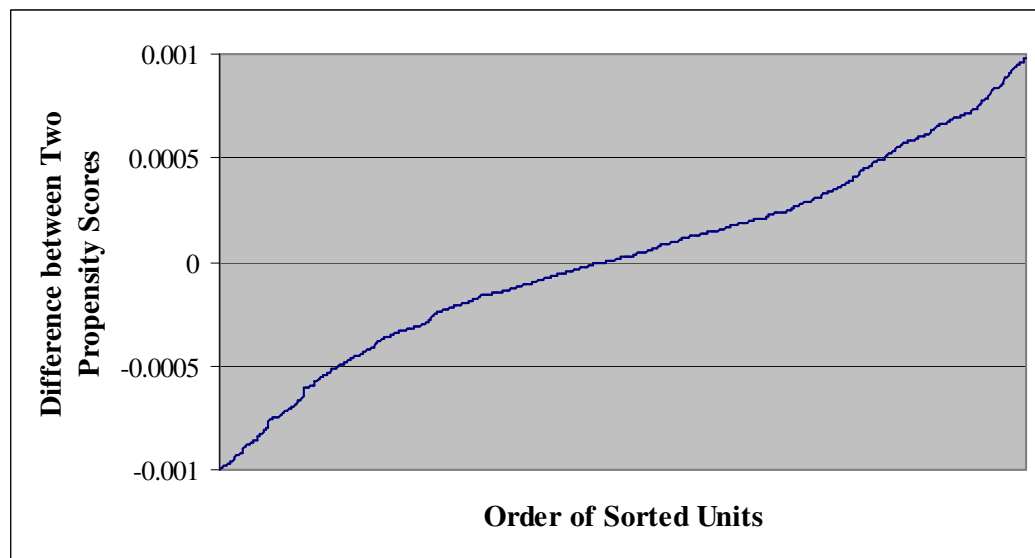


Figure C.2.4. Difference of Propensity Scores between Treated and Matched for Subperiod 1981-1990

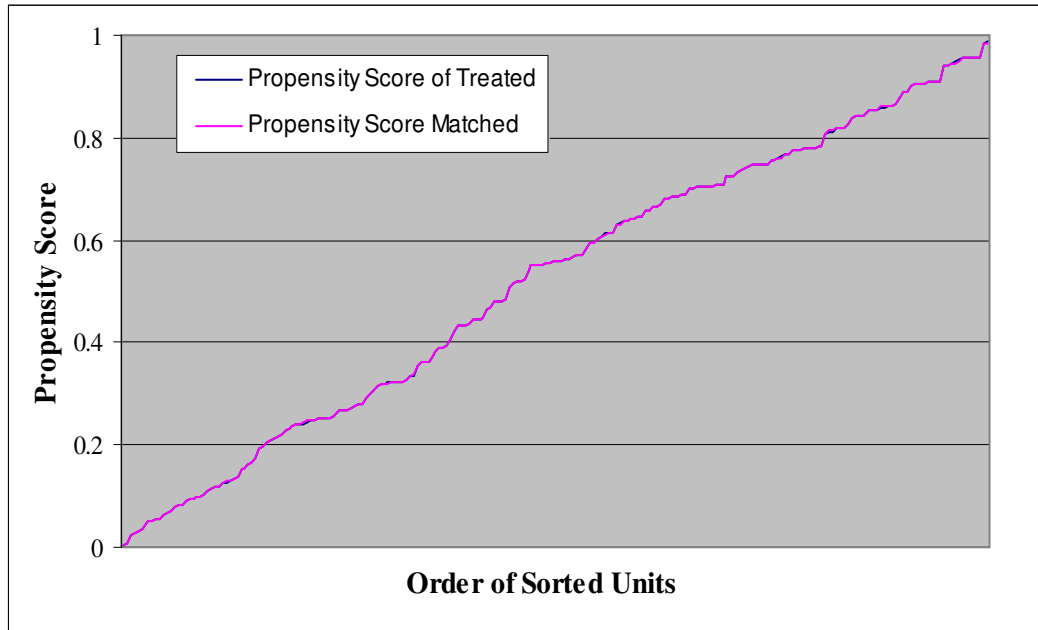


Figure C.2.5. Comparison of Propensity Scores for Subperiod 1999-2000

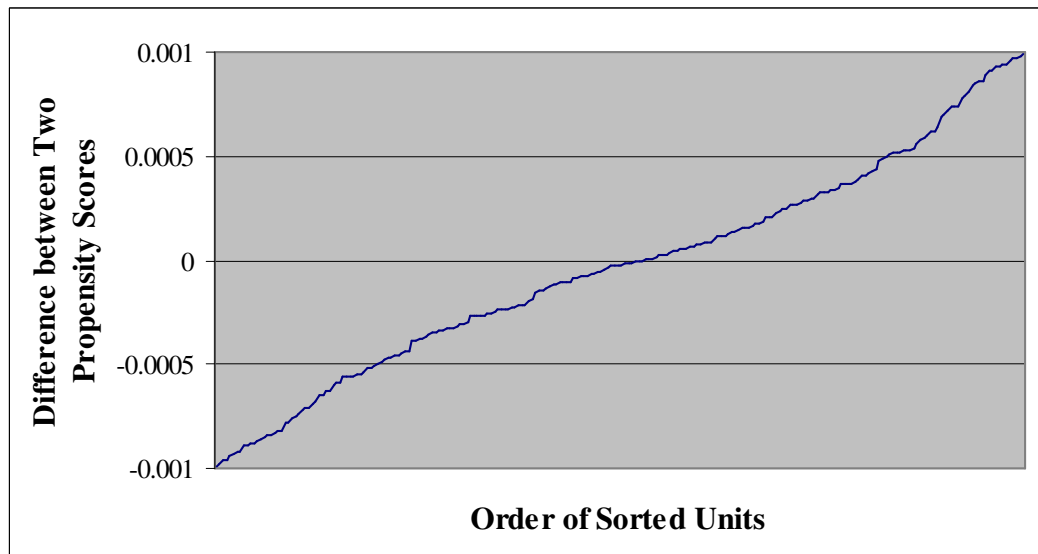


Figure C.2.6. Difference of Propensity Scores between the Treated and the Matched for Subperiod 1999-2000

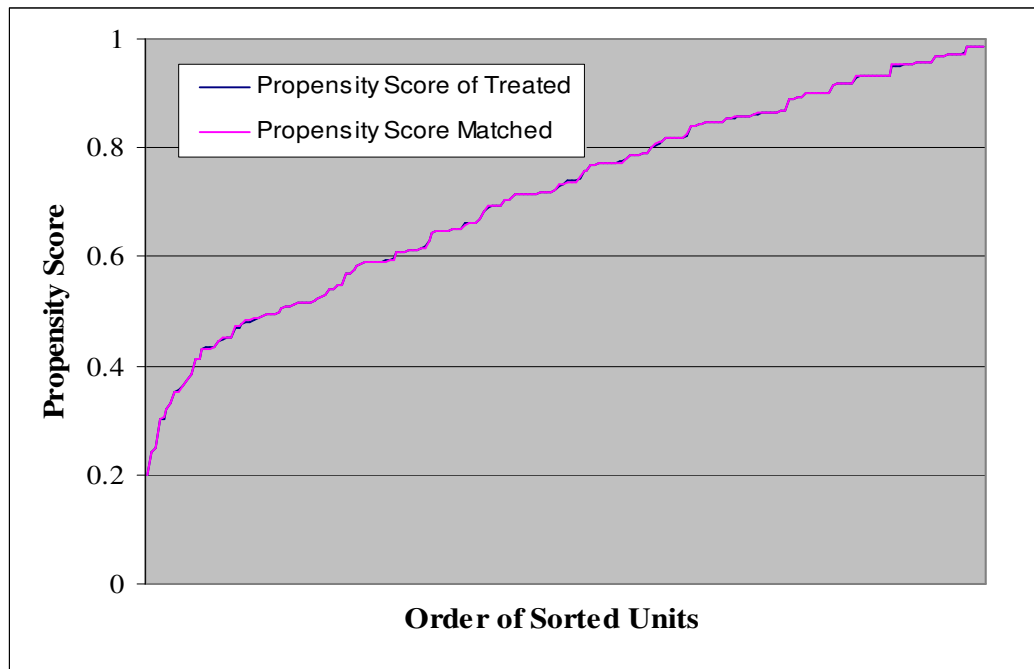


Figure C.2.7. Comparison of Propensity Scores for Above Range Subsample

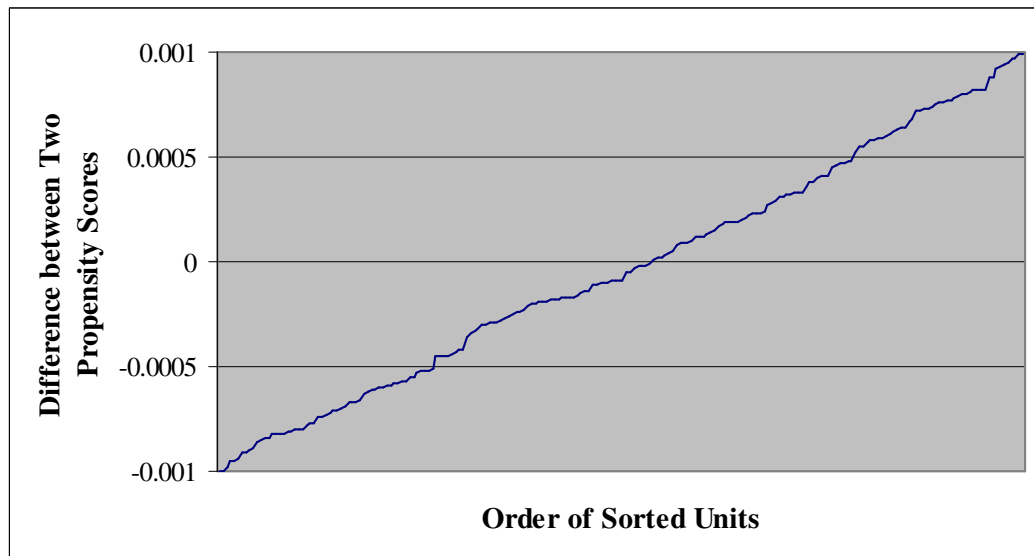


Figure C.2.8. Difference of Propensity Scores between the Treated and the Matched for Above Range Subsample

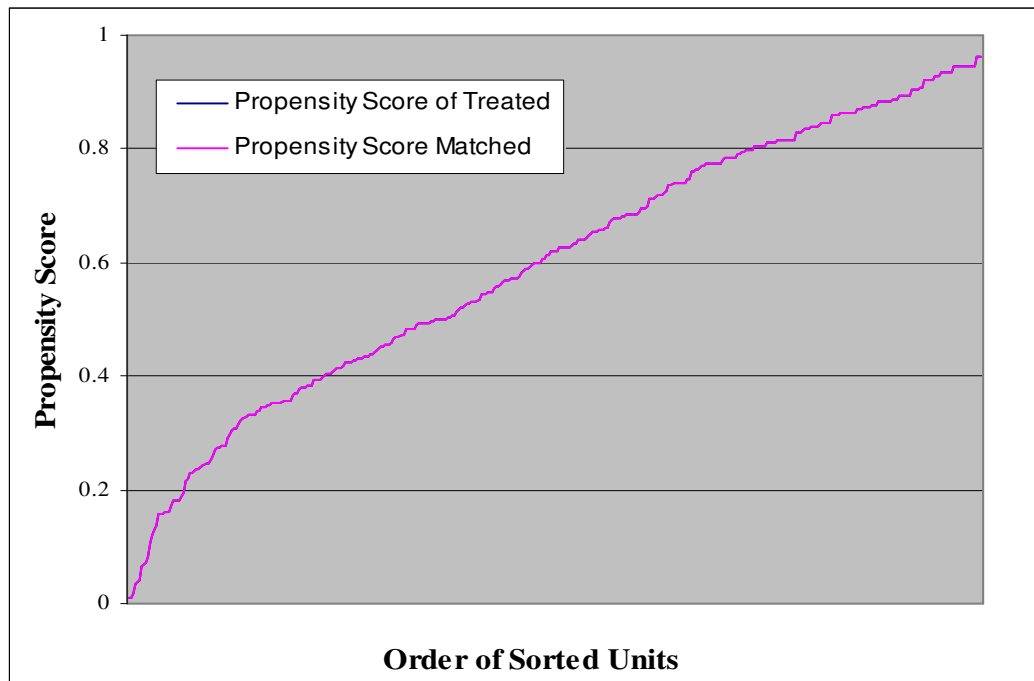


Figure C.2.9. Comparison of Propensity Scores for Within Range Subsample

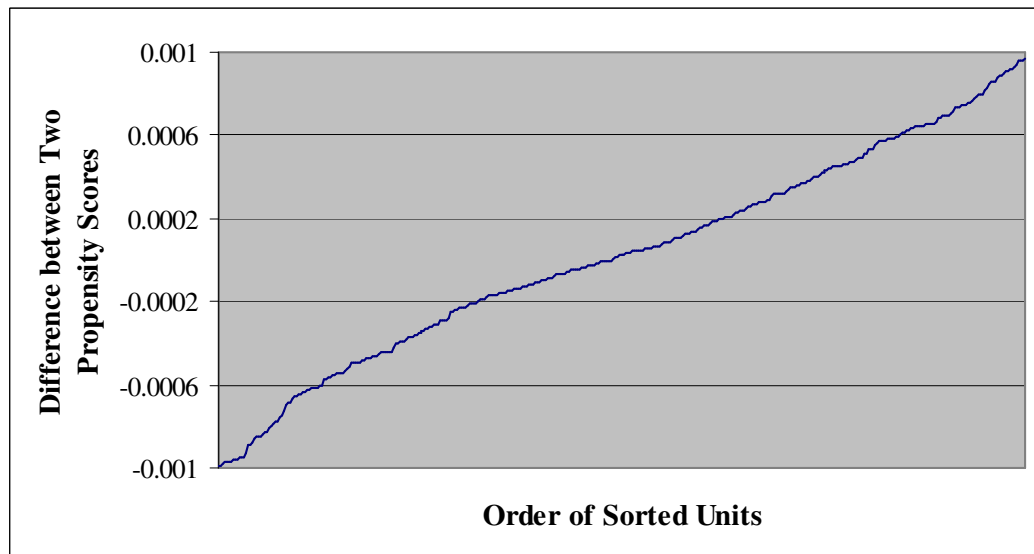


Figure C.2.10. Difference of Propensity Scores between the Treated and the Matched for Within Range Subsample

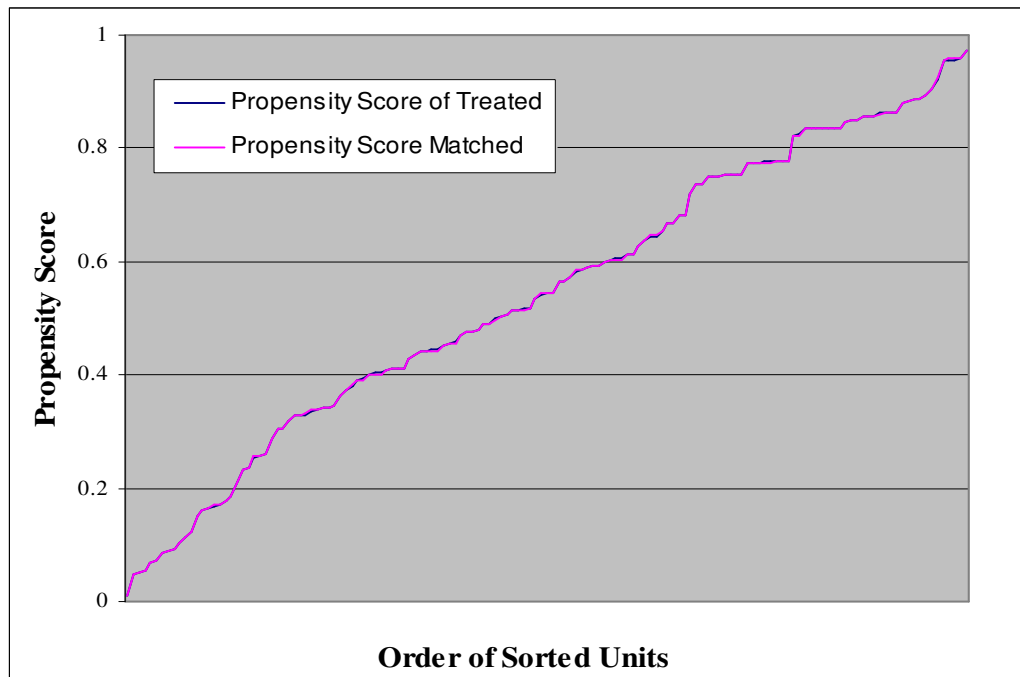


Figure C.2.11. Comparison of Propensity Scores for Below Range Subsample

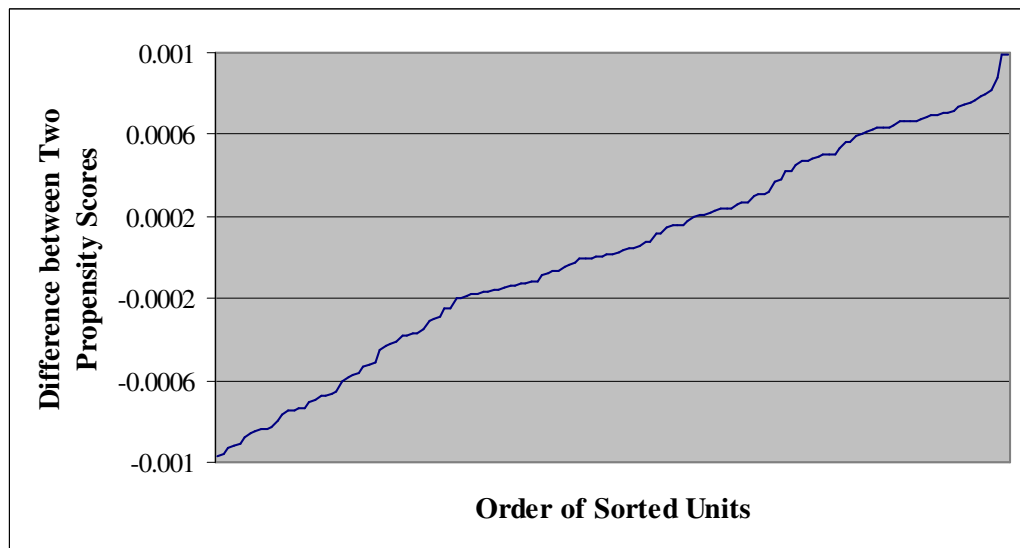


Figure C.2.12. Difference of Propensity Scores between the Treated and the Matched for Below Range Subsample