Essays on Mortgage Credit Risk

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Abstract of the Dissertation

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The dissertation composes of two essays on credit risk in mortgage lending and securitization. The first essay studies the impact of credit rating agency interactions on credit rating quality. The second essay focuses on credit risk of high loan-to-value (LTV) mortgage.

The first essay is an empirical study of credit rating agency behaviors in asset-baked security market. Credit rating agencies serve a critical function in alleviating asymmetric information in financial markets. However, their independence and objectivity have long been a concern of investors and regulators. By analyzing the credit ratings of 17,889 subprime ABS bonds, I identify strategic interactions among credit rating agencies in rating assignments and rating changes. Regression analysis of the probability of rating changes shows that credit ratings are less stable when more rating agencies rate a bond. I distinguish two competing explanations for these higher probabilities, with loose original rating standards as the main cause. The number of original ratings positively correlates with credit support for all rating agencies during the period when subprime credit worsened, demonstrating that rating accuracy decreased when more rating firms rated a bond. Since rating stability can change, I test the impact of multiple ratings on credit rating quality to rule out this alternative explanation for a higher probability of a rating change. For Standard & Poor's, I show that a higher probability of a rating change did not result from a change in rating stability choice, since the probability of a subsequent rating change was not affected by the number of original ratings. For Fitch, the test does not eliminate the alternative explanation. Further analysis of the number of rating changes is consistent with results of the first test.

The second essay takes structured credit modeling approach to show theoretically how loan-to-value (LTV) ratio affects credit risk in mortgage and quantifies the credit risk of first lien mortgage and second lien mortgage. Default risk is derived implicitly. Optionality of defaultable debt results in an upward sloping credit

supply curve in terms of a function of interest rate with respect to LTV. Current regulation in high LTV mortgage is shown to create a funding advantage in separating a high LTV mortgage into a lower funding cost first mortgage and a higher cost second mortgage.

To my dear mother, Shaofang Pan

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Chapter 1 of this dissertation contains reprint of materials in the working paper, "Credti Rating Agency Interaction and Credit Rating Quality", co-authored with Professor Wei Tan.

Chapter 1

Credit Rating Agency Interaction and Credit Rating Quality

1.1 Introduction

The quality of credit ratings is at the foundation of the global financial system because it ensures the stability and efficiency of financial markets. Credit ratings are widely used by investors to assess the credit-worthiness of public securities, and Basel II Accord recommends that banking regulators calculate regulatory capital requirements based on external credit ratings [1]. Credit ratings can mitigate asymmetric information in financial markets at two levels: between deal sponsors and investment managers and between investment beneficiaries and investment managers. If credit ratings are not accurate and misrepresent credit risk, regulations and investment practice based on ratings will be in jeopardy.

Since the subprime mortgage crisis unfolded in 2007, banks worldwide have written down more than $430 billion in structured finance assets[2]. In six separate actions from September 18, 2007, to April 30, 2008, the U.S. Federal Open Market Committee (FOMC) lowered the Federal fund target rate from 5.25% to 2% to save the U.S. economy from falling into recession[3]. During that period, the Federal fund target rate was once cut by 1.25% within 8 days, the fastest pace in 20 years. Bear Stearns, one of the top five investment banks in the U.S. and the second-largest deal sponsor of subprime securitization, almost went bankrupt and was rescued by the Federal Reserve in a forced sale to JP Morgan Chase. From July 2007 to March 2008, financial institutions laid off more than 34,000 employees[4], and another 8,000

[1] International Convergence of Capital Measurement and Capital Standards, Basel Committee on Banking Supervision, June 2006, www.bis.org/publ/bcds128.pdf.

[2] Merrill lynch Posts Fourth Straight Quarterly Loss, Bloomberg News, July 17th, 2008.

[3] Press Release, Federal Open Market Committee (FOMC).

[4] Wall Street Firms Cut 34,000 Jobs, Most Since 2001 Dot-Com Bust, March 24th 2008,

announced job cuts are scheduled for before the end of 2008.

Credit rating agencies have been criticized for causing the crisis by acting in self-interest and misleading investors. Regarding the causes and weaknesses in the financial system that have produced the turmoil, the Financial Stability Forum announced the following statement on the causes and weaknesses in the financial system that have produced the turmoil,[5]

> *Poor credit assessments by CRAs (Credit Rating Agencies) contributed both to the build up to and the unfolding of recent events. In particular, CRAs assigned high ratings to complex structured subprime debt based on inadequate historical data and in some cases flawed models. As investors realized this, they lost confidence in ratings of securitized products more generally.*
>
> *One of the important triggers of the current turmoil was the precipitous decline in confidence in ratings of structured credit products. After assigning high ratings to subprime-related RMBSs and CDOs between 2004 and 2007, and thus contributing to the phenomenal growth of subprime lending, since mid-2007 CRAs have announced an inordinate number of rapid multi-notch downgrades of these instruments. This has raised questions about the quality of credit ratings with regard to structured products.*

Why did credit rating agencies fail so badly in providing objective ratings in structured finance? There are two common explanations: conflict of interest arising in the deal-sponsor-pay business model compromised independence of credit rating agencies, and the number of credit rating agencies is too limited to achieve market efficiency. These two major concerns are not news to regulators. The Credit Rating Agency Reform Act of 2006 created a voluntary registration process for rating agencies that were willing to have their ratings used in federal securities laws to register as a nationally recognized statistical rating organization (NRSRO). The objective of the Act was to improve ratings quality for the protection of investors and to foster accountability, transparency, and competition in the credit rating agency industry in the public interest.[6] The U.S. Securities and Exchange Commission had granted 4 new credit rating agencies NRSRO status by the end of 2007[7].

Bloomberg News.

[5]Report of the Financial Stability Forum on Enhancing Market and Institutional Resilience, Financial Stability Forum, April 2008, http://www.fsforum.org/publications/r_0804.pdf.

[6]Oversight of Credit Rating Agencies Registered as Nationally Recognized Statistical Rating Organizations, Final Rule, effective June 27th 2007. http://www.sec.gov/rules/final/2007/34-55857fr.pdf.

[7]Annual Report on Nationally Recognized Statistical Rating Organizations, U.S. Securities and Exchange Commission, June 2008. http://www.sec.gov/divisions/marketreg/ratingagency/nrsroannrep0608.pdf.

However, it is not obvious how effective the new law will be in helping to improve credit rating quality. First, merely introducing more credit rating agencies may not improve efficiency in the credit rating market. In regular goods and services industries, market forces, particularly competition, increase supply and drive down equilibrium price. However, credit ratings are simply professional opinions about the credit risk of securities and are valuable to the general public only if rating agencies have established a reputation for maintaining trustworthy service; more players with little credibility will not be helpful to investors. Second, credit rating quality may not necessarily improve with more suppliers. Assuming for the moment that more suppliers of rating services do drive price down and that credit ratings are offered at the best quality for the cost paid, the credit rating quality achieved may not reach the minimum standard necessary to guide investors. Last, the two largest credit rating agencies have nearly reached market saturation in many sectors. Although credit ratings are complementary in nature, there is a limit to how many more credit ratings of the same security or debt issuer are functionally necessary and economically feasible.

Little is known about how existing credit rating agencies influence each other in rating decisions. Credit rating agencies publish periodic reviews of their own ratings, but few studies have investigated the impact of one rating agency's action on the others and the differential influence among rating agencies with various market coverage. This limitation restricts insight for financial regulators and hinders effective oversight. For example, in a report on structured finance ratings by the Bank for International Settlements, the working group had to make conjectures about the impact of rating agencies on each other, reporting that, "it would appear that the rating agencies do not treat transactions materially differently when they are the only agency to be approached than when the deal has previously been submitted to another agency." [8] This paper aims to fill in the blanks by providing more empirical evidence and offering additional facts about credit rating agencies' role in the subprime mortgage crisis. We utilize a data set of 17,889 subprime bonds and their credit ratings over 3.5 years to identify strategic behavior of credit rating agencies and analyze the influence of joint ratings on rating quality.

In the following sections, we first provide an overview of asset-backed securitization and review the credit rating market structure in Section 1.2. We summarize related literature in Section 1.3. The data is presented in Section 1.4. We discuss the potential impact of market structure in Section 1.5. Empirical findings are presented in Section 1.6, and tests are conducted in Section 1.7 to rule out alternative explanations for higher probability of rating changes. Section 1.8 discusses the overall findings, and Section 1.9 concludes the paper.

[8] The Role of Ratings in Structured Finance: Issues and Implications, Committee on the Global Financial System, Bank for International Settlements, January 2005. http://www.bis.org/publ/cgfs23.pdf.

1.2 Background

1.2.1 Asset-Backed Securities

Asset-backed securities (ABS) are securities whose cash flows are generated primarily by a discrete underlying pool of self-liquidating financial assets that are pooled and converted into asset-backed securities that can be offered and sold in the capital market.[9] ABS have a short history that begins only in the 1980s. Total ABS outstanding as of the end of 2007 were valued at $2.472 trillion, accounting for 8.4% of all debt outstanding in the U.S. debt market.[10] ABS include securities backed by subprime mortgages[11], auto loans, credit card receivables, student loans, equipment leases, manufactured housing, and even ABS securities from previous securitizations (collateralized debt obligations). Subprime mortgage ABS are the largest sector in the ABS market, with $585.6 billion-23.7% of the ABS market-outstanding.[12] Prime mortgages are securitized in the form of pass-through securities (MBS) and are not regarded as part of ABS by practitioners.

In a typical securitization, the deal sponsor originates or otherwise acquires a pool of receivables and transfers the assets into a stand-alone entity called a Special Purpose Vehicle (SPV). Cash flows from the pooled receivables are redistributed to create a number of ABS with different priorities in receiving principal and bearing losses so that each tranche receives principal cash flow before any tranches that are more junior in priority. This intricate credit subordination structure creates senior tranches with higher credit quality than the underlying pool of receivable assets. Several mezzanine and junior tranches bear higher credit risk than the underlying asset pool and are created to provide credit subordination for senior tranches. Senior tranches usually make up 70% of a subprime ABS deal and are favored by investors with less appetite for credit risk, so they are traded at tighter credit spreads. Tranching and credit subordination help deal sponsors to achieve lower cost of capital in asset securitization than would be achieved by holding the assets on a balance sheet and financing them with regular means.

Information is not equally accessible among parties involved in ABS. The most pronounced asymmetric information problem in the ABS market is that between ABS sponsors and investors. By securitizing receivable assets, sponsors relieve their own capital exposure to risks associated with the collateral, while investors assume the risks and get returns in exchange. Sponsors are either loan originators themselves or have close relationship with the originators and, as such, they have superior information about the quality of the collateral assets. Investors, on the

[9] Regulation Asset Backed, effective March 1st 2005, Securities and Exchange Commission, http://www.sec.gov/rules/final/33-8518.htm.

[10] Securities Industry and Financial Markets Association, Research Report, February 2008.

[11] Subprime mortgages are also referred to as “home equity loans” by practitioners.

[12] Same as above.

other hand, rely on basic disclosure of the underwriting guidelines and loan level characteristics by the sponsor, although they may use past experience and limited historical performance as supplemental information. To alleviate the asymmetric information problem, publicly offered securities are normally rated by third-party credit rating agencies, which can help improve investors' information disadvantage.

1.2.2 Credit Rating of Asset-Backed Securities

Standard and Poor's (S&P), Moody's, Fitch, and DBRS were the only credit rating agencies that rated subprime ABS in the U.S.[13] Rating agencies specialize in evaluating the credit risk of securities, using proprietary models to assess the default risk of the collateral and systematic approaches to evaluate the strength of the deal structure. Sponsors may also reveal non-public information to credit rating agencies.[14]

The rating agencies assign a letter grade to a specific bond based on the perceived long-term credit risk at the time of assignment. For example, Moody's states that its "ratings on long-term structured finance obligations primarily address the expected credit loss an investor might incur on or before the legal final maturity of such obligations vis--vis a defined promise." In general, credit rating grades go from the top credit quality of AAA to AA, A, BBB, BB,B, C, and down to D. Other credit rating agencies have similar letter grade systems. [15] Within each rating grade, rating agencies normally refine rating further into "+" and "-". To facilitate our analysis of rating changes, we define a uniform set of numeric grades in order to differentiate ratings. The correspondence between the numeric grades and ratings of each rating agencies are listed in Table 1.1. Our numeric grades start with 1, which corresponds to the AAA rating, so the higher the number, the higher the credit risk. Rating agencies also interpret rating grades differently. For example, Moody's assigns Aaa rating for bonds "of the highest quality, with minimal credit risk," while S&P presents AAA rating as an indication that the "obligor's capacity to meet its financial commitment on the obligation is extremely strong." Despite slight differences in rating agencies' letter grades, it is a general practice that bonds with BBB- ratings (10 in our numeric grade system) or above are "investment grade," And those

[13]By December 2007, Egan-Jones Rating Company, A.M Best Company Inc., Japan Credit Rating Agency Ltd., Rating and Investment Information Inc. were granted NRSRO status. See Annual Report on Nationally Recognized Statistical Rating Organizations, U.S. Securities and Exchange Commission, June 2008. The author verified that the newly registered NRSRO's had not rated subprime asset-backed securities as of June 2008.

[14]The Fair Disclosure regulation grants special status to credit rating agencies so that issuers or deal sponsors can selectively reveal non-public information to credit rating agencies. See http://www.sec.gov/rules/final/33-7881.htm.

[15]We adopt S&P and Fitch rating codes throughout the paper for notational simplicity. See Table 1.1 for reference.

Numeric Grades	Moody's	S&P	Fitch	DBRS
1	Aaa	AAA	AAA	AAA
2	Aa1	AA+	AA+	AAH
3	Aa2	AA	AA	AA
4	Aa3	AA-	AA-	AAL
5	A1	A+	A+	AH
6	A2	A	A	A
7	A3	A-	A-	AL
8	Baa1	BBB+	BBB+	BBBH
9	Baa2	BBB	BBB	BBB
10	Baa3	BBB-	BBB-	BBBL
11	Ba1	BB+	BB+	BBH
12	Ba2	BB	BB	BB
13	Ba3	BB-	BB-	BBL
14	B1	B+	B+	BH
15	B2	B	B	B
16	B3	B-	B-	BL
17	Caa1	CCC+		
18	Caa2	CCC	CCC	
19	Caa3			
20	Ca	CC	CC	
21	C	C	C	C
22		D	D	

Table 1.1: Rating Grade

below BBB- are "speculative grade." C or D ratings are normally for bonds already in default with, as Moody's phrases it, "little prospect for recovery of principal or interest."

Theoretically, external credit ratings are independent measures of credit risk and are publicly available to any parties that need to assess the credit risk of rated securities. In practice, external credit ratings are often used to establish investment mandates. Conventional investors, such as mutual funds, pension funds, insurance companies, and corporate treasury portfolios, are required by their investment mandates to invest only in "investment grade" bonds so, if a bond is downgraded from investment grade to speculative grade, conventional investment managers may have to take action. Certain portfolios even have restrictions to invest only in AAA-rated bonds and may have to sell the security if it is downgraded. Cantor et al. (2007) analyzed the survey results of 200 plan sponsors and investment managers in the U.S. and Europe regarding the use of credit ratings in investment activities and found that 24% of survey participants had client-specific guidelines on rating downgrades and that 16% would conduct an internal review if a bond was downgraded below retention criterion. Banking regulators also adopt external credit ratings as standards by which to assess capital efficiency. For example, Basel II assigns risk weights to bank portfolios based on external ratings provided by rating agencies [16]. White (2001) provided additional details about safety-and-soundness regulations with regard to credit ratings and bank security holdings.

Structured finance credit ratings are based on a quantitative model of default probability and losses. Moody's assigns subprime ABS rating through hundreds of cash flow projection scenarios, including some stress cases for the collateral. S&P's subprime ABS rating analytic system determines default probability and loss severity of each loan based on loan characteristics and aggregates that for the entire asset pool. All rating agencies publish and disseminate rating methodology documents and rating action reviews free of charge to the public. Most rating agencies offer their clients rating analytical software, which helps to improve transparency of rating methodologies. [17] Rating agencies also conduct periodic review of their ratings and release reports to the public on observed default frequencies for each rating categories.

Obtaining a credit rating is a crucial step in ABS securitization. With a pool of assets accumulated for securitization, sponsors first establish a tentative deal structure and collateral composition. Then they send the collateral information and deal structure to credit rating agencies to obtain rating feedback. Based on market trad-

[16] International Convergence of Capital Measurement and Capital Standards, Basel Committee on Banking Supervision, June 2006.

[17] Moody's markets its subprime ABS rating analytics, M3, to paid subscribers, and S&P makes its analytics, Levels, commercially available. However, these and other fee-based rating related services raise the concern of conflict of interests. We will discuss this issue in the next sub-section.

ing activities and discussions with credit rating agencies, sponsors may change the deal structure or the collateral composition slightly to maximize profit. The finalized asset pool and deal structure are reviewed by rating agencies, and initial ratings are assigned to the ABS, which, along with initial credit ratings, are then presented and offered to investors. In order for a bond to achieve certain credit rating, it has to satisfy credit rating agencies' requirement for credit enhancement. Credit rating agencies' rating standards thus set the minimum requirement for tranche subordination and credit enhancement.

After a bond is issued, rating agencies continue monitoring its credit quality until its maturity and may take further rating action when necessary. Rating agencies' discretion includes timing, direction, and magnitude of rating changes, and ratings can be upgraded and/or downgraded several times before a bond is fully paid off. Rating changes to bonds within the same deal are determined by asset pool performance and the strength of deal structure, and downgrades or upgrades usually occur from the bottom of the capital structure, beginning with more junior bonds; thus, the ratings of lower-rated bonds tend to be more volatile.

Given that ratings are intended to be for the long-term, a rating change indicates inaccuracy of the initial (or previous) rating. Cantor and Mann (2006) argued that there is a trade-off between credit rating accuracy and stability. For example, if a bond actually rates a credit rating below what is currently assigned, but its credit risk is perceived to be improving, the rating agency may prefer to wait till the credit risk stabilizes before taking further action, arguing that some market participants may be better served by more stable than more accurate ratings. It is up to the credit rating agency to decide how to position itself in terms of rating accuracy and stability, so credit ratings may not reflect the true credit risk at a point in time. This adds another complexity to the analysis of credit rating quality.

Several features of the credit rating process are worth special notice. First, credit rating agencies typically assign initial ratings to bonds simultaneously-all the agencies making assignments at once-instead of one after the other. Cheaper funding costs and better liquidity are primary reasons for asset securitization, so sponsors benefit from completing a securitization as soon as possible, typically within a few months. (It takes time for a sponsor to accumulate enough assets as collateral, and the credit rating process takes a month or two.) Sponsors decide early on which credit rating agencies to work with and, once the asset pool is finalized, the sponsor calls on the rating agencies all at once to start the credit-rating process. In addition, once credit ratings are assigned, they are rarely rejected by the sponsor since seeking additional ratings sequentially or rejecting preliminary ratings can be viewed by investors as a negative signal. However, deal sponsors do have discretion to release or reject ratings by a credit rating agency. Rejecting unfavorable ratings without valid reason will likely raise red flags to investors and, in extreme cases, can expose the deal sponsor to security fraud litigation. If preliminary ratings are rejected by a sponsor-difficult as it is to believe-rating agencies will not publish those ratings on their own.[18]

Second, ABS credit rating is an iterative process and credit rating agencies play a significant role in deal structuring. Because the asset pool is transferred from a sponsor's balance sheet and is isolated into a SPV, the sponsor has few constraints in the choice of capital structure. Cheaper overall funding cost is almost the only consideration in deal structuring, and the sponsor often decides what rating is desired for each tranche and structures them accordingly (IOSCO 2008)using rating agency models and analytical software. Feedback from rating agencies during the initial rating process also allows the sponsor to change the deal structure to achieve the desired ratings. Both BIS (2005) and IOSCO (2008) expressed concern that intensive involvement in deal structuring makes rating agencies more susceptible to conflict-of-interest problems.

Third, when multiple credit rating agencies are designated, they usually are aware that other agencies are working on the same deal. They do not directly discuss credit ratings with each other, but the iterative nature of the ABS rating process, which contributes to this awareness, may indirectly convey information among rating agencies. We will discuss this point in detail later.

Fourth, sponsors normally have long-term relationship with certain credit rating agencies and may benefit from working with the same credit rating agencies because of the sponsor's familiarity with the agency's rating methodologies and the agency's familiarity with the sponsor's typical deal structure. In addition, credit rating agencies offer discounted fees for large issuance volumes-another potential conflict-of-interest trap, as agencies may be disinclined to risk a lucrative relationship by presenting lower-than-expecting ratings. Of course, satisfaction with a past working relationship may also explain a long-term relationship.

Finally, in the ABS market, credit rating agencies are selected to rate a deal at its issuance and do not expand coverage to bonds that they do not rate initially. What's more, unlike in corporate credit ratings, rating agencies do not publish unsolicited ABS ratings.

1.2.3 Market Structure

Credit rating services have unique features that differentiate them from other regular goods or service markets. They belongs to the broad category of the information certification business because they express opinions about the credit quality of an asset, although the credit opinion may or may not add value to existing knowledge possessed by other market participants. Who pays for credit ratings and how much is paid have a profound impact on the efficiency of this market. In this subsection, we will discuss key market structure issues in subprime ABS credit ratings,

[18]Rating agencies do publish unsolicited ratings in corporate credit ratings. See White (2001).

namely, lack of competition, conflicts of interest, and credit rating quality.

The credit rating market is dominated by few players. White (2001) reported that there had been no more than five credit rating agencies in service in the U.S. at any point in time throughout the history of credit rating service[19], and some credit rating firms have been absorbed by others through mergers and acquisitions. The situation is similar in other countries. [20] Lack of competition in the credit rating industry has long been a concern. In the U.S., the Credit Rating Agency Reform Act of 2006 was passed into law to standardize registration and regulation of credit rating agencies and foster competition in the industry. The U.S. Senate Report states that the Act aims to "enhance competition and provide investors with more choices, higher quality ratings, and lower costs" [by] "eliminating the artificial barriers to entry".[21]

After the implementation of the Credit Rating Agency Reform Act in 2007, credit rating agencies registered as NRSROs and, by the end of 2007, there were 10 such entities. In our data sample period from 2004 to 2007, S&P and Moody's each rated more than 94% of subprime ABS bonds at origination, while Fitch and DBRS rated 56.5% and 10.9% of subprime ABS bonds, respectively. With these figures, the Herfindahl-Hirschman Index for this market is 3233, much larger than the threshold of 1800 for a highly concentrated market. Current competition in this market is roughly equivalent to three players with equal market share.

Economy of scale is a natural barrier to entry. Relationships with major sponsors help larger credit rating agencies ensure a steady flow of new business. Rating agencies establish a knowledge base about deal structure and underwriting practice through experience, which also facilitate their future business. Obviously, larger business volume will enable a rating agency to invest more in its analytical system and market surveillance infrastructure, and better analytics generally mean a better product and more customers. Reputation is another barrier to entry, since it takes time for market participants to understand and accept a new rating methodology: Rating agencies each establish their own set of rating methodology and standards, so reading rating standards literally does not shed much light on how the methodology and standards will be executed in practice. To fully grasp the rating standards, investors need to observe enough bonds rated by a new credit rating agency to be able to compare ratings with actual bond performance.

[19] Up till the time when the paper was written in 2001. As noted earlier, more credit rating agencies were granted status to offer credit rating service for public securities after 2007.

[20] White (2001) and Hill (2004) have more historical details.

[21] The U.S. Securities and Exchange Commission (SEC) granted very few bond rating service providers status as Nationally Recognized Statistical Rating Organizations (NRSRO) in the past three decades . Thus, regulatory registration has potentially limited the number of credit rating agencies. See also White (2001). (The term, NRSRO, was adopted earlier by SEC even though no law had been established to regulate NRSRO until 2006.)

Credit rating agencies are normally compensated by bond issuers[22]. In the subprime ABS market, all credit rating agencies rate bonds at sponsors' requests only and are compensated by sponsors in the form of an upfront fee. This differs from the corporate credit rating market, where Moody's and S&P rate the entire universe of corporate entities, whether solicited or unsolicited. Unsolicited ratings are euphemistically known as "investor-requested ratings". [23] The current fee charged by Moody's for deal sponsor solicited ratings is 3.25 basis points based on the original balance at issuance, with a minimum fee of $25K and maximum fee of $130K. S&P has fee schedule similar to Moody's, and Fitch charges less. Because a volume discount is generally offered to large sponsors, the exact service fee is difficult to estimate but, in general, fee income increases with deal size for these three rating agencies. DBRS has a fixed fee schedule of $50K, regardless of deal size and adjusts the charge slightly for deals with more complex structures. Since the typical ABS deal size is in the range of $200 million to $1 billion, DBRS's fee charge is cheaper than Moody's or S&P's. [24] Interestingly, credit rating agencies with the larger market coverage charge more expensive fees.

Ancillary service income adds incentives for rating agencies to promote the growth of the ABS market and may affect rating agencies' independence in rating opinions. Moody's and S&P both make their rating analytics software commercially available for pre-structuring and loss estimation, Moody's and Fitch promote a fee-based data service for the subprime ABS market, and S&P and Fitch both offer a third-party pricing service for ABS investors. Subscriptions to credit research reports and market commentaries are also offered for a fee; for example, Moody's web site, Economy.com, is accessible to paid subscribers.

In normal business conditions, credit rating agencies are very profitable. Moody's had an average 44% Return on assets from 1995 to 2000 and, from 2000 to 2007, its total assets grew 4.3 times while its average ROA was 41% and its average net profit margin was 30%.[25] Most of the growth was contributable to structured products ratings and ancillary fee income. As of June 2008, only 25 companies in the S&P 500 stock index had a profit margin of more than 30%; Moody's was in the top 5 percentile of performers. Its pricing is far from competitive, which will yield no economic profit. For Fitch, which is 80 percent owned by Paris-based Fimalac SA, a publicly listed investment company, performing structured finance ratings accounted for 51 percent of total revenue of $480.5 million in their 2006 fiscal year. New York-based McGraw-Hill Cos., which owns S&P, reported that the credit rat-

[22]Egan-Jones, which recently registered as an NRSRO in the U.S., advocates the investor-pay business model. As of June 2008, Egan-Jones did not rate ABS.

[23]S&P reportedly publicized unsolicited ratings to gain market share when it started rating insurance companies. See Doherty and Kartasheva (2008).

[24]Based on White (2001) and discussion with staff of credit rating agencies.

[25]Calculated based on Moody's annual financial report from 2000 to 2007.

ing company's revenue rose by 20 percent to $2.7 billion in 2006, and almost half of that growth was from increased sales of structured finance ratings. McGraw-Hill's shares of S&P more than doubled in value from 2003 to May 2007. [26]

Conflicts of interest arise with the business model because the deal sponsors pay for the rating service and hold a great deal of market power and because the agencies' compensation is not linked to ex post rating quality as measured by realized default and losses in any way. As noted in BIS (2005), a possible outcome of these factors could be that initial ratings are more favorable and downgrades less frequent than would be ideal.

Other professional certification services are similar to credit rating services, e.g., auditors, real estate appraisers, school ranking providers, and sell-side analysts who make investment recommendations. These face similar problems related to conflicts of interest as auditors and sell-side investment analysts are compensated either directly or indirectly by the party being evaluated. The collapse of Enron as a result of an accounting scandal led to the dissolution of Arthur Anderson, once one of the world's largest auditors. Several investment banks have also paid billions of dollars to settle charges of misleading investors. [27] Conflicts of interest jeopardized quality of service and led to disastrous outcomes in these cases. Because the number of deal sponsors in the ABS market is limited-in our data set of 17,889 bonds and 45,093 corresponding initial ratings assigned by the four credit rating agencies, there are only 92 deal sponsors and not all of them were active through the observation period-deal sponsors have tremendous market power.

Rating agencies' reputation sustains business revenue in the long term, motivating self-discipline. If a rating agency is recognized by investors for good quality, deal sponsors may be more likely to pay for their service as investors are more likely to buy bonds rated by that agency, and the rating agency may be able to charge a higher fee for its reliable "stamp of approval." Credit rating agencies also have a collective incentive to maintain a certain level of service quality to ensure sustained growth in ABS securitization since, with prosperity in this market, rating agencies will all enjoy larger fee income in the long run.

However, reputation-building has substantial time lag. On one hand, good reputation requires years of consistent effort in maintaining rigorous rating practices. On the other hand, irresponsible ratings often remain unknown until bond performance materializes. The recent subprime crisis demonstrated that reputation is not a mechanism strong enough for rating agencies to overcome conflicts of interest. No new subprime deals were issued in 2008 after the precipitous deterioration in subprime credit and the gigantic wave of rating downgrades. If rating agencies were more concerned about long-term reputation and weren't tempted by short-term greed, the ratings might have been more prudently assigned.

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[26] Bloomberg News, http://www.bloomberg.com/news/marketsmag/ratings.html

[27] BBC News, June 15, 2005.

1.3 Related Literature

Studies on a broad range of topics in information economics relate to the research of credit rating quality. As discussed in the previous sections, credit rating agencies are certification intermediaries that express opinions about the credit quality of publicly traded securities, but an asymmetric information problem is present between security issuers and investors. Setting aside for the moment the conflict of interest problem resulting from the fee payment process, even if credit ratings do not reveal additional private information to the public, they deepen market participants' awareness about others' beliefs. Once a rating is announced by a rating agency, other rating agencies will be informed and, over time, ratings may synchronize. Aumann (1976) showed that people with the same prior beliefs cannot "agree to disagree" in this way because credit rating opinions increase common knowledge and affect the path by which the market reaches consensus.

Lizzeri (1999) studied information revelation by certification intermediaries in general. In his model, specialized agent(s) search out the information held by privately informed agents and reveal part of it to uninformed parties. The paper shows that a unique equilibrium exists when a monopoly information intermediary reveals nothing and captures the entire informational surplus in the market. In the special case when a poor product generates a harmful outcome (credit loss, in this case), the information intermediary is shown to certify only types of information that do not harm the unique equilibrium. In this case, the information intermediary improves market efficiency by eliminating undesirable types of information. When there are a number of intermediaries, Lizzeri concluded that all information is revealed; at least two intermediaries will set the zero-profit price in a set of equilibria.

There are, however, notable departures from the model assumptions in the reality of the credit rating market that are critical in predicting equilibrium outcome. First, the model ignores the possibility that credit rating agencies can misrepresent credit quality so that credit rating quality cannot be perfectly observed by investors. As a result, information disclosure contracts represented by credit rating agencies before rating assignments cannot be effectively enforced. Assigning ratings better than the true credit quality of the bonds can increase the fee income of credit rating agencies and, thus, cannot be ruled out as a dominant strategy. Second, the model does not capture the dynamic nature of agencies' reputations for credit rating quality and thereby misses an important enforcement mechanism in the credit rating market. Last, it assumes that only one rating is purchased by the bond issuer and ignores the information value of multiple credit ratings. The signals that credit rating agencies receive about the asset type may be imperfect and complementary to each other, so credit rating agencies can differentiate their services and increase the information content of ratings. Prince (2005) argued that one credit rating conveys only one dimension of credit quality, and multiple ratings using different methodologies will help to reveal more about the distribution of default. Because of these significant departures in Lizzeri (1999), competition may not make credit rating agencies reveal all information or charge fees where no economic profit will be generated. A reputation crisis resulting from poor rating quality may also occur.

Few empirical studies have analyzed the impact of the interactions among credit rating agencies on credit rating quality. Cantor (1996) researched corporate bond ratings and showed that the credit rating agency with the lowest market share rates companies more generously, explaining it in terms of selection bias, i.e., the smallest agency's service is sought only when the issuing company knows that it will get a favorable rating. Given that ABS bond ratings are all solicited by deal sponsors, selection bias can be an important issue. In our empirical analysis, we use instrumental variables to control for selection bias, which is an alternative to the Heckman method applied in Cantor (1996). Cantor and et al (2007) compared joint ratings of structured finance securities and showed that differences in ratings vary substantially across sectors, are greater for below-investment grade ratings than for investment-grade ratings, and have a tendency to increase with the seasoning of the security.

Several empirical studies on the information content of credit ratings found that the market reacts to credit rating downgrades with widening spreads. Market reaction is indirect evidence that credit ratings contain information not yet known by some market participants. Using corporate bond data, Covitz and Harrison (2003) found that rating agencies are motivated primarily by reputation-related incentives and that conflicts of interest do not significantly influence rating changes. Hu and Cantor (2005) showed that new issue spreads widen after downgrade rates rise on outstanding securities within the same asset class. Ammer and Clinton (2004) used a sample of more than 1,300 ABS bonds with changes in ratings and found that rating downgrades tend to be accompanied by negative returns and widening spreads and that ABS market participants appear to rely more on rating agencies as source of negative news about credit risk; in contrast to downgrades, market reaction to ABS rating upgrades are virtually zero. Hull and et al (2004) found that reviews for downgrades contain significant information, but downgrades and negative outlooks do not.

Empirical studies of other markets have shown that revelation of product quality information enforces service providers to increase product quality. Jin (2005) studied the case of Los Angeles County's requirement that hygiene-quality grade cards be displayed in restaurant windows and showed that the requirement that the information be so publicly displayed improved restaurant hygiene and increased the sensitivity of consumer demand to changes in hygiene quality. Under the influence of conflicting financial incentives, however, credit rating agencies may not be as objective as the government staff which conducted the restaurant inspections in Los Angeles, so credit ratings may be less effective in improving security market efficiency. In terms of methodology, we adopt regression techniques similar to that used in Jin (2005). From the perspective of credit rating agency regulation, Jin (2005) suggested that publicly revealed evaluation of rating agencies' performance may help to improve rating quality.

1.4 Data

The data set is composed of 17,889 subprime mortgage bonds issued from the beginning of 2004 to the end of 2006 [28]. Each bond is identified by a unique CUSIP (a standard security ID). Bond characteristics and initial credit ratings are obtained from Intex[29] and rating agencies. Subsequent ratings-until the end of 2007- are obtained from Bloomberg. Only those bonds with CUSIPs recognized by both data sources are included.

A typical deal is presented in Table 1.2. For each bond, we observe certain deal-level characteristics, such as sponsor, Intex deal name, original balance, number of bonds, number of dealers, sponsor name, and closing date. For example, Bond 1 in Table 1.2 was issued by Countrywide ABS Trust on March 31, 2004, as part of a securitization with Intex identifier CWHE0404. The original balance of the deal was $1.674 billions, and there are 13 bonds issued with two dealers involved in selling the securities. We also observe certain bond level characteristics at the time of issuance, such as the original balance of the bond, original credit support, coupon interest rate, tranche name, and whether the bond coupon has a fixed rate. For example, Bond 1, a senior floating-rate bond with tranche name "2A," had an original balance of $340 million with original credit support of 19.05% at issuance. Its coupon interest rate was 5.52%. We also observe the number of rating agencies that rated the bond, their original rating(s), and subsequent rating change(s) by each rating agency. Using Bond 2 as an example, Moody's, S&P, and Fitch gave it original ratings of Ba3, BB+, and BB+, respectively. DBRS did not rate this bond. Moody's changed its rating to Caa1 on May 16, 2007; S&P changed its rating to B on October 15, 2007; and Fitch changed its rating twice, first to BB on May 10, 2007, and then to C on December 11, 2007.

The top section of Table 1.3 shows the total original balance of bonds that each rating agency rated in each year and the percentage of bonds that they rated respectively. Subprime ABS bond issuance volume was $368.1 billion in 2004, $458.6 billion in 2005, and $456.5 billion in 2006. During this period from 2004 to 2006, S&P had the largest market coverage and rated 98.0% of bonds in terms of balance;

[28] Bonds structured off prepayment penalty cash flows, net interest margin securities, and interest-only bonds bear little credit risk and are excluded from the data. Bonds with scratch-and-dent mortgage collateral or second-lien collateral are excluded because of the difference in collateral performance and deal structure from regular subprime ABS bonds.

[29] Intex is a major ABS analytical software vendor and data provider.

Variable Description	Bond 1	Bond 2
CUSIP	1266715F9	004421MN0
Intex Deal Name	CWHE0404	ACE05HE2
Sponsor Name	Countrywide ABS	Ace Securities Corp.
Number of Dealers	2	1
Closing Date	3/31/04	3/29/05
Tranche Name	2A	B1
Tranche Type	Senior Floater	Mezzanine Floater
Deal Original Balance ($ billions)	1.674	1.219
Bond Original Balance ($ millions)	340.0	16.5
Coupon Interest Rate (%)	5.52	8.755
Original Support of the Bond (%)	19.05	1.2
Number of Bonds in the Same Deal	13	16
Moody's Original Rating	Aaa	Ba3
S&P Original Rating	AAA	BB+
Fitch Original Rating		BB+
DBRS Original Rating		
Moody's Rating at 1st Rating Change		Caa1
Moody's 1st Rating Change Date		5/16/07
S&P Rating at 1st Rating Change		B
S&P 1st Rating Change Date		10/15/07
Fitch Rating at 1st Rating Change		BB
Fitch 1st Rating Change Date		5/10/07
Fitch Rating at 2nd Rating Change		C
Fitch 2nd Rating Change Date		12/10/07

Table 1.2: Examples of Bond Observation

Moody's rated 94.3% of bonds issued; Fitch, the third largest rating agency, rated 56.5% of bonds issued; and DBRS rated 10.9% of the bonds. The bottom section of Table 1.3 shows the number of bonds rated and the market coverage in terms of the number of bonds rated for each agency by year. The number of bonds rated increased from 4,511 in 2004 to 6,944 in 2006. The market coverage by number of bonds rated show similar pattern. S&P's market coverage was at 96.8%, followed by Moody's at 89.7%, Fitch at 53.3% and DBRS at 12.2%.

Table 1.4 shows market coverage by combinations of credit rating agencies in terms of number of bonds. The majority of bonds are jointly rated by two (45.5%) or three (42.2%) rating agencies. Bonds rated jointly by Moody's and S&P only, the combination with the largest market coverage, account for 39.0%. The second-largest combination is joint rating by Moody's, S&P, and Fitch, with market coverage of 38.3%, so 87.8% of the bonds is rated by both Moody's and S&P. Less than

Vintage	Balance ($mm)					Market Coverage by Balance (%)			
	Moody's	S&P	Fitch	DBRS	Total	Moody's	S&P	Fitch	DBRS
2004	338,894	364,833	222,025	24,168	368,054	92.1	99.1	60.3	6.6
2005	421,941	444,872	284,337	53,511	458,571	92.0	97.0	62.0	11.7
2006	449,121	447,489	218,374	62,713	456,492	98.4	98	47.8	13.7
Total	1,209,956	1,257,194	724,736	140,392	1,283,117	94.3	98.0	56.5	10.9
Vintage	# of Bonds Rated					Market Coverage by # of Bonds Rated (%)			
	Moody's	S&P	Fitch	DBRS	Total	Moody's	S&P	Fitch	DBRS
2004	3959	4445	2601	269	4511	87.8	98.5	57.7	6
2005	5443	6132	3814	889	6434	84.6	95.3	59.3	13.8
2006	6651	6748	3125	1017	6944	95.8	97.2	45	14.6
Total	16053	17325	9540	2175	17889	89.7	96.8	53.3	12.2

Table 1.3: Market Coverage

# of Joint Rating(s)	Rated by Moody's	Rated by S&P	Rated by Fitch	Rated by DBRS	# of Bonds	Market Coverage (%)
One Agency	Rated	-	-	-	54	0.3
	-	Rated	-	-	654	3.7
	-	-	Rated	-	136	0.8
	-	-	-	Rated	40	0.2
Subtotal	-	-	-	-	884	4.9
Two Agencies	Rated	Rated	-	-	6,968	39
	Rated	-	Rated	-	224	1.3
	Rated	-	-	Rated	16	0.1
	-	Rated	Rated	-	835	4.7
	-	Rated	-	Rated	69	0.4
	-	-	Rated	Rated	23	0.1
Subtotal	-	-	-	-	8,135	45.5
Three Agencies	-	Rated	Rated	Rated	79	0.4
	Rated	-	Rated	Rated	71	0.4
	Rated	Rated	-	Rated	548	3.1
	Rated	Rated	Rated	-	6,843	38.3
Subtotal	-	-	-	-	7,541	42.2
Four Agencies	Rated	Rated	Rated	Rated	1,329	7.4
Total					17,889	100

Table 1.4: Joint Market Coverage of Credit Rating Agencies

12.3% are either rated by only one rating agency or rated by all four agencies.

The distribution for original ratings is summarized in Table 1.5, sorted by numerical rating grade, as in Table 1.1. Table 1.5 shows S&P letter grades, but the corresponding letter grades for other rating agencies can be found in Table 1.1. Moody's, S&P, and Fitch resemble each other in how their original ratings are distributed; by original balance, AAA rating accounts for roughly 83.2%, 83.1%, and 82.1% for Moody's, S&P, and Fitch, respectively. By number of bonds rated, AAA ratings account for 36.2%, 34.9%, and 34.7% for Moody's, S&P, and Fitch, respectively. Since AAA bonds normally have much larger balances than do junior tranches of the capital structure, the percentage of AAA rated bonds by original balance is larger than that calculated based on the number of bonds.

Excluding AAA rated bonds, other investment-grade bonds make up 58.5%, 60.5%, and 60.5% of the bonds rated by Moody's, S&P, and Fitch, respectively, by number of bonds rated. Below-investment-grade ratings account for roughly 5.3%, 4.6%, and 4.8% of bonds rated by Moody's, S&P, and Fitch, respectively. The rare occurrence of below-investment-grade rating is attributable to proximity of collateral credit quality relative to rating agencies' investment grade standards and lack of interest from investors to invest in speculative-grade bonds. Deal sponsors normally take the concentrated risk of speculative grade tranches in the form of holding residual interest in asset-backed securitization.

DBRS' ratings distribution exhibits a distinctly different pattern from that of the other rating agencies; it assigns far fewer AAA ratings to bonds-only 77.3% by balance and 27.6% by number of bonds rated, which is 6-7% lower than the other rating agencies. DBRS also assigns more below-AAA investment-grade ratings than other rating agencies, at 66.1% by number of bonds rated, and its below-investment-grade rating percentage is higher than that of the others, at 6.3%.

The ratings distribution at the end of 2007 is summarized in Table 1.6. During the observation period from bond issuance till the end of 2007, rating agencies downgraded a substantial portion of subprime bonds. Compared with the original rating distribution (Table 1.5), there were many more bonds rated below-investment-grade at the end of 2007 across all four rating agencies; for example, the percentage of below-investment-grade bonds increased from 5.3% to 16.8% among all bonds rated by Moody's. Hundreds of bonds were downgraded to CCC or below, signaling proximity to default. Compared with other rating firms, Moody's had the most bonds downgraded into this category. S&P downgraded 927 bonds to CCC. Rarely were any AAA-rated bonds downgraded; S&P downgraded the most AAA-rated bonds of all the agencies: 25 out of 6,054 bonds or 0.58%. As a result of the pattern of rating changes, the number of investment-grade bonds is roughly 10% less across all four rating agencies by the end of 2007 than at issuance.

Our analysis of credit rating quality focuses largely on rating changes. We compare the original rating and the final rating at the end of 2007 for each bond and

Num		Moody's				S&P				Fitch				DBRS			
Grade	S&P Grade	# of Bonds	Bal $mm	% by Bal	% by #	# of Bonds	Bal $mm	% by Bal	% by #	# of Bonds	Bal $mm	% by Bal	% by #	# of Bonds	Bal $mm	% by Bal	% by #
1	AAA	5812	1008	83.2	36.2	6054	1045	83.1	34.9	3309	595	82.1	34.7	600	109	77.3	27.6
2	AA+	827	35	2.9	5.2	1234	47	3.7	7.1	670	29	4	7	166	7	5	7.6
3	AA	1208	46	3.8	7.5	1576	50	4	9.1	765	28	3.9	8	169	6	4.3	7.8
4	AA-	868	18	1.5	5.4	873	16	1.3	5	481	10	1.4	5	130	3	2.1	6
5	A+	815	16	1.3	5.1	1015	19	1.5	5.9	529	11	1.5	5.5	147	3	2.1	6.8
6	A	1202	25	2.1	7.5	1261	23	1.8	7.3	714	15	2.1	7.5	168	3	2.1	7.7
7	A-	1100	16	1.3	6.9	1080	14	1.1	6.2	641	9	1.2	6.7	160	2	1.4	7.4
8	BBB+	1132	15	1.2	7.1	1204	14	1.1	6.9	673	9	1.2	7.1	179	2	1.4	8.2
9	BBB	1174	13	1.1	7.3	1159	12	1	6.7	737	8	1.1	7.7	169	2	1.4	7.8
10	BBB-	1072	11	0.9	6.7	1071	10	0.8	6.2	560	6	0.8	5.9	149	2	1.4	6.9
11	BB+	527	5	0.4	3.3	514	5	0.4	3	296	3	0.4	3.1	89	1	0.7	4.1
12	BB	303	3	0.2	1.9	255	2	0.2	1.5	148	2	0.3	1.6	44	1	0.7	2
13	BB-	12	0	0	0.1	20	0	0	0.1	9	0	0	0.1	2	0	0	0.1
14	B+					6	0	0	0	6	0	0	0.1	3	0	0	0.1
15	B	1	0	0	0	2	0	0	0	2	0	0	0				
16	B-																
17	CCC+																
18	CCC																
19	CCC-																
20	CC																
21	C																
2-10		9398	195	16.1	58.5	10473	205	16.3	60.5	5770	125	17.2	60.5	1437	30	21.3	66.1
11+		843	8	0.7	5.3	797	7	0.6	4.6	461	5	0.7	4.8	138	2	1.4	6.3
Total		16053	1211	100	100	17324	1257	100	100	9540	725	100	100	2175	141	100	100

Table 1.5: Original Rating Distribution

Num		Moody's				S&P				Fitch				DBRS			
Grade	S&P Grade	# of Bonds	Bal $mm	% by Bal	% by #	# of Bonds	Bal $mm	% by Bal	% by #	# of Bonds	Bal $mm	% by Bal	% by #	# of Bonds	Bal $mm	% by Bal	% by #
1	AAA	5811	1004	82.9	36.2	6019	1038	82.5	34.9	3298	593	82	34.6	622	109	76.8	28.7
2	AA+	818	36	3	5.1	1201	46	3.7	7	642	28	3.9	6.7	160	6	4.2	7.4
3	AA	1179	46	3.8	7.3	1490	50	4	8.6	689	25	3.5	7.2	149	6	4.2	6.9
4	AA-	850	18	1.5	5.3	815	16	1.3	4.7	435	9	1.2	4.6	116	3	2.1	5.4
5	A+	580	12	1	3.6	907	17	1.4	5.3	474	10	1.4	5	135	3	2.1	6.2
6	A	899	19	1.6	5.6	1064	19	1.5	6.2	599	13	1.8	6.3	128	3	2.1	5.9
7	A-	843	13	1.1	5.3	847	11	0.9	4.9	525	9	1.2	5.5	148	2	1.4	6.8
8	BBB+	794	11	0.9	4.9	1004	13	1	5.8	524	7	1	5.5	106	2	1.4	4.9
9	BBB	832	10	0.8	5.2	799	9	0.7	4.6	540	7	1	5.7	93	1	0.7	4.3
10	BBB-	749	9	0.7	4.7	580	6	0.5	3.4	452	7	1	4.7	136	2	1.4	6.3
11	BB+	403	5	0.4	2.5	249	3	0.2	1.4	220	2	0.3	2.3	49	1	0.7	2.3
12	BB	321	4	0.3	2	555	9	0.7	3.2	319	5	0.7	3.3	57	1	0.7	2.6
13	BB-	194	3	0.2	1.2	29	0	0	0.2	112	1	0.1	1.2	62	1	0.7	2.9
14	B+	154	2	0.2	1	50	1	0.1	0.3	109	1	0.1	1.1	55	1	0.7	2.5
15	B	149	2	0.2	0.9	686	10	0.8	4	235	3	0.4	2.5	78	1	0.7	3.6
16	B-	475	6	0.5	3	19	0	0	0.1	11	0	0	0.1	52	0	0	2.4
17	CCC+	107	1	0.1	0.7												
18	CCC	94	1	0.1	0.6	927	10	0.8	5.4	103	1	0.1	1.1				
19	CCC-	86	1	0.1	0.5												
20	CC	239	3	0.2	1.5					38	0	0	0.4				
21	C	476	5	0.4	3					215	2	0.3	2.3	21	0	0	1
2-10		7544	174	14.4	47	8707	187	14.9	50.5	4880	115	15.9	51.2	1171	28	19.7	54
11+		2698	33	2.7	16.8	2515	33	2.6	14.6	1362	15	2.1	14.3	374	5	3.5	17.3
Total		16053	1211	100	100	17241	1258	100	100	9540	723	100	100	2167	142	100	100

Table 1.6: Rating Distribution at the End of 2007

# of Rating Changes	Moody's		S&P		Fitch		DBRS	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
0	7,018	68.5	8,486	75.3	4,261	68.4	996	63.2
1	2,552	24.9	2,172	19.3	1,792	28.8	446	28.3
2	604	5.9	536	4.8	160	2.6	105	6.7
3	67	0.7	66	0.6	16	0.3	20	1.3
4			11	0.1	2	0	7	0.4
5							1	0.1
Total	10,241	100.0	11,271	100.0	6,231	100.0	1,575	100.0

Table 1.7: Number of Rating Changes (Excluding Originally AAA Rated Bonds)

count the number of rating changes by each rating agency. Table 1.7 summarizes number of rating changes by rating agency for the entire sample, excluding AAA-rated bonds. As demonstrated earlier, AAA-rated bonds were rarely downgrade. Thus, we exclude AAA-rated bonds from subsequent analysis.

There are no more than 5 rating changes of a single bond by the same rating agency in the sample. S&P ratings are the most stable, with 75.3% bonds retaining their original rating. Moody's ratings are the second most stable, with 68.3% of bonds retaining original ratings and 28.8% of bonds having one rating change. Of all four rating agencies, DBRS ratings are the least stable. Its distribution has the lowest percentage of bonds without rating changes, at 63.3%. It also has the highest percentage of bonds with two or more rating changes.

Table 1.8 provides an overall picture of rating change probabilities when rating agencies individually or jointly rated a bond. Again, excluding AAA-rated bonds, Moody's and S&P have more rating changes when they rated a bond alone, without the participation of other rating firms. DBRS was much more likely to change a rating when it jointly rated a bond with another rating agency than when it rated a bond alone. The most stable ratings occurred when Moody's, S&P, and Fitch jointly rated a bond, but not with DBRS. In fact, this rating combination had the most stable ratings for each one of the three rating agencies.

Table 1.9 lists the magnitude of rating changes by rating agency for both upgrade and downgrade. There are many more downgrades than upgrades for all rating agencies. A possible reason for this asymmetry is a weak housing market during the observation period, when the mortgage delinquency rate increased dramatically. The collateral performances of 2005 and 2006 vintages are particularly weak. DBRS is the most balanced in its ratings upgrades and downgrades, but its number of downgrades is 10.0 times that of upgrades. Fitch is the least balanced of all four rating agencies as its number of downgrades is 58.5 times that of upgrades. The ratios for Moody's and S&P are at 35.2 and 36.8, respectively. Despite small differences, the downgrade and upgrade ratio of all credit rating agencies are surprisingly close.

# of Joint	Rated by				# of	Probability of Rating Change by			
Rating(s)	Moody's	S&P	Fitch	DBRS	Bonds	Moody's	S&P	Fitch	DBRS
One Agency	Yes	-	-	-	54	0.88	-	-	-
	-	Yes	-	-	654	-	0.49	-	-
	-	-	Yes	-	136	-	-	0.27	-
	-	-	-	Yes	40	-	-	-	0.2
Subtotal	-	-	-	-	884	0.88	0.49	0.27	0.2
Two Agencies	Yes	Yes	-	-	6968	0.22	0.15	-	-
	Yes	-	Yes	-	224	0.23	-	0.28	-
	Yes	-	-	Yes	16	1	-	-	0.69
	-	Yes	Yes	-	835	-	0.25	0.32	-
	-	Yes	-	Yes	69	-	0.41	-	0.62
	-	-	Yes	Yes	23	-	-	0.57	0.52
Subtotal	-	-	-	-	8135	0.22	0.16	0.32	0.61
Three Agencies	-	Yes	Yes	Yes	79	-	0.28	0.39	0.48
	Yes	-	Yes	Yes	71	0.35	-	0.25	0.38
	Yes	Yes	-	Yes	548	0.24	0.21	-	0.23
	Yes	Yes	Yes	-	6843	0.16	0.12	0.18	-
Subtotal	-	-	-	-	7541	0.17	0.13	0.18	0.27
Four Agencies	Yes	Yes	Yes	Yes	1329	0.26	0.2	0.26	0.24
Total					17889	0.2	0.16	0.21	0.27

Table 1.8: Rating Change Probabilities by Joint Rating Combination

On average, notch changes are larger in downgrades than in upgrades for all rating agencies. Moody's and S&P have the largest average notch change at downgrade, at -6.1 notches. Among all the bonds downgraded by Moody's, 37.5% of them were downgraded by more than 7 notches, a change severe enough to drop an AA-rated bond below investment grade. Thirty-one percent of bonds rated by S&P were downgraded more than 7 notches. The average notch downgrades were 4.3 and 3.9 for Fitch and DBRS, respectively, much less compared with Moody's and S&P. Moody's and S&P also had the largest average notch changes in upgrades. Using severity of rating changes to measure credit rating quality, then, Moody's and S&P were the weakest.

Variable descriptions and summary statistics are presented in Table 1.10. The top section shows dependent variables used in the regression analyses, while the bottom section lists independent variables. The regression analysis investigates the influence of joint ratings on rating change actions for each rating agency, and the first three dependent variables indicate whether there was a rating change by the corresponding rating agencies. Means of this set of binary variables reflect the percentage of bonds with rating changes. The next set of dependent variables is the absolute value of notch changes in ratings from issuance to the end of the observation period, and the last set of dependent variables indicate whether a bond had more than one rating change. The variables used as instrumental variables consist of the number of original ratings and the number of dealers involved in the securitization. Some characteristics of the bond or the deal are included, such as the original balance of the bond, the original balance of the deal that the bond belongs to, the number of bonds in the deal, the coupon interest rate of the bond, and an indicator for whether the bond has fixed interest rate. The variable related to credit enhancement is original credit support of the bond. The empirical models and findings are elaborated in the next section.

1.5 Potential Impacts of Joint Ratings on the Accuracy of Credit Ratings

In this section, we summarize some of the ways through which the number of rating agencies involved in an ABS deal might impact the accuracy of bond ratings. We begin with a simple setting and show that, when rating firms fully disclose their views of a bond's credit quality, the accuracy of the ratings should be independent of the number of initial ratings. We then show that, in a market with imperfect information, a number of factors might cause ratings to be influenced by the interaction among rating agencies in the market.

Downgrade	Moody's		S&P		Fitch		DBRS	
	Count	Percent	Count	Percent	Count	Percent	Count	Percent
1	260	8.3	168	6.3	369	19.1	72	13.6
2	338	10.8	196	7.3	334	17.3	84	15.9
3	293	9.4	250	9.3	363	18.8	117	22.2
4	296	9.5	246	9.2	225	11.7	103	19.5
5	266	8.5	274	10.2	129	6.7	80	15.2
6	282	9	352	13.1	100	5.2	27	5.1
7	222	7.1	360	13.4	72	3.7	9	1.7
8	230	7.3	319	11.9	60	3.1	2	0.4
9	328	10.5	166	6.2	61	3.2	6	1.1
10	281	9	121	4.5	69	3.6	10	1.9
11	176	5.6	80	3	54	2.8	6	1.1
12	77	2.5	59	2.2	37	1.9	3	0.6
13	34	1.1	28	1	18	0.9	2	0.4
14	23	0.7	27	1	11	0.6	2	0.4
15	10	0.3	24	0.9	8	0.4	2	0.4
16	6	0.2	7	0.3	3	0.2	1	0.2
17	6	0.2			6	0.3	1	0.2
18	2	0.1			7	0.4	1	0.2
19					3	0.2		
Sub Total	3130	100	2677	100	1929	100	528	100
WA Notch Change	6.1		6.1		4.3		3.9	

Upgrade	Moody's		S&P		Fitch		DBRS	
	Count	Percent	Count	Percent	Count	Percent	Count	Percent
1	32	36	46	63	26	78.8	37	72.5
2	30	33.7	10	13.7	4	12.1	8	15.7
3	21	23.6	3	4.1	3	9.1	1	2
4	0	0	2	2.7	0	0	2	3.9
5	1	1.1	7	9.6	0	0	1	2
6	2	2.2	3	4.1	0	0	1	2
7	1	1.1	1	1.4			1	2
8	1	1.1	1	1.4				
9	1	1.1	0	0				
Sub Total	89	99.9	73	100	33	100	51	100
WA Notch Change	2.2		2.1		1.3		1.6	

Table 1.9: Upgrade and Downgrade Notch Change

Variable Name	Description	Mean	Std Dev
m_rtchange_eop	Binary indicator: 1 - Moody's changed rating before end of the observation period	0.2	0.4
s_rtchange_eop	Binary indicator: 1 - S&P changed rating before end of the observation period	0.16	0.37
f_rtchange_eop	Binary indicator: 1 - Fitch changed rating before end of the observation period	0.21	0.41
additional_rtgchng1	Binary indicator: 1 - if there is more than one rating change by Moody's	0.04	0.2
additional_rtgchng2	Binary indicator: 1 - if there is more than one rating change by S&P	0.04	0.19
additional_rtgchng3	Binary indicator: 1 - if there is more than one rating change by Fitch	0.02	0.14
num_rating	Number of rating agencies that rated the bond at issuance	2.52	0.7
dealer_count	Number of dealers	2.2	1.35
deal_orig_bal	Original balance of the deal that the bond belongs to ($ billion)	1.05	0.66
count_cusip	Number of bonds in the deal that the bond belongs to	15	4.31
orig_bal	Original balance of the bond ($ million)	71.74	136.72
orig_support	Original credit support of the bond (%)	13.96	16.03
coupon	Interest rate of the bond (%)	6.17	0.94
fixed	Binary indicator: 1 - the bond is fixed rate; 0 - floating rate	0.09	0.29

Table 1.10: Variable Description and Summary Statistics

1.5.1 Credit Rating with Truthful Disclosure

We model the rating decision as follows. Suppose that there are N rating agencies, indexed by $n=1…N$, that can be selected to rate an ABS bond. The probability of default for the bond is p, and neither the rating agencies nor the investors know the value of p. Each rating agency observes imperfect information about the probability of default and then reports a credit rating to investors. After the bond is issued, each rating agency observes the performance of the bond and updates its belief about the probability of default, reporting to investors their subsequent belief about the probability of default. Since the signals and information that rating agencies observe are independent of the number of rating agencies and they truthfully report on the signals and information, the probability of rating changes os independent of the number of initial rating firms.

1.5.2 Potential Impact of Credit Rating Agency Interactions on the Accuracy of Credit Rating

A number of factors in the rating process might explain the impact of interaction among rating agencies on the quality of an initial rating. Some interactions might improve the accuracy of rating, while others reduce it, and the effects of interactions differ from agency to agency.

There are two major reasons that strategic interaction might improve the accuracy of rating.

(1) Information-Sharing Effect

Information-sharing during the rating process might help rating agencies to evaluate credit risk of a bond. Although rating agencies do not discuss ratings directly among themselves, there are a number of channels through which information can be exchanged indirectly. It is common that the rating process of an ABS deal can go through several rounds of discussion between the rating agencies and the bond sponsor, so information about opinions from one rating agency could be passed from the sponsor to competing agencies. For example, a sponsor may propose to two rating agencies that a bond be rated AAA; Agency A agrees, while Agency B requires an increase in credit support for the bond to be rated as AAA so the sponsor has to change the deal structure to provide more credit support and communicate this change to Agency A. Agency A could infer the opinion of Agency B from the changes in the deal structure. This sharing of information could be helpful in improving the accuracy of the rating. Geanakoplos (1992) showed mathematically the convergence of posterior beliefs when the information set is finite and players communicate in rounds and revise their posteriors based on information released.

(2) Reputation Effect

The reputation effect could provide incentives for a rating agency to exert more effort and set higher standards when rating bonds with other rating agencies; a rating agency may work harder to assess the credit risk of a bond so that it can distinguish itself by having a more accurate rating than its competitors.

However, competition among rating agencies may not always improve the accuracy of rating.

(3) Economic Incentive Effect

A central concern in the credit rating market is the conflict of interest problem. Rating agencies are paid by deal sponsors, rather than by investors, so the deal sponsors act as the "consumer" in the purchase of credit ratings, even though investors are the ultimate beneficiaries. When economic incentives are thus misaligned, rating agencies may lower their rating standards and give higher ratings to bonds to win future business from deal sponsors. Competition among rating agencies, in this case, very likely worsens rating accuracy.

In addition, some effects from strategic interactions might give an ambiguous prediction about the accuracy of ratings.

(3) Peer Effect

A number of studies in the financial market have found evidence of a peer effect in transactions such as recommendations from equity analysts. Similarly, rating agencies might prefer to give ratings that are close to those of their competitors. For a firm with better rating technology, competition might decrease its rating accuracy as it tries to conform to competitors with less effective rating technologies, or competition may increase the accuracy of ratings for the firms with the less effective technology.

1.6 Empirical Model

We are interested in investigating the effects of interaction among credit rating agencies on the accuracy of information provided by those agencies. As information intermediaries, credit rating agencies add value to their capital market when their credit ratings provide independent and unbiased judgment on the credit-worthiness of securities. Therefore, the accuracy of credit ratings is the most important driver of rating quality. Cantor and Mann (2006) argued that rating stability was another consideration of credit rating agencies, but we emphasize that rating accuracy is the primary concern in judging the quality of initial ratings since rating stability is not a consideration when initial ratings are assigned. We will leave a full discussion of rating stability to the next section.

We examine the quality of initial credit ratings by looking at the probability of rating changes[30]. Specifically, we investigate whether a greater number of original

[30]Bond performance is another measure of rating accuracy. However, we do not observe bond performance data.

ratings of a bond lower the probability of rating changes later on.

1.6.1 Impact of Joint Ratings on the Probability of Rating Changes

We first exclude all AAA bonds because rating changes of AAA bonds were very rare[31]. We then separate investment-grade bonds from non-investment grade bonds, since the investor groups are different. Because the accuracy of ratings might differ across rating agencies, we estimate the rating changes for each rating agency separately. Using all the bonds rated by Moody's, we first examine how Moody's rating changes might be affected by the number of original ratings. More specifically, our baseline model employs the following linear probability model:

$$Y_i = \gamma_1 NR_i + \beta_1 X_i + \beta_2 Year + \beta_3 Month + \epsilon_i \tag{1.1}$$

where the dependent variable Y is a dummy variable and equals 1 if Moody's changed the bond rating by the end of 2007.

The main explanatory variable of interest, NR, is the number of rating agencies that rated the bond on the issuance date. Under the assumption of truthful disclosure, Moody's would report its estimate of the risk level of a bond without considering the opinions of other credit rating agencies. In this case, we expect the γ_1 coefficient to be zero, which suggests that a greater number of original ratings should not affect the probability of a rating change later on. If interaction with other rating agencies improves the accuracy of Moody's rating, we expect γ_1 to be negative, i.e., Moody's would be less likely to change the rating of a bond when more rating agencies rate the bond, or to be positive if interaction decreases the accuracy of the rating.

In addition to the main explanatory variable, the number of original ratings, we also control for a number of variables in X that might affect the probability of rating changes. First, we include the number of bonds in the same ABS deal to control for the complexity of the deal. Rating agencies rate all bonds in an ABS deal, and eals have different tranche structures and differ in the number of bonds offered to investors, so the complexity of the tranche structures might affect the quality of the rating. Second, we use dummy variables for the original rating grade to control for the risk level of a bond. We also include the size and credit support of a bond, since they are important determinants of the risk level of a bond. Other explanatory variables used in the regression are the coupon rate of a bond and the dummy variable indicating whether it is a fixed-rate bond. Finally, we control for the time trend and seasonal effect by using year and month dummies. An important set of variables that we do not have are related to the characteristics of the underlying

[31] Comparing Table 1.5 and Table 1.6, Moody's downgraded only one out of 5,812 bonds initially rated AAA, S&P 35 bonds out of 6,054, Fitch 11 bonds out of 3,309, and DBRS 22 bonds out of 622. DBRS's 3.5% of AAA-rated bonds is the highest percentage of downgraded bonds among rating agencies.

assets; we address this problem by including a fixed effect of the deal sponsor, since we expect that the underlying assets are similar across deals issued by the same sponsor.

A concern related to this regression equation is the endogeneity problem of the number of original ratings. A deal sponsor balances several tradeoffs when deciding on the number of rating agencies to hire: On the one hand, it is costly to hire more rating agencies to conduct rating reviews but, on the other hand, additional bond ratings might help the investors evaluate the quality of the bond and convince them to pay a higher price for it. As such, one could argue that the deal sponsors might choose the number of original ratings strategically depending on the quality of the underlining asset pool. This complicates our analysis because the unobserved asset pool quality could determine both the number of rating agencies involved in a deal and the subsequent probability of a rating change. In the worst case, an observed correlation of the number of rating agencies and rating change probability could be completely driven by the unobserved asset pool quality. It is also difficult to predict the direction of the bias because of the selection problem; it is possible that ABS deals of lower quality may need to be rated by more rating agencies in order to convince the investors to buy them. However, one could also argue that sponsors of higher-quality bonds could be motivated to hire more rating agencies in order to signal to the investors that the quality of the bond is good.

The standard method of dealing with the selection problem is to use instrumental variables. A valid instrument needs to satisfy the number of rating agencies hired by the sponsor without affecting the probability of rating changes. We argue that the deal's original balance at issuance and the number of dealers involved in a deal could be valid instruments in this case.

The deal's original balance at issuance clearly affects the number of rating agencies hired. First, since rating agencies usually charge fees that are based on the size of a deal, deal size is a main determinant of expenditures on ratings. Second, larger deals might involve more complicated structures. Third, investors are likely to prefer more rating opinions. However, the deal balance at issuance is unlikely to affect the rating quality of a particular bond, which is only a fraction of the ABS deal. Therefore, it affects the number of rating agencies hired by the sponsor without affecting the probability of rating changes.

The number of dealers involved in a deal is another factor that might affect the need to hire additional rating agencies. Since dealers mainly help the sponsor to sell the bond to potential investors, the abilities of dealers to market the bond might affect the need to hire more rating agencies. On the other hand, most dealers are not involved in the negotiation between the deal sponsor and rating agencies on the deal structure. We do not expect the number of dealers to influence the quality of the bond rating.

Using all bonds rated by S&P and Fitch, respectively, we then examine how the rating changes might be affected by the number of original ratings, while controlling for the same set of covariates. More specifically, we use the same linear probability model as in Equation (1.1), where the dependent variable Y is a dummy variable and equals 1 if a bond had a rating change by S&P and Fitch, respectively, by the end of 2007. The other explanatory variables are the same as in the baseline model. We use the same instrument variables for the endogenous variable: the number of initial ratings.

The top panel of Table 1.11 presents the results from the baseline model using the sample of investment-grade bonds (excluding AAA-rated bonds). Columns 1, 2 and 3 present the results for the sample using bonds rated by Moody's, S&P and Fitch, respectively. We find that, as the number of original ratings increases, so does the probability of rating changes. The coefficients for the number of original ratings are at -0.015, 0.132 and 0.204 for Moody's, S&P and Fitch, respectively, although the estimate for Moody's is not significant. Thus, if these results hold, the addition of one original rating increases the probability of a rating change by 13.2% for S&P and 20.4% for Fitch.

We then look at the estimates for the rating-grade dummies. The omitted category is the dummy variable for AA. Consistent with our intuition, the lower-grade bonds are more likely to experience rating changes. BBB- bonds are 71% more likely to undergo rating changes by Moody's, 38% more likely by S&P and 20% more likely by Fitch. The estimates for the rating grade dummies provide a good comparison with the estimates for the number of original ratings. In the case of S&P, the effect of more initial ratings is fairly significant; for an AA-rated bond, the marginal effect on the rating change probability of one additional original rating is equivalent to downgrading the bond to A. For Fitch's ratings, the magnitude is even higher, as one more original rating has the same effect on the rating change probability as downgrading an AA bond to BBB-.

The results of other explanatory variables suggest some interesting findings as well. Bonds with higher coupon rates and fixed-rate bonds are more likely to see rating changes. However, the size of the bond has no impact on the probability of rating changes, although the number of bonds in a deal reduces the probability of rating changes for all three rating agencies.

The lower panel of Table 1.11 presents the results from the baseline model when the sample of non-investment grade bonds is used. Columns 1, 2 and 3 present the results for the sample using bonds rated by Moody's, S&P and Fitch, respectively. Here, we find that none of the coefficients for the number of original ratings is significant, so more original ratings did not have a significant effect on the probability of rating changes for non-investment-grade bonds.

We use the linear probability model as our baseline model because it is easy and straightforward to explain the results. However, since the outcome variable is a binary variable, a common alternative is to use the IV probit model. We report

	Moody's				S&P				Fitch			
IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-0.015	0.106	-0.14	0.89	0.132	0.066	2.01	0.04	0.204	0.103	1.98	0.05
count_cusip	-0.007	0.001	-4.63	0	-0.007	0.002	-4.9	0	-0.005	0.003	-1.56	0.12
gd2												
gd3	-0.675	0.043	-15.85	0	-0.343	0.037	-9.37	0	-0.135	0.075	-1.81	0.07
gd4	-0.692	0.036	-19.08	0	-0.342	0.032	-10.61	0	-0.13	0.063	-2.07	0.04
gd5	-0.385	0.031	-12.26	0	-0.322	0.026	-12.15	0	-0.096	0.054	-1.78	0.08
gd6	-0.319	0.028	-11.27	0	-0.268	0.023	-11.43	0	-0.061	0.046	-1.31	0.19
gd7	-0.276	0.025	-11.01	0	-0.208	0.021	-9.78	0	-0.022	0.038	-0.57	0.57
gd8	-0.167	0.02	-8.27	0	-0.191	0.019	-10.26	0	-0.008	0.03	-0.26	0.8
gd9	-0.115	0.018	-6.33	0	-0.12	0.018	-6.69	0	-0.01	0.027	-0.36	0.72
orig_bal	0	0	0.58	0.56	0	0	-0.61	0.54	-0.001	0	-1.7	0.09
orig_support	0.01	0.003	3.22	0	-0.004	0.003	-1.1	0.27	-0.007	0.005	-1.29	0.2
coupon	-0.051	0.012	-4.23	0	0.056	0.01	5.79	0	0.14	0.021	6.68	0
fixed	0.017	0.02	0.88	0.38	0.158	0.02	7.77	0	0.279	0.039	7.23	0
constant	1.181	0.312	3.79	0	-0.361	0.219	-1.65	0.1	-1.146	0.405	-2.83	0.01
Below IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-0.065	0.405	-0.16	0.87	0.004	0.791	0	1	3.114	6.669	0.47	0.64
count_cusip	0.005	0.005	1.06	0.29	-0.018	0.004	-4.41	0	-0.019	0.065	-0.29	0.77
gd11	-0.046	0.11	-0.42	0.68	-0.19	0.641	-0.3	0.77	-3.063	6.793	-0.45	0.65
gd12	-0.025	0.12	-0.21	0.83	-0.209	0.659	-0.32	0.75	-2.707	5.929	-0.46	0.65
gd13					-0.164	0.965	-0.17	0.87	-1.411	3.113	-0.45	0.65
gd14					-0.418	0.745	-0.56	0.58	-1.879	4.05	-0.46	0.64
orig_bal	0.009	0.004	2.43	0.02	0.002	0.013	0.13	0.9	-0.04	0.105	-0.38	0.71
orig_support	-0.027	0.031	-0.88	0.38	-0.069	0.153	-0.45	0.65	-0.208	0.402	-0.52	0.61
coupon	-0.026	0.039	-0.66	0.51	-0.069	0.103	-0.68	0.5	-0.701	1.406	-0.5	0.62
fixed	0.258	0.12	2.14	0.03	-0.117	0.138	-0.85	0.4	-1.098	2.092	-0.52	0.6
constant	1.168	0.721	1.62	0.11	1.858	0.653	2.85	0.01	3.751	6.735	0.56	0.58

Table 1.11: Rating Change Probability - OLS Estimation

the results from the IV probit model in Table 1.12. Qualitatively, the results are similar to the finding from the linear probability model. For all investment-grade bonds (excluding AAA bonds), the estimates for the main coefficients of number of ratings are 0.351, 0.705 and 0.758 for Moody's, S&P, and Fitch, respectively. Only the estimates for S&P and Fitch are significant. Estimates for other coefficients are of the same signs as we have seen in the linear regression model. For non-investment-grade bonds, none of the estimates is significant.

1.6.2 Additional Specifications

In our baseline model, we use the rating change of a bond as a measure of the quality of the initial rating. Other than the rating change decision itself, another important measure of quality of rating is the magnitude of the rating change, since a significant change of rating indicates a poorer quality of original rating than does a minor change. A good measure of rating change magnitude is whether an investment-grade bond is downgraded to non-investment grade, as this is a much more severe rating change than a downgrade within the domain of investment-grade. Thus, we estimate how the number of original ratings affects the probability of an investment-grade bond's being downgraded to non-investment grade.

We first look at the probability of Moody's downgrading an investment-grade bond to non-investment-grade using all the investment-grade bonds initially rated by Moody's. Specifically, the regression equation we employ is:

$$Y_i = \gamma_1 NR_i + \beta_1 X_i + \beta_2 Year + \beta_3 Month + \beta_4 IssueFE + \epsilon_i, \qquad (1.2)$$

where Y equals 1 if a bond rated investment-grade by Moody's is downgraded to non-investment-grade by the end of the observation period. The explanatory variables are the same as in the baseline model, and we use the same instrument variables for the endogenous variable: the number of initial ratings. After estimating the probability of downgrades by Moody's, we examine the same factors for S&P and Fitch.

Table 1.13 presents the results for this IV regression. The estimates for the main coefficients of interest are -0.128, 0.102 and 0.17 for Moody's, S&P and Fitch, respectively, although only the estimate for Fitch is significant. Therefore, we conclude that an increase in the number of original ratings raises the probability of a bond rated investment-grade by Fitch being downgraded to non-investment grade.

To summarize, we find that an increase in the number of original ratings increases the probability of rating changes for S&P and Fitch, but not for Moody's. In addition, Fitch's ratings of investment-grade bonds are more likely to be downgraded to non-investment grade when more rating agencies are involved in a deal. Thus, our findings reject the hypothesis that there is no strategic interaction among

	Moody's				S&P				Fitch			
IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	0.351	0.656	0.53	0.59	0.705	0.342	2.06	0.04	0.758	0.43	1.76	0.08
count_cusip	-0.042	0.009	-4.81	0	-0.039	0.008	-4.92	0	-0.02	0.014	-1.48	0.14
gd2	-4.88	0.34	-14.35	0	-1.755	0.251	-6.98	0				
gd3	-4.145	0.276	-15.01	0	-1.283	0.19	-6.73	0	0.571	0.152	3.76	0
gd4	-4.301	0.238	-18.04	0	-1.23	0.163	-7.57	0	0.703	0.194	3.63	0
gd5	-2.14	0.183	-11.68	0	-1.081	0.127	-8.49	0	0.889	0.221	4.02	0
gd6	-1.66	0.163	-10.21	0	-0.819	0.109	-7.5	0	1.025	0.243	4.21	0
gd7	-1.398	0.139	-10.03	0	-0.572	0.094	-6.11	0	1.149	0.29	3.96	0
gd8	-0.836	0.109	-7.69	0	-0.563	0.079	-7.09	0	1.157	0.332	3.49	0
gd9	-0.539	0.096	-5.64	0	-0.359	0.076	-4.71	0	1.108	0.372	2.98	0
gd10									1.083	0.375	2.88	0
orig_bal	-0.004	0.003	-1.21	0.23	-0.002	0.002	-0.92	0.36	-0.004	0.002	-1.58	0.11
orig_support	0.106	0.019	5.72	0	-0.022	0.018	-1.22	0.22	-0.024	0.022	-1.06	0.29
coupon	-0.104	0.064	-1.64	0.1	0.3	0.044	6.76	0	0.545	0.086	6.34	0
fixed	0.087	0.112	0.78	0.43	0.761	0.099	7.68	0	1.192	0.157	7.59	0
constant	1.012	1.911	0.53	0.6	-4.514	1.12	-4.03	0	-7.648	1.413	-5.41	0
Below IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-0.625	2.721	-0.23	0.82	-2.715	4.502	-0.6	0.55	5.597	5.001	1.12	0.26
count_cusip	0.059	0.036	1.61	0.11	-0.07	0.041	-1.68	0.09	0.04	0.132	0.31	0.76
gd11	0.461	0.615	0.75	0.45	-1.736	1358.314	0	1	-9.05	2468.019	0	1
gd12	0.778	0.702	1.11	0.27	-1.91	1358.314	0	1	-8.128	2468.017	0	1
gd13					-3.346	1358.31	0	1	-6.926	2468.015	0	1
gd14					-3.269	1358.312	0	1	-6.148	2468.015	0	1
orig_bal	0.048	0.025	1.94	0.05	0.061	0.063	0.97	0.33	0.021	0.057	0.37	0.71
orig_support	-0.188	0.207	-0.91	0.37	0.177	0.819	0.22	0.83	-0.37	0.281	-1.31	0.19
coupon	-0.239	0.306	-0.78	0.44	0.044	0.759	0.06	0.95	-0.723	0.779	-0.93	0.35
fixed	1.019	0.877	1.16	0.25	0.047	1.032	0.05	0.96	-1.398	1.489	-0.94	0.35
constant	7.463	3.423	2.18	0.03	9.558	6.612	1.45	0.15	4.549	7.691	0.59	0.55

Table 1.12: Rating Change Probability - Probit Estimation

rating agencies and suggest that an increase in the number of original ratings might lower the quality of original ratings.

1.7 Inaccurate Rating Or Change in Rating Stability

The primary interest of our study is to determine whether an increase in the number of original ratings affects their quality. Our empirical evidence demonstrates that more original ratings increase the probability of rating changes. One possible explanation for this is that the interaction among rating firms lowers the accuracy of ratings because of impaired rating standards. Before reaching that conclusion, however, we have to rule out an alternative explanation. Cantor and Mann (2006) argued that there is a trade-off between rating stability and accuracy when credit rating agencies best utilize the available analytical methods. Because of portfolio governance rules and triggers based on credit ratings, market participants want credit ratings that are both accurate and stable. If rating agencies change the level of rating stability and become more responsive to changes in credit conditions, it will result in higher probabilities of rating changes. With this alternative explanation, our observation that a greater number of original ratings raise the probability of rating changes may not, by itself, be a sign of lower rating quality.

The peer effect is a likely reason for rating agency's changing their rating stability when more than one agency rates a bond, since a rating firm may be reluctant to change ratings if others have not done so. The economic incentive has less impact on rating stability than on rating accuracy since the choice to change a rating is made after the rating service fee is paid; however, agencies are also aware of the impact of a downgraded rating on their future relationship with a sponsor.

In this section, we address the alternative explanation for the positive relationship between the number of original ratings and rating change probabilities using the following tests:

(1) Our first test examines whether rating firms set lower rating standards when more rating agencies rate a bond. Our measure of rating stringency is the original support of a bond, which is the percentage of tranches in the deal junior to the bond; a bond is less likely to suffer a loss if more subordination is in place. Thus, if rating firms do lower standards when more agencies rate the bond, we expect that the original support of the bond will be lower, all else being equal.

(2) We then test whether rating changes might be influenced by concerns about stability. We argue that, if the positive correlation between the probability of a rating change and the number of original ratings is mainly due to changes in rating stability, rather than the accuracy of the initial rating, the probability of subsequent rating changes after a first rating change, should also positively correlate with the number of original ratings. Our intuition is that the intention to maintain a certain level of

	Moody's				S&P				Fitch			
	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-0.128	0.1	-1.28	0.2	0.102	0.059	1.73	0.08	0.172	0.08	2.15	0.03
count_cusip	-0.004	0.001	-3.18	0	-0.006	0.001	-4.12	0	-0.001	0.003	-0.2	0.84
gd3	-0.609	0.04	-15.14	0	-0.415	0.033	-12.65	0	-0.349	0.058	-6.03	0
gd4	-0.604	0.034	-17.64	0	-0.416	0.029	-14.38	0	-0.379	0.049	-7.77	0
gd5	-0.573	0.03	-19.3	0	-0.394	0.024	-16.62	0	-0.371	0.042	-8.91	0
gd6	-0.445	0.027	-16.66	0	-0.336	0.021	-15.94	0	-0.353	0.036	-9.82	0
gd7	-0.34	0.024	-14.33	0	-0.293	0.019	-15.38	0	-0.325	0.029	-11.02	0
gd8	-0.207	0.019	-10.86	0	-0.224	0.017	-13.44	0	-0.224	0.024	-9.51	0
gd9	-0.111	0.017	-6.49	0	-0.127	0.016	-7.9	0	-0.101	0.021	-4.81	0
orig_bal	0.001	0	2.19	0.03	0	0	-0.81	0.42	-0.001	0	-3.06	0
orig_support	0.005	0.003	1.93	0.05	-0.001	0.003	-0.24	0.81	0.009	0.004	2.18	0.03
coupon	-0.017	0.011	-1.48	0.14	0.055	0.009	6.32	0	0.15	0.016	9.25	0
fixed	0.031	0.019	1.66	0.1	0.145	0.018	7.96	0	0.23	0.03	7.71	0
constant	1.116	0.295	3.79	0	-0.287	0.196	-1.46	0.14	-1.118	0.314	-3.56	0

Table 1.13: Rating Change Probability from Investment Grade to Below Investment Grade - OLS Estimation

	Moody's				S&P				Fitch			
	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-0.378	0.825	-0.46	0.65	0.986	0.43	2.29	0.02	1.178	0.593	1.99	0.05
count_cusip	-0.047	0.012	-3.87	0	-0.042	0.009	-4.62	0	-0.008	0.018	-0.45	0.65
gd2	-5.968	0.39	-15.3	0	-2.587	0.336	-7.7	0				
gd3	-5.028	0.298	-16.85	0	-2.032	0.243	-8.37	0	0.851	0.337	2.52	0.01
gd4	-4.598	0.279	-16.49	0	-1.928	0.205	-9.42	0	0.661	0.415	1.59	0.11
gd5	-3.988	0.251	-15.88	0	-1.585	0.153	-10.34	0	1.184	0.419	2.83	0.01
gd6	-2.804	0.193	-14.51	0	-1.169	0.127	-9.22	0	1.569	0.441	3.55	0
gd7	-2.027	0.172	-11.79	0	-0.949	0.105	-9.03	0	2.085	0.495	4.21	0
gd8	-1.204	0.128	-9.43	0	-0.71	0.086	-8.28	0	2.713	0.55	4.94	0
gd9	-0.577	0.106	-5.44	0	-0.408	0.082	-4.97	0	3.119	0.601	5.19	0
gd10									3.46	0.607	5.7	0
orig_bal	0.001	0.004	0.27	0.79	-0.01	0.003	-2.95	0	-0.014	0.005	-2.78	0.01
orig_support	0.1	0.02	5.1	0	-0.004	0.023	-0.19	0.85	0.1	0.032	3.17	0
coupon	0.03	0.069	0.44	0.66	0.4	0.05	8.06	0	0.73	0.111	6.59	0
fixed	0.162	0.126	1.28	0.2	0.933	0.113	8.23	0	1.239	0.212	5.84	0
constant	1.729	2.322	0.74	0.46	-6.286	1.372	-4.58	0	-12.645	1.96	-6.45	0

Table 1.14: Rating Change Probability from Investment Grade to Below Investment Grade - Probit Estimation

rating stability should influence the first rating change to the same extent as that in all subsequent rating changes. In addition, after the first rating change, the accuracy of the initial rating should not affect subsequent rating change decisions. Thus, we can validate the two competing explanations by determining whether the number of original ratings has any impact on the probability of rating changes subsequent to a first rating change.

(3) Similarly, frequency of rating changes can be used to separate the two competing explanations. If rating stability choice plays the main role, the number of original ratings should affect the number of times that a bond undergoes rating changes subsequent to a first rating change. Initial rating accuracy is not likely to affect the number of times that a bond receives subsequent rating changes after a first rating change.

1.7.1 Bond Original Support

Our first test inspects the original support of a bond rated by Moody's. Using all the bonds rated by Moody's, we employ the empirical model:

$$Y_i = \gamma_1 NR_i + \beta_1 X_i + \beta_2 Year + \beta_3 Month + \epsilon_i$$

where Y_i is the original support of a bond. We control for the same set of covariates as in the baseline model, except that we use the number of dealers as the instrumental variable for the number of original rating firms and put the deal balance variable as an explanatory variable. This is because deal size might affect the decision regarding the original support level. After estimating the effects of the number of original ratings on the original support level of Moody's rated bonds, we conduct the same analysis for S&P and Fitch.

Using the sample of investment-grade bonds, excluding AAA bonds, the top panel of Table 1.15 shows the results. Columns 1, 2, and 3 list the results for bonds rated by Moody's, S&P and Fitch, respectively. We find that an increase in the number of original ratings reduces the original support for bonds rated by all three rating firms. The coefficient for the number of original ratings is negative at -2.153, -2.252 and -3.663 for Moody's, S&P and Fitch, respectively, although the estimate for Moody's is not significant. Thus, one additional original rating reduces the original support level by 2.25% for S&P and 3.66% for Fitch.

We then look at the estimates for the rating-grade dummies. The omitted category is a dummy variable for BBB-. Consistent with our intuition, the higher-grade bonds have higher original support level. The coefficients for AA+ bonds are 13.66%, 9.48%, and 11.86%, suggesting more original support than BBB- rated bonds for Moody's, S&P and Fitch, respectively.

To further evaluate the impact of the number of original ratings on original bond support, we compare the coefficient of the number of original ratings with that of

	Moody's				S&P				Fitch			
IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-2.153	1.837	-1.17	0.24	-2.252	1.059	-2.13	0.03	-3.663	1.111	-3.3	0
count_cusip	0.033	0.012	2.83	0.01	0.097	0.016	5.98	0	0.13	0.029	4.53	0
deal_orig_bal	-0.878	0.151	-5.82	0	-1.233	0.111	-11.13	0	-1.011	0.134	-7.57	0
gd2	13.664	0.24	57.04	0	9.489	0.207	45.92	0	11.857	0.333	35.64	0
gd3	10.323	0.226	45.63	0	6.718	0.193	34.86	0	8.42	0.337	24.99	0
gd4	8.971	0.217	41.28	0	5.772	0.194	29.83	0	7.164	0.316	22.69	0
gd5	7.18	0.22	32.61	0	4.096	0.185	22.19	0	5.671	0.295	19.2	0
gd6	5.472	0.199	27.53	0	3.018	0.171	17.7	0	4.27	0.274	15.61	0
gd7	4.199	0.194	21.59	0	2.254	0.172	13.09	0	3.322	0.252	13.18	0
gd8	2.632	0.159	16.55	0	1.428	0.171	8.34	0	2.217	0.226	9.8	0
gd9	1.432	0.145	9.9	0	0.789	0.161	4.9	0	1.29	0.221	5.83	0
orig_bal	0.032	0.003	10.94	0	0.062	0.003	18.6	0	0.035	0.004	8.38	0
coupon	0.468	0.088	5.33	0	-0.878	0.125	-7.02	0	-0.474	0.192	-2.47	0.01
fixed	0.347	0.155	2.24	0.03	-1.028	0.206	-4.98	0	0.267	0.287	0.93	0.35
constant	4.841	5.059	0.96	0.34	14.726	3.692	3.99	0	15.192	4.33	3.51	0
Below IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	1.633	1.527	1.07	0.29	3.269	3.532	0.93	0.36	-11.059	41.091	-0.27	0.79
count_cusip	0.039	0.024	1.65	0.1	-0.005	0.031	-0.15	0.88	0.137	0.443	0.31	0.76
deal_orig_bal	-0.237	0.206	-1.15	0.25	0.054	0.463	0.12	0.91	-0.929	2.028	-0.46	0.65
gd11	1.179	0.523	2.25	0.03	-2.632	4.326	-0.61	0.54	14.303	45.789	0.31	0.76
gd12	0.362	0.531	0.68	0.5	-2.875	3.748	-0.77	0.44	11.285	38.115	0.3	0.77
gd13					-1.782	2.514	-0.71	0.48	4.761	17.541	0.27	0.79
gd14					-2.919	3.177	-0.92	0.36	6.211	23.406	0.27	0.79
gd15					-5.11	6.341	-0.81	0.42				
orig_bal	-0.02	0.018	-1.11	0.27	-0.058	0.068	-0.84	0.4	0.208	0.701	0.3	0.77
coupon	0.03	0.169	0.18	0.86	-0.362	0.548	-0.66	0.51	2.05	8.209	0.25	0.8
fixed	0.005	0.512	0.01	0.99	-0.341	0.793	-0.43	0.67	2.395	11.142	0.21	0.83
constant	-3.295	2.721	-1.21	0.23	3.034	4.877	0.62	0.53	-8.532	36.485	-0.23	0.82

Table 1.15: Impact on Bond Credit Support

various rating grades. For S&P, one additional original rating decreases average credit support by 2.25%. The difference in average credit support between A–rated bonds and BBB-rated bonds is also roughly 2.25%. Thus, one additional rating has an equivalent impact on rating standards as assigning an A- rating to a bond that is essentially worth only a BBB- rating. For Fitch, the impact of one additional rating on credit support is even greater but, in both cases, rating standards were loosened by more than 3 notches, which is quite dramatic.

1.7.2 Subsequent Rating Change

We then analyze subsequent rating changes, using all the Moody's-rated bonds that have received rating change from Moody's. Specifically, the empirical model we employ is:

$$Y_i = \gamma_1 NR_i + \beta_1 X_i + \beta_2 Year + \beta_3 Month + \epsilon_i$$

where the dependent variable Y is a dummy variable and equals 1 if the bond receives rating changes subsequent to a first rating change from Moody's by the end of 2007. The explanatory and instrumental variables are the same as in the baseline model. After estimating the probability of subsequent rating changes by Moody's, we also examine the subsequent rating changes for S&P and Fitch.

The results of the linear probability models are shown in Table 1.16. The top panel shows the results when using all investment-grade bonds, while the bottom panel shows the results for non-investment grade bonds. For investment-grade bonds, we find that the coefficients for the number of original ratings are insignificant for Moody's and S&P but significant, at 1.22, for Fitch. Thus, the probability of subsequent rating changes after a first change is not correlated with the number of original ratings for Moody's and S&P, but a greater number of original ratings increases the probability of subsequent rating changes for Fitch. In addition, the result of the bottom panel shows that none of the estimates for the number of original ratings is significant for non-investment-grade bonds.

The results of the IV probit models are shown in Table 1.17, and these results are qualitatively similar to those of the linear probability model. Using the investment-grade bonds, the coefficients for the number of ratings are insignificant for Moody's and S&P, but significant at 6.235 for Fitch. On the other hand, the estimates for the number of rating agencies are insignificant for non-investment-grade bonds.

The results from both the linear probability model and the IV probit model suggest that the subsequent rating changes are affected by the number of original ratings for Fitch, but not for Moody's and S&P. Given our baseline estimates, the number of original ratings affects the probability for rating changes for S&P and Fitch, but not for Moody's. Thus, it is not surprising to find that the probability of rating changes subsequent to a first change for Moody's is not affected by the number of original

	Moody's				S&P				Fitch			
IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	0.199	0.182	1.09	0.27	0.171	0.191	0.89	0.37	1.22	0.614	1.99	0.05
count_cusip	-0.008	0.003	-2.99	0	0.002	0.003	0.69	0.49	-0.004	0.008	-0.47	0.64
gd2	-0.713	0.172	-4.15	0								
gd3	-0.348	0.142	-2.46	0.01	0.048	0.083	0.57	0.57	0.032	0.132	0.24	0.81
gd4	-0.127	0.131	-0.97	0.33	0.017	0.116	0.15	0.88	-0.096	0.151	-0.63	0.53
gd5	-0.424	0.083	-5.09	0	0.011	0.124	0.09	0.93	-0.114	0.164	-0.7	0.49
gd6	-0.345	0.068	-5.09	0	0.116	0.137	0.85	0.4	-0.171	0.188	-0.91	0.36
gd7	-0.297	0.055	-5.42	0	0.104	0.156	0.66	0.51	-0.272	0.227	-1.2	0.23
gd8	-0.211	0.038	-5.48	0	0.15	0.17	0.88	0.38	-0.349	0.274	-1.28	0.2
gd9	-0.1	0.03	-3.37	0	0.077	0.183	0.42	0.67	-0.44	0.337	-1.3	0.19
gd10					0.128	0.175	0.73	0.46	-0.328	0.3	-1.09	0.28
orig_bal	-0.001	0.001	-0.97	0.33	-0.001	0.002	-0.82	0.41	0.002	0.002	1.03	0.3
orig_support	0.032	0.012	2.73	0.01	-0.009	0.013	-0.67	0.5	-0.028	0.019	-1.49	0.14
coupon	0.039	0.024	1.67	0.1	0.04	0.017	2.27	0.02	0.196	0.097	2.02	0.04
fixed	0.119	0.039	3.03	0	0.136	0.045	3.03	0	0.121	0.11	1.11	0.27
constant	-0.651	0.479	-1.36	0.17	-0.569	0.349	-1.63	0.1	-4.145	2.088	-1.98	0.05
Below IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	0.377	0.275	1.37	0.17	1.981	1.655	1.2	0.23	0.231	0.843	0.27	0.78
count_cusip	-0.003	0.008	-0.36	0.72	0.071	0.057	1.24	0.22	0.003	0.013	0.22	0.83
gd11					1.219	2.128	0.57	0.57	-0.491	0.941	-0.52	0.6
gd12	0.043	0.05	0.86	0.39	1.39	2.237	0.62	0.54	-0.455	0.878	-0.52	0.61
gd13	0.074	0.189	0.39	0.7	1.891	2.589	0.73	0.47	-0.077	0.643	-0.12	0.9
gd14					2.707	3.287	0.82	0.41	-0.225	0.724	-0.31	0.76
gd23					4.158	4.134	1.01	0.32				
orig_bal	0.005	-1.06	0.29	-0.02	-0.035	0.03	-1.16	0.25	0.002	0.012	0.14	0.89
orig_support	0.029	-1.65	0.1	-0.1	-0.224	0.252	-0.89	0.38	-0.031	0.057	-0.54	0.59
coupon	0.063	-1.05	0.3	-0.19	-0.12	0.187	-0.64	0.52	-0.007	0.351	-0.02	0.98
fixed	0.186	-0.55	0.58	-0.47	0.15	0.412	0.36	0.72	-0.06	0.828	-0.07	0.94
constant	0.67	0.93	0.35	-0.69	-2.922	3.483	-0.84	0.4	0.411	2.401	0.17	0.86

Table 1.16: Regression Analysis of Additional Rating Change Conditional on First Rating Change

	Moody's				S&P				Fitch			
IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	0.629	0.912	0.69	0.49	1.46	1.289	1.13	0.26	6.235	3.28	1.9	0.06
count_cusip	-0.031	0.015	-2.04	0.04	0.002	0.016	0.1	0.92	0.014	0.059	0.23	0.82
gd2	-4.511	0.929	-4.86	0					-0.81	2.272	-0.36	0.72
gd3	-2.63	0.746	-3.53	0	0.751	0.633	1.19	0.24	0.209	1.928	0.11	0.91
gd4	-1.573	0.674	-2.33	0.02	0.525	0.795	0.66	0.51				
gd5	-2.899	0.47	-6.17	0	0.464	0.846	0.55	0.58	-0.828	1.216	-0.68	0.5
gd6	-2.219	0.385	-5.76	0	1.009	0.924	1.09	0.28	-0.499	1.009	-0.49	0.62
gd7	-1.895	0.318	-5.96	0	0.904	1.032	0.88	0.38	-0.947	0.749	-1.26	0.21
gd8	-1.183	0.22	-5.37	0	1.035	1.134	0.91	0.36	-0.812	0.53	-1.53	0.13
gd9	-0.507	0.167	-3.04	0	0.704	1.198	0.59	0.56	-0.872	0.503	-1.73	0.08
gd10					0.954	1.14	0.84	0.4				
orig_bal	-0.006	0.008	-0.75	0.46	-0.011	0.01	-1.07	0.28	0.003	0.013	0.25	0.8
orig_support	0.19	0.056	3.38	0	-0.078	0.087	-0.9	0.37	-0.005	0.112	-0.05	0.96
coupon	0.183	0.146	1.25	0.21	0.184	0.087	2.12	0.03	1.039	0.503	2.07	0.04
fixed	0.569	0.236	2.41	0.02	0.611	0.226	2.7	0.01	-0.154	0.87	-0.18	0.86
constant	-4.733	2.502	-1.89	0.06	-6.455	2.236	-2.89	0	-24.924	11.937	-2.09	0.04
Below IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	1.491	1.081	1.38	0.17	7.853	6.355	1.24	0.22	1.599	3.299	0.48	0.63
count_cusip	-0.03	0.03	-1	0.32	0.298	0.238	1.25	0.21	0.043	0.059	0.73	0.46
gd11	-0.807	0.729	-1.11	0.27	-15.754	9.591	-1.64	0.1	-1.344	2.165	-0.62	0.54
gd12	-0.666	0.733	-0.91	0.36	-15.086	9.186	-1.64	0.1	-1.362	1.933	-0.7	0.48
gd13					-12.091	7.867	-1.54	0.12	1.235	1.93	0.64	0.52
orig_bal	-0.012	0.02	-0.59	0.56	-0.139	0.119	-1.17	0.24	0.018	0.044	0.41	0.68
orig_support	-0.165	0.101	-1.64	0.1	-0.919	0.974	-0.94	0.35	-0.212	0.198	-1.07	0.29
coupon	-0.268	0.233	-1.15	0.25	-0.423	0.738	-0.57	0.57	-0.059	1.368	-0.04	0.97
fixed	-0.452	0.698	-0.65	0.52	0.589	1.688	0.35	0.73	-0.335	3.24	-0.1	0.92
constant	0.865	2.482	0.35	0.73	7.313	7.981	0.92	0.36	-7.632	7.326	-1.04	0.3

Table 1.17: Regression Analysis of Additional Rating Change Conditional on First Rating Change-Probit Estimation

ratings. For S&P, the number of original ratings impacts the probability of a first rating change, but not the probability of subsequent rating changes. Finally, for Fitch, both the probability of a first rating change and the probability of a subsequent rating change are affected by the number of original ratings.

1.7.3 Frequency of Rating Change

Our final tests examine the frequency of rating changes by each rating agency, using bonds with rating changes. We first look at the frequency of changes in Moody's ratings, using the empirical model:

$$Y_i = \gamma_1 NR_i + \beta_1 X_i + \beta_2 Year + \beta_3 Month + \beta_4 IssueFE + \epsilon_i$$

where the dependent variable Y is the number of times that a bond received subsequent rating changes from Moody's by the end of 2007. The explanatory and instrument variables are the same as in the baseline model. We then examine the frequency of rating changes for S&P and Fitch in a similar fashion.

The results from using the investment-grade and non-investment-grade bonds are shown in the top and bottom panels of Table 1.18, respectively. For investment-grade bonds, the coefficients of the number of rating agencies are insignificant for Moody's and S&P, but significant at 1.592 for Fitch. Moreover, the results for non-investment-grade bonds suggest that none of the estimates are significant.

The analysis of the frequency of rating changes shows similar results as the previous analysis of rating changes subsequent to a first rating change. The number of original ratings affects the frequency of rating changes for bonds rated by Fitch, but not for those rated by S&P and Moody's.

1.8 Discussion of Results

This section summarizes our main findings and discusses possible explanations for these findings.

(1) Credit ratings are not independent

Despite the claims by credit rating agencies that their ratings are "unbiased and independent," our findings raise serious doubts. We provide evidence that rating standards and decisions about rating changes are influenced by the ratings of other rating agencies, and influence in either respect demonstrates bias. To avoid repetition, we focus on rating change decisions here and discuss rating standards under the next point.

First, for investment-grade bonds, the number of original ratings increases the probability of rating changes for S&P and Fitch, but not for Moody's. Second, a greater number of original ratings increase the probability of downgrades from

	Moody's				S&P				Fitch			
IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	-0.003	0.21	-0.02	0.99	0.105	0.223	0.47	0.64	1.592	0.785	2.03	0.04
count_cusip	-0.007	0.003	-2.32	0.02	0.008	0.004	1.98	0.05	-0.007	0.011	-0.69	0.49
gd2	-0.98	0.198	-4.95	0								
gd3	-0.517	0.164	-3.16	0	0.103	0.097	1.06	0.29	0.037	0.168	0.22	0.83
gd4	-0.304	0.151	-2.01	0.04	0.132	0.135	0.97	0.33	-0.134	0.193	-0.69	0.49
gd5	-0.551	0.096	-5.72	0	0.112	0.144	0.78	0.44	-0.171	0.21	-0.81	0.42
gd6	-0.44	0.078	-5.62	0	0.249	0.16	1.56	0.12	-0.25	0.24	-1.04	0.3
gd7	-0.354	0.063	-5.6	0	0.235	0.181	1.29	0.2	-0.383	0.29	-1.32	0.19
gd8	-0.241	0.044	-5.43	0	0.288	0.198	1.45	0.15	-0.49	0.35	-1.4	0.16
gd9	-0.104	0.034	-3.03	0	0.214	0.213	1.01	0.32	-0.611	0.431	-1.42	0.16
gd10					0.27	0.203	1.33	0.19	-0.466	0.384	-1.21	0.23
orig_bal	-0.002	0.001	-1.36	0.17	-0.001	0.002	-0.48	0.63	0.002	0.002	0.98	0.33
orig_support	0.054	0.013	4.01	0	0.001	0.015	0.05	0.96	-0.038	0.024	-1.6	0.11
coupon	0.055	0.027	2.02	0.04	0.056	0.02	2.76	0.01	0.249	0.124	2.01	0.05
fixed	0.153	0.045	3.4	0	0.184	0.052	3.5	0	0.072	0.14	0.52	0.61
constant	0.779	0.553	1.41	0.16	0.329	0.407	0.81	0.42	-4.361	2.67	-1.63	0.1
Below IG	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$	coef	Std. Err	t-Stat	$P > \|t\|$
num_rating	0.538	0.33	1.63	0.1	2.198	1.872	1.17	0.24	-0.707	1.317	-0.54	0.59
count_cusip	-0.007	0.01	-0.72	0.47	0.087	0.065	1.34	0.18	0.027	0.021	1.3	0.2
gd11					0.437	2.407	0.18	0.86	0.53	1.47	0.36	0.72
gd12	0.022	0.06	0.36	0.72	0.623	2.531	0.25	0.81	0.497	1.373	0.36	0.72
gd13	0.048	0.226	0.21	0.83	1.254	2.929	0.43	0.67	0.502	1.005	0.5	0.62
gd14					2.096	3.718	0.56	0.57	0.347	1.132	0.31	0.76
orig_bal	-0.012	0.007	-1.89	0.06	-0.041	0.034	-1.2	0.23	0.021	0.019	1.08	0.28
orig_support	-0.08	0.034	-2.32	0.02	-0.236	0.286	-0.83	0.41	0.034	0.088	0.38	0.7
coupon	-0.085	0.076	-1.12	0.26	-0.132	0.211	-0.62	0.53	0.391	0.549	0.71	0.48
fixed	-0.158	0.223	-0.71	0.48	0.193	0.466	0.41	0.68	0.775	1.294	0.6	0.55
constant	1.566	0.802	1.95	0.05	-1.491	3.94	-0.38	0.71	-1.597	3.751	-0.43	0.67

Table 1.18: Number of Rating Changes Conditional on First Rating Change

investment-grade to non-investment-grade for Fitch and S&P. Third, the number of original ratings affects the probability of rating changes subsequent to a first rating change and the frequency of rating changes for bonds rated by Fitch.

However, we also find evidence of considerable variation across firms. Moody's ratings are the least affected by the number of original ratings, as more original ratings affect neither the probability nor the frequency of rating changes. S&P shows mixed results: a greater number of original ratings increases both the probability and the frequency of rating changes, but the probability and frequency of subsequent rating changes are not affected by the number of original ratings. Fitch's ratings are most likely to be influenced by the number of original ratings.

(2) More joint ratings decrease quality of credit rating

A more surprising finding of our study is that a greater number of original ratings decrease the quality of the ratings. We find in the baseline model that, for Fitch and S&P, more original ratings increase the probability of rating changes and that more original ratings in general lower the rating stringency standards. For all three rating firms, more original ratings lead to lower requirements for original support of a bond; the reduction in original credit support among bonds rated by multiple agencies is sizeable, suggesting that competition among rating firms helps a deal sponsor qualify its bond for a higher grade. As discussed in Section 1.7, a lower original support requirement is direct evidence of less accurate ratings, based on when rating agencies subsequently downgraded a large portion of the bonds. This rules out the alternative explanation that more rating changes can result from a change in rating stability.

Supplementary to the examination of original credit support, to rule out the alternative explanation, we consider the probability and frequency of rating changes subsequent to a first rating change. For S&P ratings, we do not find a significant impact for more than one original rating in these two tests. Together with the result in the baseline model, these findings also rule out the competing rating stability explanation and demonstrate that S&P's rating quality did decrease when S&P rated a bond at the same time as other rating agencies. For Fitch's ratings, we do find significant influence from other rating agencies on its subsequent rating changes. Therefore, these two supplementary tests do not help to rule out a change in rating stability as an explanation for a higher probability of rating changes for Fitch.

Overall, then, it is evident that a greater number of original ratings decrease the quality of the rating.

1.9 Conclusion

Credit rating agencies serve an important function in alleviating the asymmetric information problem in asset securitization and the public security market in general. Since credit rating agencies are compensated by deal sponsors, their independence has long been of concern to investors and regulators. By analyzing a data set of 17,889 subprime ABS bonds and their credit ratings, we identify strategic interactions among credit rating agencies in rating assignments and rating changes. We further distinguish two competing explanations for higher probabilities of rating changes and single out loose original rating standards as the main cause. The main findings are that (1) Credit ratings are not independent and (2) More original ratings decrease the quality of ratings.

Analysis of the probability of rating changes shows that credit ratings are less stable when more rating agencies rate a bond. Further study of required credit support reveals a positive correlation between the number of original ratings and credit support for all rating agencies during the period when subprime credit worsened. These two findings demonstrate that the accuracy of ratings decreased when more rating firms rated a bond. Since rating stability can change, we test the impact of multiple initial ratings on the quality of credit ratings subsequent to a first rating change to rule out the alternative explanation for the higher probability of rating changes. For S&P, we show that a higher probability of rating change did not result from changes in the choice of rating stability, since the probability of subsequent rating changes was not affected by the number of original ratings. For Fitch, the test does not eliminate the alternative explanation. Further analysis of the number of rating changes after a first rating change is consistent with the results of the first test.

It is striking that more initial ratings actually decreased the quality of the ratings. Theoretical research, such as that in Lissari (1999), who modeled credit rating as a one-round sequential game, has shown that competition among credit rating agencies can lead to full information revelation. Several notable departures between the model assumptions and the reality of the credit rating market make the theoretical results less convincing. Empirical findings in this research do not support higher rating quality as an outcome of more initial rating agencies. Further theoretical work that models reputation of rating agencies and other mechanisms enforcing credibility is needed to decipher the consequences of competition in the credit rating industry.

The Credit Rating Agency Reform Act of 2006 was implemented with a goal to improve the quality of credit rating services by opening up registration and potentially increasing competition in the industry. However, this paper studies strategic interactions among credit rating agencies and shows that the quality of credit ratings would not improve by merely having more ratings. Furthermore, the impact of multiple ratings on rating quality is not equal across rating agencies.

Subprime credit has deteriorated to the extent that a full credit crisis was triggered worldwide. The subprime bond data set used in this research provides a unique insight into credit rating agencies' involvement in the crisis, what happened at the epicenter of the storm and what caused the precipitous deterioration in credit quality.

Chapter 2

Risk-Based Pricing of High Loan-To-Value Mortgage

2.1 Introduction

In the past few years, mortgage lending market has changed dramatically. New products have been developed to meet the needs of borrowers to achieve home ownership. It is estimated that there are more than 200 kinds of mortgage products in the market[1]. Many of the new products are tailored to the population that may not otherwise qualify for a traditional mortgage, either by lowering borrower's monthly payment or reducing down payment of a mortgage loan. It has not been enough time for most of the new mortgage products to go through a full credit cycle. As the housing market cools down, little is known about their likely performance in the near future. Certain sectors of the mortgage market, such as sub-prime, raise red flags to banks, regulators, and mortgage investors in general. It is imperative to study and understand the credit risk taken in these new and riskier products. I dedicate this paper to analyze high loan-to-value mortgage and its credit risk.

Loan-to-value ratio (LTV), is the ratio of outstanding mortgage loan balance over appraised property value. High LTV residential mortgage is defined by regulators as "any loan, line of credit, or combination of credits secured by liens on or interests in owner-occupied 1- to 4-family residential property that equals or exceeds 90 percent of the real estate's appraised value, unless the loan has appropriate credit support".[2] High LTV mortgage can take two forms. The first form is a single senior lien mortgage with LTV ratio greater than 90%. The second form is a combination of a senior lien loan and a junior lien loan. The senior lien loan normally have LTV ratio below

[1] "Increasing Risks in Mortgage Lending", Supervisory Letter, 2006.

[2] "Interagency Guidance on High LTV Residential Real Estate Lending", Office of the Comptroller of the Currency, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, and Office of Thrift Supervision, October 1999.

80% and the combined senior and junior loan balance have close to 100% LTV ratio.

In traditional prime mortgage market, borrowers are required to provide at least 2 years of income and asset verification, make down payment with LTV ratio below 80%, and have high FICO scores. With unprecedented housing price appreciation, high LTV first mortgage opens doors to home buyers without sufficient savings to pay for the required 20% down payment. Existing home owners use second lien loan to cash out gain in home value.

Most high LTV first mortgage is issued in Alt-A market. Alt-A mortgage is a major non-prime sector. It refers to loans with non-standard features such as high LTV ratio and issued mostly to borrowers with good but less than perfect credit. Alt-A origination volume increased from 11.0 billion in 1996 to 206.1 billion in 2006.[3] 46% of all Alt-A mortgage origination have LTV ratio higher than 80% and 17% with LTV ratio more than 90%.[4]

Second lien loans can be originated simultaneously with a first mortgage or later on. It is estimated that in the first half of 2004, about 42% of home purchase mortgage loan involved with a simultaneous second lien mortgage.[5] More recent industry survey shows that simultaneous second mortgage accounts for 39% of Alt-A mortgage origination in 2006, up by 36% from 3% in 2002.[6] Simultaneous second mortgage normally have very high combined LTV ratio. About 80% of simultaneous second lien mortgage have 100% combined LTV ratio.[7] A popular choice is borrowing a 80% LTV first lien together with a 20% LTV second lien mortgage loan. It is popularly referred to as "80/20" mortgage.

From mortgage originators' perspective, as prime mortgage profit margin shrinks, issuing new product like high LTV mortgage are ways to stay profitable. Mortgage companies are in the business of managing risk. If risks are measured properly, lenders can price additional risk into higher lending rates and be profitable. If not, lenders will face tremendous risks that lead to a situation like what happened recently in sub-prime market. Regulators are concerned about risks in high LTV mortgage and issued Interagency Guidance in late 1999. It cited increased default risk and losses and limited default remedies as major credit risk concerns.

Currently, high LTV mortgage origination is regulated by policies set forth in the Interagency Guidelines for Real Estate Lending Policies (the Guidelines), jointly issued by four federal regulators. The regulation is based on capital reserve requirement, which limits banks's ability to leverage out on equity. It requires that lenders apply 100 percent of *total capital* to holdings of high LTV mortgage loans. *Total*

[3]"Alt-A Credit Deterioration", UBS Mortgage Strategies, February 2007.

[4]"Fixed-Rate Alt-A MBS: Commonly Asked Questions Answered", Credit Suisse, October 2004.

[5]According to Calhoun (2005), SMR Research Corporation conducted a study with such findings.

[6]"Alt-A Credit Deterioration", UBS Mortgage Strategies, February 2007.

[7]"Silent Are Not Golden: Silent Seconds and Subprime Home Equity ABS," Credit Suisse, March 2005.

capital refers to the aggregate of a company's equity, certain subordinated debt, and loss reserves. It is a broader definition of equity capital. As a comparison, the 1988 Basel Accord assigns regular mortgage portfolio holdings a risk weighting of 50%. That requires only 2% *tier one* (equity) capital. Banks originating and holding high LTV mortgage loans are thus facing significant capital constraints. Since debt normally demands a lower rate of return than equity, the capital requirement on high LTV loans increases the cost of funds to originate them.

Given the fact that high LTV mortgage has higher credit risk, it is a proper step for regulators to set up more stringent capital requirement. The policies established in the Guidelines, however, do not differentiate nuances in high LTV mortgage loans. Its definition of high LTV mortgage applies to first mortgage with LTV greater or equal to 90% but does not apply to a first mortgage with LTV lower than 90% having a second mortgage with combined LTV greater or equal to 90%. In the later case, only the second mortgage falls into high LTV category and requires higher capital requirement. This exception provides lenders with capital arbitrage opportunities to separate a high LTV loan into a package of a conforming first mortgage and a simultaneous second mortgage.

In the paper, I will show how LTV ratio affects credit risk of mortgage. A structured credit modeling approach is taken to quantify the credit risk of first mortgage and second mortgage. The total risk in a combination of first and second mortgage is shown to be equal to that of a first mortgage with the same aggregate LTV. Default risk is derived implicitly. Optionality of defaultable debt results in an upward sloping credit supply curve as a function of interest rate with respect to LTV. Funding advantage in separating a high LTV into a lower funding cost first mortgage and a higher cost second mortgage is shown to create new market equilibrium.

2.2 The Model of Home Financing

In this section, we outline a basic credit model of property finance. To ensure availability of analytical solutions, I make the assumption that property value follows a Geometric Brownian Motion process. It follows the structured credit modeling methodology originated from Merton (1974). I analyze the payoff of home owner, senior lien debt, and junior lien debt holders. For simplicity, both senior and junior debts are assumed to be zero coupon bonds that are issued at discount and paid off by a lump sum payment at maturity.

In this simplified setting, credit risk is caused by volatility of property value and borrower's leverage in mortgage financing. Down payment and interest rates on senior and junior debts are the key determinants that impact each party's payoff and risk. Since the focus is credit risk, interest rate and prepayment risk are ignored. I assume there is no principal amortization and prepayment. In housing market, dynamic hedging of exposure to property value is not possible. Therefore, risk-neutral valuation and Black-Shole's option pricing formula cannot be applied. Expected payoffs in the future with probability measure in the real world are each party's objective for decision making.

Home buyers use their own financial assets and borrow money from bank to finance purchasing of a property. A property financing package is a combination (D, B_S, B_J, r_S, r_J), where

$$\begin{aligned} D &: \text{ Borrower's down payment} \\ B_S &: \text{ Senior debt amount borrowed} \\ B_J &: \text{ Junior debt amount borrowed} \\ r_S &: \text{ Senior debt interest rate} \\ r_J &: \text{ Junior debt interest rate} \end{aligned}$$

It is possible that the borrower finances purchase of the property without junior lien debt. In that case, $B_J = 0$. All interest rates are continuously compounded. The maturity date of debt is T. Debt is zero coupon. Principal and interest are due at debt maturity and there is no interim payment. Assume that borrower is not allowed to borrow more money than the initial property value $H(0)$. It is straight forward that,

$$H(0) = D + B_S + B_J. \tag{2.1}$$

Down payment is home owner's equity and is often confused with personal wealth. If we compare home financing with capital structure of a corporation, the home owner is at a position no different from that of equity holder of a corporation. Equity ownership is obtained when the home owner acquires the property. It will not change by how much equity the home owner has. Down payment determines leverage of the financing and the payoff structure. It also affects how much home owner's personal financial asset is at risk for the property investment. With debt financing, home owner can leverage out and afford a larger property than that solely using his own financial asset. When property value decreases, home owner can default and protect himself from further loss beyond down payment. However, when that happens, home equity will all be taken by debt holder. It is thus not favorable to have a disproportionately high home equity position. As we will discuss later, home owner's payoff is equivalent to a call option with debt payment as strike price. The call option represents home owner's equity value. Down payment is a cash outflow to pay for that call option. The moment the property is financed with debt, home owner no longer owns the down payment. Instead, he owns only that call option.

Down payment should be considered with opportunity cost in terms of returns from alternative investment. By putting money down as equity in property investment, home owner expects a return no worse than that from alternative investment opportunities. Otherwise, it is rational for home owner to reduce home equity and invest it in the higher earning investment. The liquidity cost for home owner can be thought of as the return on available alternative investment or the interest rate on other means of borrowing. We also have to recognize that in reality home owners normally view home more than a financial investment. In that sense, home equity is not exactly a decision driven by investment return. The emotional factor may reduce home owner's required rate of return on home equity.

Home buyer is liquidity constrained with an opportunity cost of η. With the above understanding about borrower's opportunity cost, η can take a low value when the borrower see home with high emotional value and a high value when the borrower is focused on investment return.

Banks' funding cost for senior debt is η_S and that for junior debt η_J. Funding costs are both above the risk-free rate r. For high LTV mortgage loans, the regulatory capital requirement, as mentioned in the introduction section, will make banks' funding cost on senior mortgage jump to a higher level after first lien LTV reaches 90%. If senior mortgage LTV is lower than 90% and CLTV is greater than 90%, senior debt funding cost will be at the lower level while junior debt funding cost will be at the higher level,

$$\eta_J > \eta_S > r.$$

The difference in senior and junior debt is in their priority to claim the underlying collateral. Whenever the borrower defaults, senior lien holder has claim to the property liquidation value before junior lien holder. Junior lien holder will not be able to recover anything until senior debt is fully repaid. Intuitively, junior lien holder bears higher risk than senior lien holder. This also justifies a higher funding cost for junior debt.

Property value and total outstanding liabilities are the only two factors that matter in borrower's decision to repay debt or default. At payment due date, if property value is less than the total outstanding balance of liabilities, whether borrower defaults on either one or both of the liabilities, lender will start foreclosure process. Property will be liquidated to repay debt. Lenders' losses are affected by priority in claim to collateral but not the order of default.

We introduce the blended lending rate, $\bar{r}$. Define the blended lending interest rate $\bar{r}$ as

$$\bar{r} = \frac{1}{T} ln(\frac{B_S e^{r_S T} + B_J e^{r_J T}}{B_S + B_J}) \tag{2.2}$$

Applying blended rate $\bar{r}$ to combined balance of senior and junior debt, the payment due at debt maturity will equal the total payment due on senior and junior debt. It will help us to understand payoff of the borrower and risk of junior debt holder in the next few sections.

LTV ratio is widely used in mortgage underwriting as a standard measure of borrower's leverage. The higher the LTV is, the higher the leverage of the borrower and the higher the risk of debt. We will use LTV to denote the senior debt LTV only. By assumption,

$$LTV(0) = \frac{B_S}{H(0)} \tag{2.3}$$

Similarly, Combined-Loan-To-Value or CLTV is the combined borrowed amount of senior and junior debt over property value.

$$CLTV(0) = \frac{B_S + B_J}{H(0)}.$$

Assume that property value $H(t)$ follows a Geometric Brownian Motion process with drift parameter $\mu - q$ and volatility parameter σ,

$$\frac{dH(t)}{H(t)} = (\mu - q)dt + \sigma dz(t), \tag{2.4}$$

where $dz(t)$ is a standard Brownian Motion process. The parameter q represents the rent equivalent of property's function as a shelter for property owner. The parameter μ is the average rate of housing price appreciation (HPA) after adjusting for rent equivalent income. For example, if national HPA is 5% and rent equivalent income is 4%, μ would be 9%. Property value is log Normally distributed,

$$lnH(t) \sim N(lnH(0) + (\mu - q - \frac{\sigma^2}{2})t, \sigma\sqrt{t}),$$

with expected value given by

$$E[H(t)] = H(0)e^{(\mu-q)t} \tag{2.5}$$

and variance by

$$Var[H(t)] = H(0)^2 e^{2(\mu-q)t}(e^{\sigma^2 t} - 1).$$

This assumption about property value is similar to that of a dividend paying stock in Black-Shole's option pricing model. In the world of Black-Shole's, financial derivatives can be replicated by dynamically trading the underlying assets and therefore risk-neutral pricing can be applied. In risk-neutral world, all assets grow at the risk-free rate and all risky payoffs can be discounted at risk-free rate to derive the present value. In Merton's seminal paper on corporate credit, similar assumption is made for firm value. Unfortunately, properties are illiquid assets and are not traded regularly. Without dynamic replication, risky asset pricing cannot be transformed to their equivalent in the risk-neutral world and has to be discounted with risk-adjusted rate of return. Before determining the risk-adjusted rate of return, financial derivatives cannot be priced properly.

In this model, however, we assume the risk-adjusted return as exogenous variables. Banks' funding rates are the risk-adjusted rate of returns required of senior and junior mortgage debt. Regulators normally set up economic capital reserve requirements that banks have to satisfy. Capital reserve requirement limits banks' ability to borrow funding at cheaper financing rate and constrains banks' leverage. I am interested in knowing the interaction among market participants and the market equilibrium lending rates as a consequence of bank regulation. Exogenous funding rate can be viewed as an instrument that central bank can utilize to control retail banks's leverage. This assumption will not alter the qualitative outcomes of the model. It would be of interest from regulator's perspective to determine regulator capital requirement that truly reflects the riskiness of debt lending and direct financial resources efficiently. This framework can act as a benchmark for empirical study to value the efficiency of regulatory policies.

With the underlying asset following Geometric Brownian motion process, expected value of option payoff has closed form solution. Since $H(t)$ is log normally distributed, it can be proved that

$$E[Max(H(T) - X, 0)] = E[H(T)]N(\delta_1) - XN(\delta_2) \tag{2.6}$$

and that

$$E[Max(X - H(T), 0)] = XN(-\delta_2) - E[H(T)]N(-\delta_1). \tag{2.7}$$

where

$$\delta_1 = \frac{ln[E(H(T)/X)] + \sigma^2/2}{\sigma\sqrt(T)} \tag{2.8}$$

and

$$\delta_2 = \delta_1 - \sigma\sqrt(T). \tag{2.9}$$

These two relationships will be used to analyze each party's payoffs through out this paper. The associate probability measure is the real world probability measure on which the Geometric Brownian motion process in Equation (2.4) is defined.

2.3 Home Buyer

At debt maturity, if property value is greater than or equal to total liabilities due, borrower will repay debt and obtain the gain in property value. Otherwise, he will default on debt. Borrower's payoff at time T is

$$C(T) = Max(H(T) - B_S e^{r_S T} - B_J e^{r_J T}, 0).$$

It is equivalent to the payoff of a call option on property value with a strike price of $B_S e^{r_S T} + B_J e^{r_J T}$. Call option entitles the borrower to upside gain without downside pain.

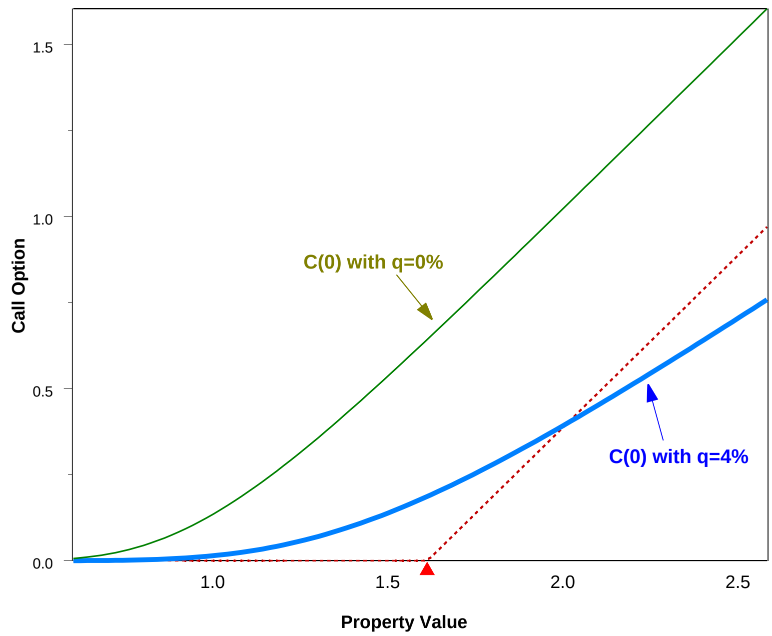

Figure 2.1: Borrower's Expected Call Option Value and Property Value

A call option is said to be in-the-money if the underlying asset value is greater than the option strike price. The more the call option is in the money, the more it is worth. If the underlying asset value is less than the option strike price, the call option value is still positive due to volatility or possibility of property value increase at maturity. Figure 2.1 illustrates borrower's call option value with respect to property value. I use Black-Shole's option pricing formula for illustrative purpose only. Parameters are close to reality. They are shown in Table 1. Except otherwise specified,

H_0	σ	$\bar{r}$	r	μ	q	T	η_S	η_J
1	5%	7%	4.5%	9.5%	4%	10	5.5%	6%

Table 2.1: Parameters Used in Figure 2.1

I use the same set of parameters in other figures or examples. In Figure 2.1, another case with $q = 0$ is demonstrated as well. The dotted line shows terminal payoff of the option. It starts at zero value. After crossing the strike price, it coincides with the 45 degree line above x-Axis. The thin brown line shows the option value when $q = 0$. It is always above the terminal payoff. Due to long maturity, it is quite high above the terminal payoff line. The thick blue line shows the option value when

$q = 4\%$. With positive rent equivalent cash flow, the option value is lower as if property is less valuable.
Since CLTV provides a normalized measure of leverage irrespective of property value, it will be helpful to see how CLTV affects expected call option value. Let's express the call option strike price by CLTV, blended lending rate, and property value,

$$B_S e^{r_S T} + B_J e^{r_J T} = CLTV(0)H(0)e^{\bar{r}T}.$$

At time 0, expected value of borrower's terminal payoff can be determined using Equation (2.6). Denote it as $E[C(T)]$,

$$\begin{aligned} E[C(T)] &= H(0)e^{(\mu-q)T}N(d_1) - (B_S e^{r_S T} + B_J e^{r_J T})e^{-rT}N(d_2), \\ &= H(0)[e^{(\mu-q)T}N(d_1) - CLTV(0)e^{\bar{r}T}N(d_2)]. \end{aligned} \tag{2.10}$$

where

$$\begin{aligned} d_1 &= \frac{ln(H(0)/(B_S e^{r_S T} + B_J e^{r_J T})) + (\mu - q + \sigma^2/2)T}{\sigma\sqrt{T}}, \\ &= \frac{-lnCLTV(0) + ((\mu - q) - \bar{r} + \sigma^2/2)T}{\sigma\sqrt{T}} \end{aligned} \tag{2.11}$$

and

$$d_2 = d_1 - \sigma\sqrt{T}. \tag{2.12}$$

$N(.)$ is the cumulative Normal distribution function.

As CLTV goes up, the call option value is lower. I will discuss later that higher CLTV will lead to higher credit risk and debt holders will charge a higher risk premium. Higher interest rates will increase the strike price and decrease the option value. For the moment, I neglect this complication and assume constant interest rates. Formally, the relationship between CLTV and borrower's expected call option value is stated in Proposition 1.

Proposition 1: CLTV and Borrower's Expected Call Option Value
Holding interest rates constant, the higher the CLTV, the lower the borrower's expected call option value. Mathematically,

$$\frac{\partial E[C(T)]}{\partial CLTV(0)} = -H(0) \cdot e^{\bar{r}T} \cdot N(d_2) < 0$$

where d_2 is defined as in Equation (2.12). Moreover, the rate of decreasing in the borrower's call option value decreases as CLTV increases,

$$\frac{\partial^2 E[C(T)]}{\partial CLTV(0)^2} = \frac{H(0) \cdot e^{\bar{r}T} \cdot N'(d_2)}{\sigma\sqrt{T} \cdot CLTV(0)} > 0.$$

Proof of Proposition 1:

Take partial derivative of $C(0)$ with respect to $CLTV(0)$ in Equation (2.10) yields,

$$\begin{aligned}\frac{\partial C(0)}{\partial CLTV(0)} &= H(0)[e^{-qT}N'(d_1)\frac{\partial d_1}{\partial CLTV(0)} \\ &\quad -e^{(\bar{r}-r)T}N(d_2) - CLTV(0)e^{(\bar{r}-r)T}N'(d_2)\frac{\partial d_2}{\partial CLTV(0)}]\end{aligned}$$

It can be easily shown that

$$\frac{\partial d_1}{\partial CLTV(0)} = -\frac{1}{\sigma\sqrt{T}CLTV(0)} < 0$$

and

$$\frac{\partial d_2}{\partial CLTV(0)} = \frac{\partial d_1}{\partial CLTV(0)}.$$

Combining terms and applying Normal distribution density function, we can get

$$\begin{aligned}\frac{\partial C(0)}{\partial CLTV(0)} &= -\frac{H(0)}{\sigma\sqrt{2\pi T}CLTV(0)}[e^{-qT-d_1^2/2} - CLTV(0)e^{-d_2^2/2+(\bar{r}-r)T}] \\ &\quad -e^{(\bar{r}-r)T}N(d_2)\end{aligned}$$

Applying the relationship between d_1 and d_2, it can be shown that the part inside the rectangular bracket equals 0. It is a very useful relationship to prove other propositions. I state it formally and refer to it as "very important relationship" in other sections,

$$e^{-qT}N'(d_1) - e^{(\bar{r}-r)T}N(d_2) - CLTV(0)e^{(\bar{r}-r)T}N'(d_2) = 0. \tag{2.13}$$

We are then ready to see that

$$\frac{\partial C(0)}{\partial CLTV(0)} = -H(0)e^{(\bar{r}-r)T}N(d_2) < 0.$$

The second order derivative can be taken from the above equation and shown to be positive. ■

The expected call option value as a function of CLTV is plotted in Figure 2.2. It is the solid blue line. The expected option value is at its maximum of 1.71 when CLTV is at the lowest, 0%. Expected option value decreases as CLTV increases and is always positive. It approaches 0 as CLTV increases towards 100%.

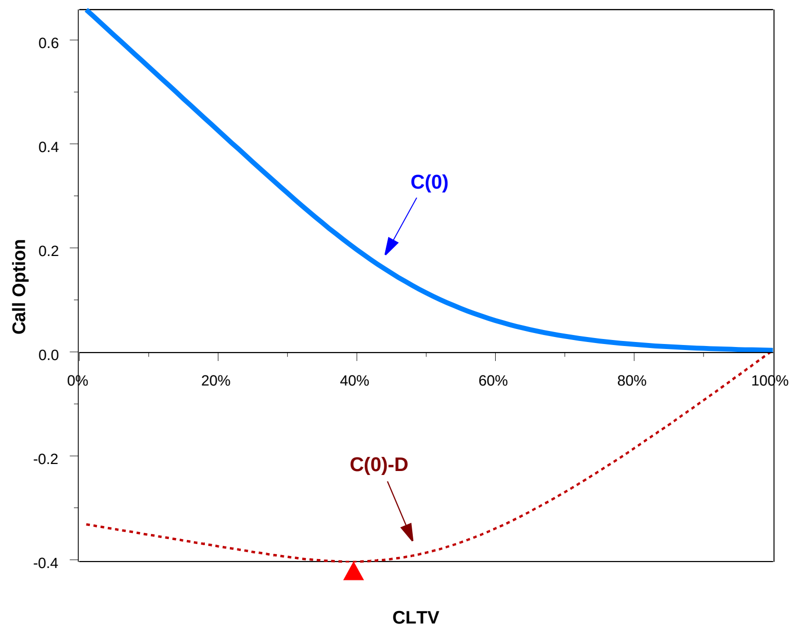

Figure 2.2: Borrower's Call Option Value and CLTV

It is easy to see that the higher the lending rates, the higher the call option strike. Higher lending rates will decrease expected call option value and lower borrower's net worth. The impact of lending rate to home buyer's payoff is stated in Proposition 2. It can be proved by applying the "very important relationship" defined in the proof of Proposition 1.

Proposition 2: Blended Interest Rate and Borrower's Expected Call Option Value
The borrower's expected call option value is a decreasing function of blended lending rate $\bar{r}$ so that

$$\frac{\partial E[C(T)]}{\partial \bar{r}} = -T \cdot H(0) \cdot CLTV(0) \cdot e^{\bar{r}T} N(d_2) < 0 \tag{2.14}$$

Turning to the borrower's net worth, the ultimate objective to consider when purchasing a property, the borrower's expected net worth at acquiring the property, $E(W(T)]$, is the expected call option value less the down payment with interest accrued at η, so

$$E[W(T)] = E[C(T)] - De^{\eta T} \tag{2.15}$$

Although the call option is more valuable with a lower CLTV, a lower CLTV also corresponds to a higher down payment. If the borrower makes a down payment more than the value of the call option, his initial net worth will be negative. The borrower's net worth at time 0 as a function of CLTV is shown in Figure **??**. In the graph, the borrower's net worth starts at \$0.33 when the down payment is zero and gradually drops to the minimum as CLTV increases. After passing a certain point, the net worth increases toward \$0 as CLTV gets closer to 100%. The borrower's minimum net worth is reached when CLTV is around 39%, marked with a red triangle in the graph. When CLTV exceeds 99%, the borrower's net worth starts to be positive (although it is not shown very clearly in the graph because of the scale). If we use a lower rent equivalent income parameter, q, the borrower's net worth will become positive with a lower CLTV. From the borrower's perspective, then, it is beneficial to borrow at a CLTV as close to 100% as possible.

We state the impact of CLTV on the borrower's net worth $W(0)$ rigorously below. The proof is omitted. It utilizes the fact that, if $\eta \geq \bar{r}$, then

$$e^{(\eta-\bar{r})T} \geq 1 > N(d_2). \tag{2.16}$$

Proposition 3: CLTV and Borrower's Expected Net Worth
Borrower's expected net worth $E[W(T)]$ is affected by CLTV. The rate of change is given by,

$$\frac{\partial E[W(T)]}{\partial CLTV(0)} = H(0) \cdot [e^{\eta T} - e^{\bar{r}T} N(d_2)]. \tag{2.17}$$

If borrower's liquidity constraint is higher than the blended mortgage rate, $\eta \geq \bar{r}$, the expected net worth is increasing with respect to CLTV.

The impact of the blended interest rate on the borrower's net worth is the same as that on the call option value, so we develop proposition 4.

Proposition 4: Blended Debt Interest Rate and Borrower's Expected Net Worth
Borrower's expected net worth $E[W(T)]$ is a decreasing function of blended debt interest rate $\bar{r}$,

$$\frac{\partial E[W(T)]}{\partial \bar{r}} = -H(0) \cdot CLTV(0) \cdot T \cdot e^{\bar{r}T} \cdot N(d_2) < 0. \tag{2.18}$$

The borrower's expected net worth at $t = 0$ as a function of CLTV and blended interest rate is plotted in Figure 2.3. The maximum is achieved at the right-hand side corner, as identified by a red Triangle. The senior debt interest rate has to be equal to the risk-free rate to get there, so the maximum is not obtainable. The borrower's expected net worth is much more sensitive to CLTV than to the blended interest rate. In this example, for a loan with 100% CLTV, the borrower's expected net worth will

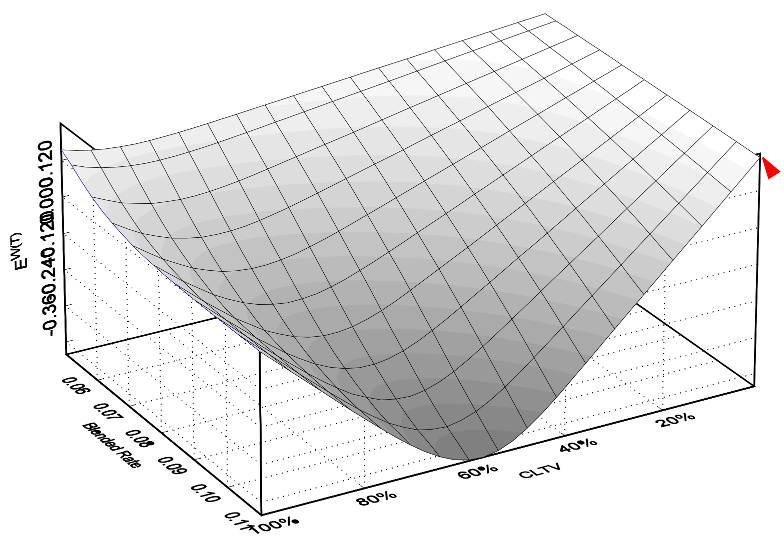

Figure 2.3: Borrower's Expected Net Worth Surface - CLTV and Blended Interest Rate

decrease by \$0.003 if the blended lending rate changes from 7% to 10%. Holding the blended lending rate the same at 7%, the borrower's expected net worth will decrease by \$0.010 if the CLTV drops from 100% to 99%.

Based on the propositions 3 and 4 regarding the borrower's expected net worth, we develop proposition 5 concerning the borrower's debt financing objective.

Proposition 5: Borrower's Debt Financing Objective
Borrower's objective function is,

$$\begin{aligned} MAX_{CLTV} &\quad E[W(T)] \\ s.t. &\quad \bar{r}(CLTV). \end{aligned} \tag{2.19}$$

where $\bar{r}(CLTV)$ *is lender's credit supply function. Borrower's marginal rate of substitution between the blended interest rate and CLTV to maintain the same expected net worth is,*

$$\begin{aligned} MSR^B_{\bar{r},CLTV} &= -\frac{\partial E[W(T)]}{\partial CLTV(0)} / \frac{\partial E[W(T)]}{\partial \bar{r}} \\ &= \frac{1}{T \cdot CLTV(0)} \cdot \frac{e^{\eta T} - e^{\bar{r}T} N(d_2)}{e^{rT} N(d_2)}. \end{aligned} \tag{2.20}$$

If the borrower has a liquidity constraint higher than the blended lending rate, it is beneficial to borrow with as high a CLTV as possible for the same reason as shown in Equation (2.16).

2.4 Senior Debt Holder

At debt maturity, if a property is worth less than the liabilities, the borrower will default on the debt. The senior debt holder's risk lies in the possibility that the property liquidation value will not fully cover the outstanding balance of the senior debt when the default occurs. The senior lien holder's payoff at maturity, $SL(T)$, is the lesser of the senior lien notional amount and the property value, such that

$$\begin{aligned} SL(T) &= Min(H(T), B_S e^{r_S T}) \\ &= B_S e^{r_S T} - Max(B_S e^{r_S T} - H(T), 0) \end{aligned}$$

The last term in the equation is the terminal payoff of a put option with a strike price of $B_S e^{r_S T}$. Essentially, the senior lien holder takes a long position in a risk-free bond and a short position in a put option on a property value with a strike price at the senior debt balance at maturity. Denoting the put option value at time t as $P_S(t)$, we have

$$SL(t) = B_S e^{r_S T - r(T-t)} - P_S(t) \tag{2.21}$$

By Equation (2.7), at $t = 0$, the expected put option terminal value is,

$$E[P_S(T)] \quad = \quad H(0)[LTV(0)e^{r_S T}N(-d_4) - e^{(\mu-q)T}N(-d_3)] \qquad (2.22)$$

where

$$\begin{aligned} d_3 &= \frac{lnH(0)/B_S + (\mu - r_S - q + \sigma^2/2)T}{\sigma\sqrt{T}} \\ &= \frac{-lnLTV(0) + (\mu - r_S - q + \sigma^2/2)T}{\sigma\sqrt{T}} \end{aligned} \qquad (2.23)$$

and

$$d_4 = d_3 - \sigma\sqrt{T} \qquad (2.24)$$

The junior debt balance is not involved in Equation (2.22).

Proposition 6: The Impact of Junior Debt on Senior Debt
The senior debt holder's risk is determined by the LTV of the senior debt, and the existence of junior debt is irrelevant.

Calhoun (2005) argued that a simultaneous second lien loans exposes senior debt holders to greater credit risk. Proposition 6 dismisses that argument.

The expected put option and senior debt value is plotted in Figure 2.4, with the assumption that $r_S = 6.5\%$. The expected put option value increases as LTV increases and reaches its maximum of \$0.50 at 100% LTV. If we take it a step further, the impact of LTV on the expected put option value can be quantified as

$$\frac{\partial E[P_S(T)]}{\partial LTV(0)} = H(0)e^{r_S T}N(-d_4) > 0 \qquad (2.25)$$

and

$$\frac{\partial^2 E[P_S(T)]}{\partial (LTV(0))^2} = H(0)e^{r_S T}N'(-d_4)\frac{\sqrt{T}}{\sigma} > 0$$

The senior debt interest rate of r_S affects the expected senior debt value only through the embedded put option. It has a negative impact on the senior debt value. For the same balance borrowed, a higher interest rate makes the borrower more likely to default. The LTV has additional influence through the debt balance. The senior debt holder's expected profit is the expected senior debt value minus funding costs, such that

$$E[\Pi_S(T)] = H(0) \cdot LTV(0) \cdot (e^{r_S T} - e^{\eta_S T}) - E[P_S(T)].$$

We state the LTV's and senior debt interest rate's impact on expected senior debt value in propositions 7 and 8, without proof.

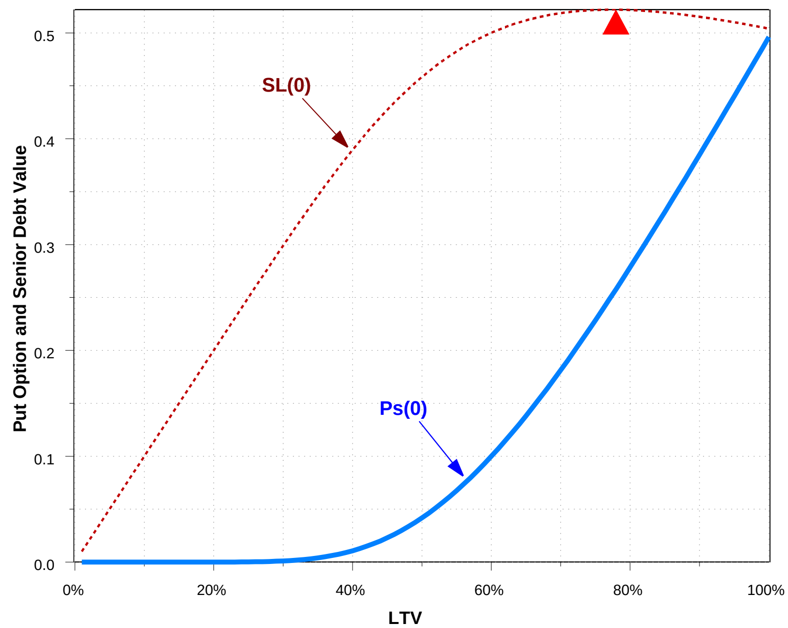

Figure 2.4: Expected Senior Debt and Put Option Value

Proposition 7: Senior Debt Interest Rate and Expected Profit
The impact of the senior debt interest rate on the expected senior debt profit is,

$$\frac{\partial E[\Pi_S(T)]}{\partial r_S} = H(0) \cdot LTV(0) \cdot T \cdot e^{r_S T}(1 - N(-d_4)) > 0.$$

Proposition 8: LTV and Expected Senior Debt Profit
The impact of the LTV on the senior debt expected profit is,

$$\frac{\partial E[\Pi_S(T)]}{\partial LTV(0)} = H(0)[e^{r_S T}(1 - N(-d_4)) - e^{\eta_S T}]. \tag{2.26}$$

We define the breaking point, $L\hat{T}V(r_S)$*, such that*

$$e^{r_S T}(1 - N(-d_4)) = e^{\eta_S T}.$$

The expected profit from the senior debt increases with the LTV when the LTV is below $L\hat{T}V(r_S)$*, and decreases when the LTV is above* $L\hat{T}V(r_S)$*.*

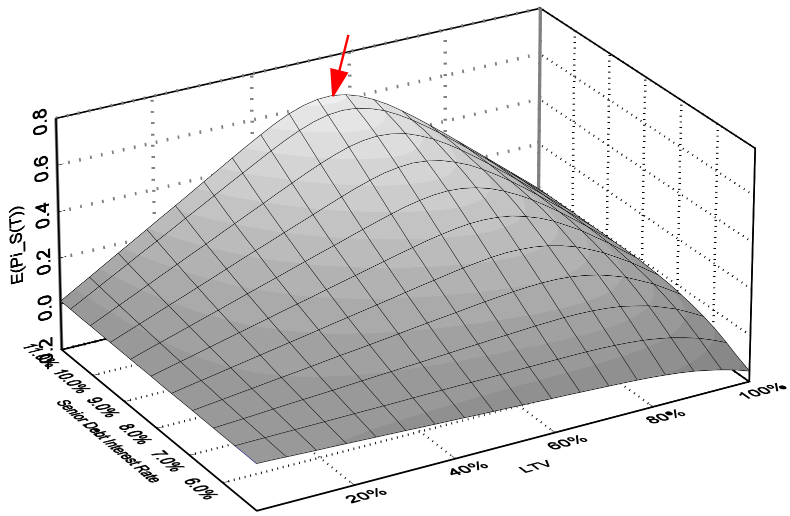

Figure 2.5: Senior Debt Expected Profit Surface - LTV and Senior Debt Interest Rate

The expected profit from senior debt as a function of the LTV is depicted in Figure 2.4 by the dotted red line. With a short position in an embedded put option, the expected profit from senior debt initially increases with the LTV, then decreases after the LTV passes 72%. Its peak value of \$0.123 is marked by a red triangle in the graph.

Proposition 9: Senior Debt Holder's Lending Decision
To the senior debt holder, the marginal rate of substitution between the senior debt interest rate and the LTV is

$$\begin{aligned} MSR^{SL}_{r_S,LTV(0)} &= -\frac{\partial E[\Pi_S(T)]}{\partial LTV(0)} / \frac{\partial E[\Pi_S(T)]}{\partial r_S} \\ &= \frac{e^{\eta_S T} - e^{r_S T}(1 - N(-d_4))}{T \cdot LTV(0) \cdot e^{r_S T}(1 - N(-d_4))}. \end{aligned} \tag{2.27}$$

This section concludes with the graph of the expected profit from senior debt as a function of the LTV and the senior debt interest rate of r_S. In Figure 2.5, the surface is tilted higher towards the direction of higher senior debt interest rate and is humped at the breaking point of the LTV for every senior debt interest rate above the funding rate. The lower the senior debt interest rate, the higher the LTV breaking point. If the senior debt interest rate is 10%, the LTV breaking point is 60%, marked on the graph by a red arrow.

2.5 Junior Debt Holder

The junior lien holder will encounter a loss equaling the excess of total liabilities over the property value up to the junior lien notional amount if the property is worth less than the total liabilities of both the senior and junior debt at maturity. The junior debt holder's payoff at maturity, $JL(T)$, is the lesser of the junior liability balance and the property value after the senior debt claim has been paid, such that

$$JL(T) \quad = Min(Max(H(T) - B_S e^{r_S T}, 0), B_J e^{r_J T})).$$

The terminal payoff of the junior debt can be re-written as,

$$JL(T) = B_J e^{r_J T} - Max(B_J e^{r_J T} - Max(H(T) - B_S e^{r_S T}, 0), 0). \tag{2.28}$$

which is equivalent to the payoff of a risk-free bond, less the value of a compound option. The compound option is a put option on a call with the put strike price at $B_J e^{r_J T}$ and the call strike price at $B_S e^{r_S T}$. Pricing a compound option is more involved than a vanilla option. Since we assume that the senior and junior debt have the same maturity, we assume that the property value equals the total of the senior debt, junior debt, and the homeowner's call option, such that

$$JL(t) = H(t) - C(t) - SL(t). \tag{2.29}$$

Proposition 10 is proven by observing that both the senior debt and the borrower's call option enters into the junior debt's value in Equation (2.29).

Proposition 10: The Impact of Senior Debt on Junior Debt
The junior debt holder's risk is determined by the LTV of the senior debt and the CLTV.

The junior debt's risk sensitivities to LTV and CLTV are straightforward from the results in the previous sections. The junior debt holder's expected profit is:

$$E[\Pi_J(T)] = E[H(T)] - E[C(T)] - E[SL(T)] - B_J \cdot e^{\eta_J T}.$$

The impact of r_J, LTV and $CLTV$ on the terminal profit of the junior debt is stated in Proposition 11.

Proposition 11: The Impact of r_J, LTV, and $CLTV$ on Junior Debt Holder's Expected Profit
Junior debt holder's profit is affected by its interest rate r_J, LTV of the senior debt, and the $CLTV$ such that

$$\frac{\partial E[\Pi_J(T)]}{\partial r_J} = H(0) \cdot e^{r_J T} \cdot (CLTV - LTV) \cdot N(d_2) > 0, \quad (2.30)$$

$$\frac{\partial E[\Pi_J(T)]}{\partial LTV(0)} = -\frac{\partial E[SL(T)]}{\partial LTV(0)}$$

$$= H(0) \cdot e^{r_S T} \cdot (N(-d_4) - 1) < 0, \quad (2.31)$$

$$\frac{\partial E[\Pi_J(T)]}{\partial CLTV(0)} = H(0)[e^{r_J T}(CLTV - LTV)N(d_2)] > 0 \quad (2.32)$$

The junior debt holder's expected profit increases with r_J and decreases with the LTV. The CLTV has a positive impact on the junior debt holder's profit.

2.6 Market Equilibrium

To derive the market equilibrium, we assume the lending market is an oligopoly and that multiple lenders engage in Bertrend competition. Consequently, interest rates will be at a level at which lenders make zero economic profit. In reality, the mortgage market is well represented by this market structure; there are more than 20 major originators in each product sector of the mortgage lending business, each with no more than 10% of the market share.

The senior debt supply schedule is a function of the senior debt interest rate with respect to the LTV. The senior debt interest rate and the LTV satisfy

$$E[\Pi_S(T)] = 0 \quad (2.33)$$

In Figure 2.6, the senior debt supply schedule without high-LTV regulation is shown by the dashed green line. The senior debt rate starts close to funding cost at 5.5% when the LTV is 65%. As the LTV rises, the senior debt originator will charge a higher interest rate to compensate for higher credit risk. The interest rate is flat for LTVs below 80% and is is only 7 bp higher when the LTV increases from 65% to 80%. The curve is still flat going from 80% LTV to 90%. The interest rate is at 5.86% when the LTV is 90% but rises dramatically after the LTV exceeds 95%. When the LTV approaches 100%, the interest rate will be high enough to prohibit borrowing.

Current regulations result in a higher funding cost for senior debt after the LTV reaches 90%. If we assume that funding costs will increase by 50 bp (or 0.5%) to

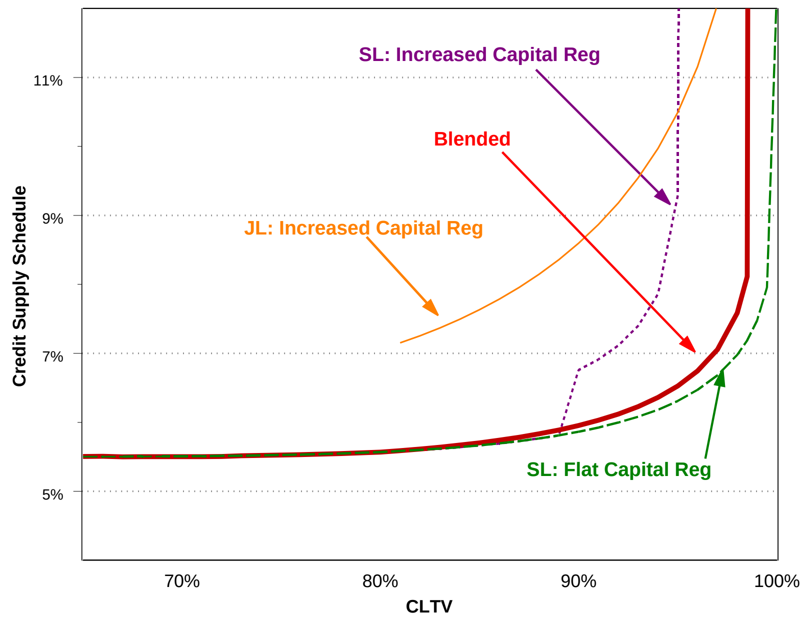

Figure 2.6: Lenders' Credit Supply Schedule

6% for high-LTV loans, the senior debt supply schedule shifts to the dotted purple line after the LTV passes 90%.

The junior debt supply function will solve the zero expected profit condition for the junior debt holder,

$$E[\Pi_J(T)] = 0. \tag{2.34}$$

In Figure 2.6, it is demonstrated by the thin, solid orange line. We assumed that the senior debt in front of the junior debt has 80% LTV. Since junior debt takes a subordinate position to senior debt, the junior debt interest rate is much higher than the senior debt at the same LTV. At 80% LTV, the junior debt interest rate is at 7.15% for 81% CLTV, which is 1.57% higher than the senior debt interest rate at the same LTV. The junior debt interest rate rises as CLTV increases and is always above the senior debt rate. Compared with that of the senior debt, the rate of increase in the junior debt interest rate is gradual after the CLTV exceeds 95%.

The blended lending rate is depicted by the thick, solid red line; it is above the unregulated senior lending rate but much lower than the regulated senior lending rate.

Borrowers with different liquidity constraints will have different demand schedule. Borrowers will be willing to borrow at an interest rate lower than or equal to what makes their expected net worth zero. Mathematically, the demand schedule is

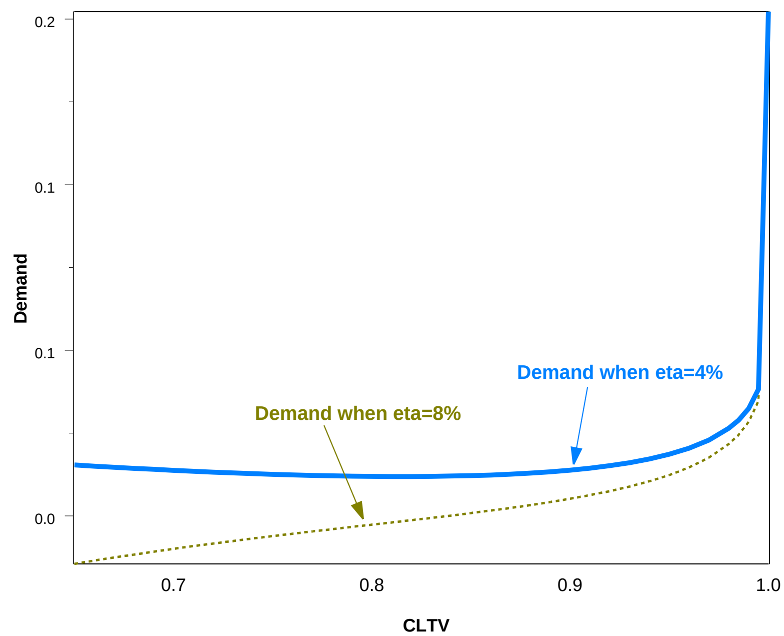

Figure 2.7: Borrower's Credit Demand Schedule

$\bar{r}(LTV) < \bar{r}^*$ and $\bar{r}^*$ such that,

$$E[W(T)] = 0. \tag{2.35}$$

As shown in Proposition 3 in Equation (2.17), borrowers with liquidity constraints higher than the blended lending rate will have a demand schedule that is an increasing function of CLTV. For those with lower liquidity constraints, the demand schedule will reach bottom at a certain point and pick up again. It is clear from the definition of the borrower's expected net worth, as in Equation (2.15), that, all else being equal, the borrower with lower liquidity constraints will have higher expected net worth.

The borrower's demand schedule is shown in Figure 2.7. The solid blue line shows the demand of a borrower with liquidity constraint $\eta = 8\%$, and the dotted brown line is that of a borrower with liquidity constraint $\eta = 4\%$.

Market equilibrium is achieved when the borrower can borrow at an interest rate at or below his demand schedule, and lenders can lend at an interest rate at or above their supply schedule.

Market equilibrium is shown in Figure 2.8. The demand schedule shown is for $\eta = 4\%$, and demand is the shaded blue area. Borrowers are screened on their liquidity constraint so that only those with liquidity constraints low enough for demand to

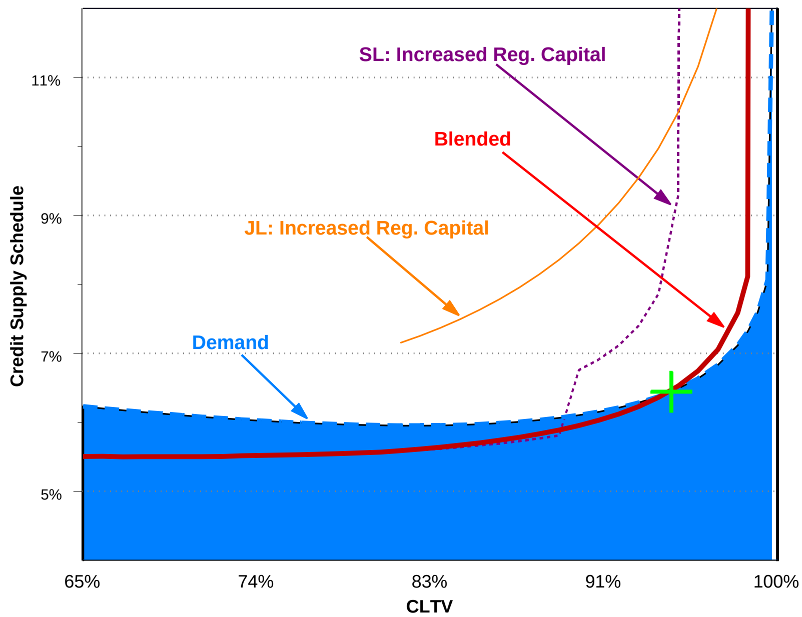

Figure 2.8: Market Equilibrium

be above the blended supply schedule will be offered credit. Borrowers will search for the best combination of senior and junior debt for the lowest blended lending rate, and senior lien holders will supply credit until the blended lending rate is lower than the senior debt rate. Market equilibrium is achieved on a series of combinations of CLTV and interest rate along the blended supply schedule. A borrower with liquidity constraint $\eta = 4\%$ will borrow along the blended supply schedule depicted by the solid, thick red line until it intersects with his demand schedule, marked by a green cross.

2.7 Expected Default Rate and Losses

Default occurs when a property value drops below the balance of liabilities at debt maturity. The expected default rate is quantified in Proposition 12.

Proposition 12: Expected Default Rate
The expected default rate on mortgage debt is $N(-d_2)$.

Proof of Proposition 12:
By put-call parity, the borrower's call option is equivalent to holding the property,

lodging a put option on it, and borrowing debt with a balance of the strike price.

$$C(0) = H(0) + P(0) - H(0) \cdot CLTV$$

where the payoff of the put at maturity is

$$P(T) = Max(H(0) \cdot CLTV \cdot e^{\bar{r}T} - H(T), 0).$$

Therefore, the expected default rate is the probability that the put option is exercised at maturity with a real-world probability measure. By Equation (2.7), the expected default rate is $N(-d_2)$. ■

The expected default rate is increasing in both CLTV and $\bar{r}$.

$$\frac{\partial N(-d_2)}{\partial CLTV} = \frac{N'(-d_2)}{\sigma\sqrt{T}CLTV} > 0$$

and

$$\frac{\partial N(-d_2)}{\partial \bar{r}} = \frac{\sqrt{T}N'(-d_2)}{\sigma} > 0.$$

Dubitsky and Guo (2005) showed that the 80/20 first lien piggyback loan is more likely to become delinquent than are 80% true LTV loans. The higher delinquency rate on senior debt is consistent with our model. If we use the same set of parameters as in the example of sub-section (2.3), the loan package of 80% LTV and 100% CLTV will have a delinquency rate of 7.7%, and the loan package with only 80% senior debt LTV and no junior debt will have a delinquency rate of 1.7%. The delinquency rate is much higher on the senior debt with junior debt subordinate to it, even though the LTV is the same.

However, the expected loss on senior debt is the same, irrespective of the existence of junior debt. It is the value of the put option $P_S(0)$, as defined in Equation (2.22).

The expected loss on junior debt depends on both senior debt LTV and CLTV. It is the value of the compound option, as defined in Equation (2.28), and can be expressed explicitly using compound option pricing, as discussed in Geske (1979).

2.8 High LTV Mortgage Regulation

Current regulations require banks to reserve capital according to the LTV on holdings of residential mortgage loans[8]. This regulation limits banks' high-LTV

[8] "Interagency Guidance on High-LTV Residential Real Estate Lending," Office of the Comptroller of the Currency, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, Office of the Thrift Supervision, October 8, 1999.

holdings to less than *total capital*, so it limits banks' ability to leverage high-LTV mortgage holdings. The interpretation of the policy as it is stated in the Guidance applies the limit to holdings of high-LTV senior mortgages and high-CLTV junior mortgages, but it does not apply to senior mortgages originated below the 90% LTV threshold in a high-CLTV senior-and-junior-mortgage combination if the bank does not originate the senior mortgage or sells it to the secondary market. For example, if a bank originates senior mortgage debt with an LTV of 100%, it will have to apply higher funding costs; but if it originates an 80/20 mortgage package and keeps only the junior mortgage, the regulation will not apply to the 80% LTV senior mortgage.

If the risk of a mortgage is measured by the expected loss as a percentage of outstanding balance, junior mortgages will be much riskier. As demonstrated in Section 2.5, the expected loss from junior mortgages is much higher than that from senior mortgages with the same CLTV because junior mortgages take subordinated positions. Current regulation will reduce origination of high-LTV senior mortgages, but it will induce banks to engage in capital arbitrage to increase origination volume in high-CLTV junior mortgages, which have an even higher credit risk.

If there is no regulation on high-LTV loans, market forces will price the credit risk properly. As shown in Section 2.6, the credit supply schedule will be based on LTV and CLTV, and market equilibrium will be achieved on the unregulated credit supply curve. The need for regulation of high-LTV mortgages is not well justified.

2.9 Conclusion

This paper takes a structured credit modeling approach to quantify the credit risk of first and second mortgages. LTV as a measure of leverage is the most important indicator of credit risk. We derived default probabilities and expected losses on mortgage debt. Optionality of defaultable debt results in an upward sloping credit supply curve as a function of interest rate with respect to LTV. Market force alone is shown to be sufficient enough to match supply with demand and still account for credit risk.

Current regulation in high-LTV mortgage creates a funding advantage in separating a high-LTV mortgage into a first mortgage with lower funding costs and a higher-cost second mortgage. This explains the increased origination volume in second mortgages, although the credit risk in high-LTV mortgages may not be reduced as the regulation intended, given that second mortgages have more concentrated risk because of their subordination.

In the simplified model, there is no principal amortization or prepayment. Therefore, the model does not account for interim default at periodical payment due date (for interest and scheduled principal). The model could underestimate default risk in the sense that there is less chance for default to occur; and it could also overestimate default in the sense that principal amortization reduces the option strike price. In a model with interim payments, the effect on credit risk of other credit characteristics of mortgage loans, such as income verification and credit score, will kick in. The linkage between junior mortgage and senior mortgage can differ because a junior mortgage increases the borrower's burden of payments and the probability of default. We will be able to model adverse selection from the lenders' perspective to screen applicants with a higher risk of interim default using income verification and credit scoring. Interim default can be introduced to the current simplified model by an additional independent hazard process, which will be the next step for future research.

It will also be useful to test empirically whether high-LTV mortgage interest rates in the current market are appropriate to compensate for the credit risk. This research will be helpful for regulators in testing the efficiency of regulation and for mortgage originators in measuring the pricing of products with significant credit risk.

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