The Reliance of Structured Finance Investors on Credit Rating Agencies Before and After the Financial Crisis

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Abstract

Credit rating agencies (CRAs) have been widely criticised as one of the factors leading to the 2008 crisis. Such criticism on the ratings offered to structured finance products (Asset-backed securities, ABS) is even heavier. We investigate whether the behaviour patterns of structured finance investors have significantly changed after the shock of the global financial crisis: did investors trust CRAs before 2008 and, if so, are they still trusting those institutions after the crisis?

Our paper contributes to the related research in three directions: by 1) including diversified types of assets backing the ABS, 2) comparing the results before and after the 2008 crisis to show the investors' behaviour pattern following the credit ratings and 3) including not only the issuance data, which most of the researchers have considered, but also taking transaction data into account to analyse the effects of rating events on transaction prices.

The outline of our paper is as follows. A statistical analysis of the credit pattern transformation is firstly conducted to demonstrate the effect of the crisis on the rating industry. Afterwards, we run cross-sectional regressions to study the correlation between ABS prices and the issuance credit ratings in pre-and post-crisis periods. We find evidence of a weaker reliance of ABS investors on the ratings offered by credit rating agencies after the financial crisis. To supplement the static-regression analysis, we use time-series-event-analysis methods to identify the ABS price reactions to the rating events in the two periods and evaluate the transformation of price reaction degree around the crisis.

We conclude that before the 2008 crisis, ABS investors' decisions, reflected in prices, were significantly associated with the ratings offered by CRAs while the post-crisis period has seen a weaker link between prices and CRAs' announcements, indicating a smaller influence of CRAs on the structured finance market.

1 Introduction

The US subprime mortgage crisis (2007) and the accompanying global financial crisis (2008) highlight the role played by credit rating agencies and the importance of the asset securitization market. CRAs (credit rating agencies) have been criticized for providing structured finance products, securities issued in the asset securitization market, with inaccurate and biased ratings (Morkötter et al, 2009; Griffin et al, 2011; He et al, 2011; Kraft, 2015). Investors relied on the ratings concerning the performance of those products and created a huge bubble in the securitization market, which shocked the entire financial system of the United States and of other main economies in the world when it eventually burst.

In these events, one key element is the reliance of structured finance investors on CRAs. Investors rely on opinions and signals released by CRAs, who provided inaccurate ratings. Those ratings convinced investors to invest in an astonishing amount of ABS (asset-backed securities), particularly MBS (mortgage-backed securities) (Friedman and Posner, 2011). In this light, , this paper is designed to study the market reliance on CRAs with regard to structured finance products (ABS, including MBS) and the possible change in such reliance in the wake of the financial crisis.

CRAs are specific institutions offering assessments of borrowers' creditworthiness and ability to pay their debts. With a history of around 100 years, CRAs are essential participants in the modern financial market due to their power to influence other participants. Structured finance products (ABS), created in the mid-1980s, are one of the biggest financial innovations in modern finance history because of their special characteristics of pooling and tranching. The reason for selecting ABS in order to study CRAs is not merely that ABS were the first sector to collapse in the financial crisis but that ABS investors are believed to have relied on CRAs to a greater extent than other types of investors through the following channels: information intermediate function, historical behavioral reliance and rating-based regulations (Fender and Mitchell, 2005; Coval et al, 2009).

Finance inherently involves information. Access to sufficient and efficient information is no doubt the principal demand of all financial market participants. The reliance of investors on CRAs is a natural phenomenon under a condition of information asymmetry. Investors can only have access to limited information on securities or companies of their interests due to a lack of strong discourse power.

However, as institutions with large market influence, CRAs (particularly the top three, Moody's, Standard & Poor's and Fitch) are trusted by investors due to their ability to collect information on debt issuers which cannot be obtained by investors themselves (Canton and Packer, 1994). The information intermediate function is more significant in a structured finance market because of the complexity of ABS securities. Since the securitization process is relatively sophisticated and difficult for investors to address, particularly simple (individual) investors, they tend to turn to CRAs to obtain a simplified opinion (in a form of alphanumeric credit ratings) regarding the credit risk of ABS of their interests.

Besides, due to their historical reputation, leading CRAs have 'trained' investors for a behavioral pattern of relying on their ratings. CRAs have a long history and had accumulated a reputation sufficient to have profoundly changed investors' behavior. For example, many market participants use credit ratings offered by the top three CRAs as a 'trigger' of commercial contracts. Some investors require traders to sell certain securities immediately if they are downgraded below certain boundaries, such as BBB notch, for example. For the structured finance market, the behavioral reliance of investors on CRAs still exists because structured finance products were created at least 70 years after credit rating industry was created so structured finance investors inherited the thinking pattern of relying on CRAs (Servigny and Jobst, 2007).

Another reason for investors' reliance on CRAs is financial regulations. Before the 1970s, although CRAs were expanding their market share, they did not attract investors interest to the same extent as they do currently because US and international financial regulators did not attach great importance to them (Darbellay, 2013). However, since the 1970s the SEC (Securities and Exchange Commission of US) has gradually taken action to link regulatory requirements to CRAs. In Basel II, at least two types of regulation, risk-sensitive capitals and investment limitation, are based on credit ratings. When calculating capital, financial institutions (particularly banks) are allowed by the policy to use different weights on securities with different credit ratings. Hence, as institutional investors, banks have to rely on CRAs, adjusting their investment portfolio according to credit ratings given to interested securities. Another regulation concerning ratings is investment limitation, whereby certain investors are not allowed to hold securities under certain levels of rating grades (Darbellay, 2013).

However, the three channels mentioned above have undergone some changes since the 2007 subprime crisis. The function of as information intermediates has been questioned (Mattarocci, 2013); their reputation has been dramatically undermined (Lynch, 2008) and regulators have expressed their willingness to remove credit ratings from regulatory requirements (Darbellay, 2013).

CRAs failed to foretell the collapse of subprime securities before the crisis occurred. Such poor performances are not consistent with the role of s information providers which CRAs should have played. Therefore, they were subject to a large number of harsh comments (Lynch, 2008; Morkötter et al, 2009; Griffin et al, 2011; He et al, 2011; Mattarocci, 2013; Kraft, 2015) .It was questioned whether CRAs could remove information asymmetry as they are required to do and investors may not regard ratings provided by them as sources of extra information. Thus, due to the harsh criticism of CRAs' poor performances, investors' behavioral reliance was weakened.

Regarding regulation changes in the rating industry, the most significant action taken by US regulators has been the release of the Dodd-Frank Act 2010. This is a financial market reform plan signed by President Obama aiming to re-regulate the financial system in response to the financial disaster. This Act highlights that credit ratings should be gradually removed from the criteria of financial regulations Reformers claim that the removal of rating-based regulations can eliminate the reliance of investors and of the entire financial system from the regulatory perspective.

In the context, this paper conducts an empirical test on the reliance of investors on CRAs before and after the recent financial crisis. The main objective of this research is to assess the extent of investors' reliance on CRAs and judge whether the financial crisis has weakened such reliance, as many articles suggest (Lynch, 2008; Darbellay, 2013; Mattarocci, 2013) and as the regulators expect. Reliance on CRAs is essential not only for investors and rating agencies themselves, but also for the normal operation of the financial system. On the one hand, the reliance of investors on CRAs provides a possibility of realizing information symmetry, which is a vital element of the efficient market theory. However, on the other hand, since conflict of interest exists in the rating market, reliance of investors on CRAs may bias investors or even the system. Conflicts of interest result from the issuer-pay business model of CRAs and an oligopolistic trend of the rating industry (high concentration of the Big Three and barriers to new entrants) and collective market power of the Big Three (Mattarocci, 2013). These three factors (conflicts of interest, oligopoly trend and Big Three collective market power) can all be enhanced by investors' reliance. Investors' trust in CRAs makes issuers more willing to maintain the issuer-pay model and pay CRAs for a satisfied rating to attract investors. Besides, the reliance of investors creates a high profit of leading CRAs, exacerbating the concentration in the rating industry and raising the barrier to small and new CRAs. Thus, reliance on CRAs may undermine market efficiency via conflicts of interest and enhance conflicts of interest at the same time.

This paper is structured as follows. Section 2 consists of an introduction to CRAs and ABS, a literature review of related research by other scholars and a list of the contributions of this paper beyond the existing literature. In Section 3, we present our two main hypotheses and four sub-hypotheses about the reliance of investors on CRAs and state the methodology used to test these hypotheses for both the primary market data and secondary market data. Section 4 describes the dataset used and our empirical results as well as robustness test results. Section 5 concludes the paper.

2 Background, related research and contribution

2.1 Relationship between investors and CRAs

The credit rating industry has a history dating back over a century. The first credit rating was released in 1909 by Moody's on a railway bond deal. Since 1909, a series of M&A (Merge and Acquisition) events have taken place among the individual CRAs, shaping this industry into its current pattern of a three-party oligopoly of Moody's, Standard & Poors, and Fitch).

Although the credit rating industry has existed for over 100 years, it did not gain the systemic power to influence different parties in the financial market until a series of policies were issued to set credit ratings as a key reference of regulatory requirement decision (Darbellay, 2013). Due to the enhanced link between credit ratings and financial regulations, regulators gradually 'enfeoffed' part of their power to the Big Three CRAs. Companies willing to issue debts and the financial institutions who serve as servicers or trustees in the issuance process view 'satisfying' ratings given by CRAs as a special signl of recognition approved by regulators. Thus, the reliance of investors on CRAs is a by-product of such regulatory recognition. Sy (2009) uses a buy-sell interaction model to describe the effect of the regulatory recognition. The buy-side of the ratings includes mutual funds, pension funds and insurance companies whose incentive for buying ratings is to ensure compliance with regulatory requirements, while the sell-side of the ratings (broker-dealers) aims to determine the counterparty collateral levels. The buy-sell interactions bridged by credit ratings enhance the importance of CRAs due to the rating changes' systemic impact on the financial markets, particularly those abrupt downgrades.

Other than the regulation factor, another fact to investors' reliance on CRAs which can be attributed to is the information intermediate function. Partnoy (2009) argues that there are three conditions under which the information intermediate function can really work: significant reputational capital, higher expected loss than expected gain from false certification, and variable services costs related to the degree of informational asymmetry.

The research on the relationship between investors and CRAs can be divided into two streams: theoretical research and empirical research. Theoretical research mainly describes the relationship between investors and CRAs from a mathematical perspective and empirical research analyses it from a statistical perspective. To present previous scholars' contributions comprehensively, we list the related research outcomes in both streams in the following paragraphs.

Theoretical papers aim to study the economic equilibrium between credit rating providers (CRAs) and investors. Bolton et al. (2012) establish a game theory model on the equilibrium of the behaviors of CRAs, debt issuers and investors in order to investigate the effect of CRA competition on the rating quality given by the agencies and to investigate the relationship between the trusting of investors and the rating quality. They state that CRAs may tend to 'fraud rating' when there are more 'trusting investors' in the markets and when CRA pay less when the fraud is observed. Fender and Mitchell (2005) successfully foretell the possibility of model risk of rating agencies due to the over reliance on ratings. Noh and Dong Woo (2014) build a game theory model of five participants: one issuer, one private credit rating agency, one public credit rating agency, one 'rater' with information acquisition technology and a continuum of investors. They conclude that a reform creating a 'public CRA' can work only if the distribution of type of issuer projects and impact of high rating benefits are known.

In terms of empirical research on market (investors') reactions to the credit ratings, early papers focus on the credit ratings of conventional bonds. West (1973) conducted initial research on the relationship between bond prices and credit ratings. He found empirical evidence from Fisher's data of corporate bond issues to show a significant influence of bond ratings on bond yields. However, only four years after that, Weinstein (1977) presents a contradictory result using monthly returns on straight debt issues over the period July 1962 through July 1974, finding no significant return reactions during and six months after the months when a credit rating change was announced by Moody's. Recent papers have tried to find more details about the bond price reactions to credit ratings. Kliger and Sarig (2000) checked the bond ratings' influence on the firm, debt and equity values and implied options prices. They found a shock of Moody's announcements on firms' debt values, equity values, and as option-implied volatilities. Iannotta (2013) introduced the concept of 'quality spread' (the yield difference between the Baa and Aaa tranches) to represent the predictive power of ratings and demonstrated that the influence of credit ratings on issuance spreads is greater if the 'quality spread' is higher. Abad et al. (2015) tested the historical rating change announcements and their effects on the risk-return binomial, concluding that the CRAs' rating announcements reveal new information to the market.

Other than normal bonds, other types of bonds have also attracted the attention from academic studies. Liu and Thakor (1984) investigated the independent impact of ratings on state bond yields, while. Stover (1991) focused on the relationship between the yield of newly issued municipal bonds and bond ratings. In addition, many scholars have discussed the relationship between share prices and rating announcements. Hand et al. (1992) compared the result of the stock market with that of the bond market. They tested the significance of excess returns around rating announcements and concluded that unless 'expected' rating changes are excluded, the excess returns are insignificant. However, they found asymmetric effects between negative and positive announcements, as well as distinct effects on investment-grade securities and non-investment-grade securities. Dichev and Piotroski (2001) tested the long-run variation of stock returns following corresponding bond rating changes. Similar to Hand et al. research, they also found empirical evidence of the asymmetric effects of negative and positive announcements on stock abnormal returns: negative announcements are accompanied by 10% to 14% negative abnormal returns but positive announcements are accompanied by no significant positive abnormal returns. Jung et al. (2016) examined how credit ratings affect the behavior of stock analysts' earnings forecast revision. They found asymmetric effects of negative and positive ratings but no effect difference between investment grades and non-investment grades.

Apart from traditional financial instruments, bonds and stocks, related derivatives such as CDS (credit default swap) are of interest to many scholars. Hull et al. (2004) integrated CDS with normal bonds and analysed their price reactions to rating announcements by Moody's. They found that downgrade reviews contain significant information that impacts on the price returns but that downgrade outlooks do not contain such information. Chava et al. (2012) studied whether a firm's stock and bond price reliance on credit rating downgrades differ if that firm issues CDS or not and found that firms with traded CDS have a weaker reaction to negative rating announcements. Drago and Gallo (2016) investigated Euro area CDS and its relationship with sovereign ratings. They concluded that investors' risk perception is associated with downgrade or upgrade announcements and there are spill-over effects of CDS price variation over different countries only for downgrade announcements, providing an example of the asymmetric effect phenomenon.

The empirical literature also covers the impact of credit ratings on activities in the financial market, such as payment methods in the M&A process (Karampatsas et al., 2014), capital structure decisions (Kisgen, 2006), sovereign issuance funding (Kiff et al., 2012) and real private investment (Chen et al., 2013). Moreover, other studies (e.g. Kräussl, 2005) cover the impact of sovereign rating announcements on countries' indicators of macro-economic activities, exchange rate, interest rate and stock market index.

2.2 Credit ratings of structured finance products

This paper focuses on the credit ratings of structured finance products. Structured finance (Asset-Backed Security, known as ABS) is an important outcome of financial innovation in the 20th century. It splits the risks of buyers and sellers of a single security by establishing a security pool whose payments to investors are based on the incomes of the backing securities (also called collateralized securities). In contrast to traditional investment instruments through which the issuers and investors of the securities transact directly, in ABS transactions, an institution called a Special Purpose Vehicle (SPV) organizes the transactions as a bridge between the specific issuer and the general investors. The investors receive the payments in an order based on their payment priority, reflecting the purchasing prices or spreads (this procedure is called ‘tranching’ and each of the payment obligations with specific payment priority is called a ‘tranche’).

The process described above is also called asset securitization. The incentives driving the creation and evolution of asset securitization were summarized by Cowan (2003), who points out that traditional mortgages were illiquid for investors exposing lenders to the risk that they may not be able to find buyers when they would like to sell the securities they hold.

Credit ratings are essential to asset securitization because according to the regulation, simultaneously to issuing the different tranches of an ABS, the issuers need to turn to the CRAs asking them to give each of the tranches a ‘rating’, demonstrating its default risk. Due to the complexity of ABS stemming from the pooling and tranching procedures, investors tend to believe the opinions offered by the CRAs via their rating results on the securities.

Some studies indicate the reliance of ABS investors on CRAs by testing the association between ABS issuance spreads and their credit ratings controlling other variables constant. Ashcraft et al. (2011) investigated the relationship between the rating given by CRAs and the prices of MBS. They selected a set of independent variables for rating and prices, regressed the ratings and the prices of the sample MBS separately on the set of controls measuring the security’s level of credit risk and collected the residuals in these two regressions. By plotting the two residuals in a graph to capture their relationships, they found that rating and yields were always correlated: higher rating, lower yields. Similarly, Fabozzi and Vink (2012) tested European ABS data to assess the significance of the ratings’ parameters on the yield spreads (focusing only on the AAA tranches which attract most attention from the market).

In contrast to the papers above that directly regress issuance spreads on the ratings, other scholars use alternative factors to indicate ratings’ influences. Mählmann (2012) used the CDO-ABS issuance yield’s ability to predict the future outcomes (the level of collateral loss percentage in the financial crisis or whether they default in the crisis) controlling the issuance rating variables to discover whether the issuance rating is a variable that affects the predictive ability of yield spread. The conclusion of his research is that issuance ratings have an effect on the predictive ability of yield issuance. Thus, CRAs can, to a certain degree, affect the opinions of CDO-ABS investors.

2.3 Contribution of the research

In contrast to majority of researchers who focus on traditional financial products' (bonds and stocks) reaction to credit ratings, only a very small group of researchers have studied structured finance products. Even among that limited number of papers concerning structured finance market ratings, almost all discuss mortgage-backed securities while omitting other types of ABS in their datasets. This research includes not only MBS but also other non-MBS in order to reflect the entire structured finance market.

Furthermore, previous research focuses on the pre-crisis situation while our research aims to compare the situations pre- and post-crisis to determine the shock of the financial crisis on the credit rating industry. The reason for differentiating between pre-crisis and post-crisis performances of the credit rating reliance of ABS investors is that the recent financial crisis has undermined CRAs' reputation by a considerable number media reports making negative comments on CRAs' role in the crisis. Whether such great reputational loss has led to a decrease in the reliance of investors on CRAs' opinions has not been studied previously, to our knowledge. Furthermore, the comparative study of pre- and post- crisis performances of investors regarding CRAs assesses the effects of US credit rating reforms which aim to remove the rating-based regulations by testing whether investors still rely on those ratings to the same extent as they did in the pre-crisis era.

Although research on the traditional bond or stock markets uses data of the secondary market, most of the previous research on structured finance products investigates only primary market data, which covers the security issuance stage but not the transaction stage. This leaves a gap in the research on the reliance of structured finance products on credit ratings. As mentioned in the Introduction section, three bridges between investors and CRAs are the information intermediate function of CRAs, rating-based regulations, and investors' behaviour. The primary market's reliance on CRAs can partially reflect CRAs' function of information intermediates because investors indirectly capture non-public information on issued ABS via the ratings, as well as their function as providers of rating-based regulatory licence (some regulations about ABS are based on their initial ratings). The secondary market's reliance is a reflection of the function of informaSectiontion intermediates (investors view downgrading as a negative signal) and regulatory licence providers (some market participants are required by regulations to sell certain securities if they are downgraded). It also reflects the behavioral reliance of investors (for instance, homogeneous selling following a downgrade) due to the feature of real-time trading in the secondary market. Therefore, as an essential part of the asset securitization market, the transaction stage of structured finance products should not be ignored. In this paper, to cover ABS comprehensively, we investigate both the primary and the secondary ABS markets. The cross-sectional and the panel data analyses are conducted to demonstrate the reliance of investors on CRAs in those two markets, respectively.

3 Hypotheses and methodology

3.1 Hypotheses

As mentioned in Section 2.3, we split our empirical test into two parts: issuance data for the primary market and transaction data for the secondary market.

Two hypotheses are proposed to test the reliance of investors on CRAs and the potential change in such reliance after the financial crisis.

Hypothesis 1: There exists a significant association between security prices and their credit ratings in the ABS market.

Hypothesis 2: The association between security prices and their credit ratings in the ABS market. has become significantly weaker after the financial crisis.

For Hypothesis 1, two sub-hypotheses are designed to reflect the situations in the primary market and the secondary market, respectively.

Hypothesis 1a: In the issuance stage of ABS, controlling a set of characteristics variables, the ABS issuance spreads are significantly associated with their issuance credit ratings.

For issuance data, the reliance of investors on credit ratings is reflected by the association between the variation of issuance credit ratings among different ABS tranches and the variation of issuance spreads[1] of those ABS tranches after controlling identified risk characteristics of the tranches. Fabozzi et al.

[1] Issuance spread: In the issuance stage, ABSs are priced relative to a benchmark interest rate in a form of 'yield'. Issuance spread is the part of issuance yield above the benchmark rate. A higher issuance spread is equivalent to a lower issuance price.

(2012) state that the issuance credit ratings mirror information of ABS's risk characteristics and that those characteristics are open to ABS investors in the ABS issuance reports. Therefore, if after we control all of the characteristics equally, the issuance ratings still affect the issuance spreads, thenit is reasonable to claim that the investors take extra information besides open information into account when they price new-issued ABS.

Hypothesis 1b: In the transaction stage of ABS, a significant price decrease occurs in certain time windows after one ABS receives negative rating announcements from CRAs.

For transaction data, the investors' reliance on CRAs can be evaluated through the price reactions to rating change announcements. When an ABS receives negative credit rating announcements from CRAs, investors react to them by accepting lower transaction prices, which is reflected by a significant price decrease in certain windows after the announcements are released.

In our research, 'rating change announcements' are identified as four types of announcements offered by CRAs about certain ABS (shown in Table 1).

[Insert Table 1 here]

According to many studies (Hand et al., 1992; Dichev and Piotroski, 2001; Jung et al., 2016; Drago and Gallo, 2016), shocks of positive announcements on stock or bond prices are weaker than those of negative announcements. In our research about ABS' price reactions, we also find consistent evidence of such asymmetric shocks (shown in Appendices 2 and 3). Therefore, in this paper we use only negative announcements (actual downgrade and possible downgrade) as the testing sample. 'Actual downgrade' refers to an announcement indicating that the CRA has decided to downgrade the ratings of certain ABS while a 'possible downgrade' announcement is just a warning that the CRA may downgrade that ABS at a certain time in the future.

Hypothesis 1b implies that the immediate price reactions to negative rating announcements can be a proxy of investors' attitudes towards those announcements. If we can find evidence to show that, compared to non-announcement dates and controlling for relevant variables, days in a certain window around negative rating announcements see more negative price returns, then it can be claimed that investors follow the CRAs' downgrade suggestions by accepting a lower transaction price of that downgraded ABS.

Similar to Hypothesis 1, we also divide Hypothesis 2, which indicates a decreased reliance on CRAs, into two sub-hypotheses according to the market division:

Hypothesis 2a: Compared to the pre-crisis period, the association between the ABS issuance spreads and issuance ratings has become weaker since the financial crisis.

Hypothesis 2b: Compared to the pre-crisis period, the size of ABS transaction price decrease following negative credit rating announcements has gotten weaker after the financial crisis.

Each sub-hypothesis works for each market (primary or secondary), indicating a lower degree of investor confidence in CRAs.

3.2 Methodology

We conduct different analyses on the primary and the secondary market situations to test our hypotheses.

3.2.1 Primary market (Hypotheses 1a and 2a)

For the issuance dataset, an OLS regression analysis is designed to test the association between the issuance spreads of ABS and the rating-related variables, the time dummy variables and the interaction terms of those two types of variables, viewing the tranche characteristics as control variables.

The dataset is divided into two sub-samples: MBS and non-MBS. MBS is a special type of ABS whose backing securities are mortgage-related. The reason for separating MBS from other ABS is that the spread determining regime, the risk characteristics, and the credit rating features differs between mortgage-backed securities and other types of asset-backed securities[2]. All of the research on the primary market is conducted separately for MBS and non-MBS datasets.

Our main regressions are displayed in Equations (1) and (2).

$$\ln(spread_i) = \alpha_i + \beta_1 NR_i + \beta_2 N_i + \sum_{p=1}^{10} \beta_{(p+2)} C_{pi} + \varepsilon_i \qquad (1)$$

[2] For instance, Fabozzi and Vink (2012) state that due to the unique feature of prepayment among MBS, the spreads of MBS contain not only the credit risk compensation, but also the prepayment risk compensation while this is not the case with other types of ABS.

$$\ln(spread_i) = \alpha_i + \beta_1 NR_i + \beta_2 N_i + \beta_3 DC_i + \beta_4 PC_i + \beta_5 NR_i \times DC_i + \beta_6 NR_i \times PC_i + \sum_{p=1}^{10} \beta_{(p+6)} C_{pi} + \varepsilon_i \quad (2)$$

A description of all the variables is given in Table 2 (the detail of variable NR_i is shown in Table 3) and C_{pi}s refer to the nine variables of tranche characteristics playing the role of control variables in this regression. Some of the control variables are introduced in Fabozzi's paper (2012) and the rating-related and dummy-related variables are introduced in this paper in order to test Hypotheses 1a and 2a.

[Insert Table 2 here]

[Insert Table 3 here]

Equation (1) is linked to Hypothesis 1a: β_1 indicates effects of ratings on the issuance spreads, while β_2 indicates the effects of competition among the different CRAs on the issuance spreads[3]. A significant positive β_1 supports Hypothesis 1a by showing a positive association between a lower rating (equal to a higher NR_i) and a lower price (equal to a higher $\ln(spread_i)$) when controlling all of the ABS characteristics. This implies that even when investors see the open information on ABS characteristics, they still offer lower prices to purchase an ABS if CRAs rate that ABS at a lower rating degree.

Equation (2) is designed for hypothesis 2a: β_1 and β_2 indicate same items as those in Equation (1). β_3 and β_4 indicate the change of issuance spreads before and after the financial crisis, β_5 and β_6 indicate the change of effects of ratings on the issuance prices during and after the financial crisis compared to pre-crisis period. A negative β_6 enhances hypothesis 2a by indicating a lower β_1 after the financial crisis than before. Since, as described in Equation (1), the positive β_1 reflects a positive association between a lower rating and a lower price, a negative β_6 means that such association becomes weaker after the crisis.

[3] Becker and Milbourn (2008) and Dittrich (2007) discuss the relationship between rating-industry competition and rating quality as well as issuer preference. Moreover, regulators are trying to enhance the competition of rating industry (US Credit rating agency reform Act 2006 and EU CRA Regulation 2009). Therefore, we add competition-related independent variables to control the effects of intra-industry competition on issuers' attitudes.

3.2.2 Secondary market (Hypotheses 1b and 2b)

In contrast to an issuance dataset which contains static cross-section data, a transaction dataset is a panel consisting of several security IDs, each of which has a daily time series of transaction prices. To test the price shock of negative rating announcements on transaction prices of ABS, as well as the change of shock degree after the financial crisis, we use fixed-effect panel data regressions, regressing price returns on event-dummy, post-crisis dummy and their interaction.

$$return_{i,t} = \alpha_i + \beta_1 \times dE_{i,t} + u_{i,t} \quad (3)$$

$$return_{i,t} = \alpha_i + \beta_1 \times dE_{i,t} + \beta_2 \times dP_{i,t} + \delta \times \left(dP_{i,t} \times dE_{i,t}\right) + u_{i,t} \quad (4)$$

The dependent variable, $return_{i,t}$ refers to the price return of the ABS security i at time t[4]. $dE_{i,t}$ is the event-dummy which is equal to 1 if at the day t, the security i is within the pre-defined time windows (1 day, 3 days or 5 days) after a negative rating event occurs. $dP_{i,t}$ is the period dummy which is equal to 1 if the day t is in the post-crisis period (after Sep 15th, 2007) and 0 otherwise. $dP_{i,t} \times dE_{i,t}$ is the interaction term, α_i refers to the unobserved time-invariant individual effect and $u_{i,t}$ represents the error term.

Equation (3) tests Hypothesis 1b by testing whether the returns react negatively to negative rating announcements. A significantly negative β_1 would support Hypothesis 1b by showing that compared with normal days without rating announcements, prices of ABS significantly decrease within a certain window after the release of negative rating announcements. .

Equation (4) tests hypothesis 2b by checking whether estimated $\hat{\delta}$ is significantly positive. The interested estimated coefficient δ can be interpreted as Equation (5).

$$\hat{\delta} = \left(\overline{return_{1,1}} - \overline{return_{1,2}}\right) - \left(\overline{return_{2,1}} - \overline{return_{2,2}}\right) \quad (5)$$

, where $\overline{return_{1,1}}$=Average return after the crisis within the pre-defined time windows after a rating event; $\overline{return_{1,2}}$=Average return after the crisis beyond the pre-defined time windows after a rating event; $\overline{return_{2,1}}$: Average return before the crisis within the pre-defined time windows after a rating

[4] $return_{i,t}$= $p_{i,t} - p_{i,t-1}$, $p_{i,t}$ is the reported price of security i at day t and $p_{i,t-1}$ is the reported price of security i at one day before t.

event and $\overline{return_{2,2}}$: Average return before the crisis beyond the pre-defined time windows after a rating event.

The item in the first bracket refers to the rating events' shock after the crisis. The item in the second bracket refers to the rating events' shock before the crisis. Therefore, the $\hat{\delta}$ is an estimate of the difference between those two shocks, indicating the change of the shock of the events on market returns after the crisis compared with the pre-crisis period. As we state in Equation (3), negative rating announcements are associated with negative price returns (reflected by a negative β_1 in both Equation (3) and (4). Then a positive $\hat{\delta}$ would imply a negative price decrease but with a smaller size after the finance crisis, supporting hypothesis 2b.

Survivorship bias[5] is a non-negligible factor that may invalidate the results of empirical tests for panel data (Elton et al., 1996). In the context of our analysis, potential survivorship bias is due to the expiration of some ABS before financial crisis. Those expired ABS did not perform after the financial crisis so we did not observe or take into account their price reactions to negative rating announcements in our tests.

However, we assume that the expiration of ABS does not cause survivorship bias because their maturity is independent of both the financial crisis and the price reactions to negative rating announcements.

For all the 72 ABS analysed, 22 expired before the financial crisis (before September 2007); all of these ended due to natural expiration based on ABS contracts but not default. Furthermore, all 22 ABS were issued before the financial crisis (from October 1992 to June 2003). According to the contracts, maturities were all determined when the ABS were issued. Thus, the expiration dates were determined before the financial crisis and are therefore independent of the financial crisis. In addition, since the issuers could not 'foresee' the occurrence of negative rating announcements about their ABS and take that into account when they set expiration dates at the issuance stage, the expiration dates are independent of the rating announcements. Therefore, we assume a random expiration of the ABS regarding the financial crisis and rating announcements. Random expirations do not cause survivorship

[5] Survivorship bias refers to the bias caused by only selecting items which have survived in analysis and neglecting 'dead' ones whose performances are not observed.

bias because if the expirations are not related to the financial crisis or rating downgrades then it is reasonable to state that if those expired ABS had not expired before the financial crisis, their performances following the credit downgrades would not have been significantly different from other ABS. Thus, we assume that there is no survivorship bias in our study.

4 Data, empirical results and robustness tests

In this section, we display the data description, empirical results and robustness test results for the primary and the secondary markets.

4.1 Data

The issuance dataset is collected from Bloomberg database and Moody's website. Information on ABS's credit ratings is hand-collected from Moody's issuance rating reports downloaded from Moody's official website (https://www.moodys.com/) and information on ABS's risk characteristics is from the Bloomberg database. Data from these sources are merged into a unique sample containing variables shown in Table 2. All of the tranches in this dataset were issued in the period between August 2002 and January 2015 and only the floating-rate tranches are included in the dataset as we do not have access to the benchmark used to estimate the fixed-rate tranches (Fabozzi and Vink, 2012). A total of 24,458 tranches (7,381 MBS tranches and 17,077 non-MBS tranches) from 5,702 ABS deals[6] (1,484 MBS deals and 4,218 non-MBS deals) are in our sample. We separate the MBS) from the non-MBS and conduct every analysis in both the MBS data and the non-MBS data respectively.

Appendix Table 1 shows the distribution of tranche/deal numbers in three periods. Two features can be observed here, 1) there are many more pre-crisis issued tranches/deals than during-crisis and post-crisis ones; 2) there are significantly more non-MBS tranches/deals than MBS ones.

We calculate the descriptive statistics of all the variables in three periods respectively. Due to space constraints we do not display them here, but we describe some pertinent details. The explained variable, issuance spreads significantly increase after the financial crisis from 4.15% to 5.31% for non-MBS and

[6] There are a couple of tranches in each of the deals. For each tranche, a seniority number is set to indicate the payment collecting sequence. The regression analysis is conducted on the tranche basis (not on a deal basis).

from 3.88% to 5.05% for MBS (a similar decrease in price) but the average ratings of those securities issued after the crisis are even more positive than in the pre-crisis period (indicated by a fall in NR from 3.72 to 2.73 for non-MBS and from 4.24 to 3.10 for MBS). This phenomenon seems contradictory: the issuance prices do not recover to pre-crisis level when the market recovers although the CRAs' rating levels recover at the same time. However, if we return to our topic, investors' reliance on the credit ratings before and after the financial crisis, such 'contradictory' phenomenon should be interpreted as preliminary evidence for the statement that investors' reliance on CRAs at issuance ABS (including MBS) is weaker after the financial crisis. Even if the CRAs convey their confidence in the quality of ABS during the recovery period, the issuance prices remain at a low level which indicates that the issuers do not accept the positive signal from the CRAs.

The transaction price dataset is collected from Thomson Rectus Datastream and the information on rating changes is hand-collected from Moody's website. We merge data from these two sources into a unique sample.

The sample covers time series between Feb 2001 and Feb 2016[7] (daily) and 72 ABS securities. During this period, 894 rating events on these securities are identified. Due to the fact that rating events in the secondary market are relatively rare compared to rating offering actions for the primary market, the number of rating events and the tranches involved in these events is smaller than the issuance dataset. Therefore, MBS and non-MBS are analysed together in this part of the study. Some details are displayed in the Appendix. In Appendix Table 2, we show the number of negative/positive events in the pre-/post-crisis periods separately and in Appendix Table 3 we test the price returns following negative/positive events in both time periods in different observation time windows[8]. A pattern can be observed in

[7] The reason for selecting Feb 2001 as the starting point is to balance the time periods before and after the crisis (around seven years before the crisis, 2001-2007 and seven years after the crisis, 2009-2016).

[8] The implications of the time window indicators are (n=1,3, or 5):
(-n,0): returns in the corresponding columns are calculated as the price difference between the EXACT day of announcement and the average of n days BEFORE the rating event;
(0,+n): returns in the corresponding columns are calculated as the price difference between the average of n days AFTER the rating events and the EXACT day of announcement;
(-n, +n): returns in the corresponding columns are calculated as the price difference between the average of n days AFTER the rating event and the average of n days BEFORE the rating event;
The t-test is for returns of all negative/positive events in each time window.

Appendix Table 3: for negative events, pre-crisis events are associated with significantly negative reactions, but post-crisis reactions are not significant. This shows preliminary evidence of decreased reliance of investors on rating agencies (Hypothesis 2b, specifically): at the transaction stage, investors' attitudes (reflected by market prices) are associated with the rating events before the crisis but such reliance is not significant after the crisis. For positive events, nearly all of the price reactions are statistically insignificant. It is consistent with the statement that the shocks of negative/positive rating announcements are asymmetric: investors focus on negative announcements more than on positive ones.

4.2 Empirical results

4.2.1 Issuance dataset

For each equation, (1) and (2), we run two regressions on the MBS sample and the non-MBS sample respectively. The regression results are shown in Table 4.

[Insert Table 4 here]

The regressions designed for Equation (1) (see Columns A and C in Table 4) generate a result enhancing Hypothesis 1a by significantly positive estimated coefficients on the variable NR (β_1 in Equation (1). The figures are 0.043 for non-MBS and 0.171 for MBS dataset. They can be interpreted in the following way: after we keep the other risk characteristics equal, if the average rating given by CRAs goes down by one notch (for example, from Ba3 to Ba2), the issuance spreads increase by 18.77% (4.39%)[9] for (non-) MBS dataset, which is equivalent to a drop in the issuance prices. It shows that regardless of the observed information collected from ABS issuance report, investors 'follow' CRAs by demanding a lower purchasing price after seeing a lower rating notch provided by CRAs.

Regressions designed for Equation (2) (see Columns B and D in Table 4) enhance Hypothesis 2a given the significantly negative estimated coefficients on the interaction terms between NR and PC (β_6 in Equation (2)). The figures are -0.143 for the non-MBS dataset and -0.146 for the MBS dataset. They can be interpreted as follows: for the non-MBS dataset, before the financial crisis, β_1 is 0.200 (0.172) and after the financial crisis, that coefficient decreases to $\beta_1 + \beta_6$ =0.200-0.143=0.057 (0.172-

[9] The figures of spreads' increase are calculated from the estimated coefficients β_1 following the equation: Spread increase proportion=exp(β_1)-1

0.146=0.026). Similarly, before the crisis, one notch of rating uplift is associated with 22.14% (18.77%) uplift of issuance spreads but after the crisis, it is only associated with 5.87% (2.63%) uplift of issuance spreads. Such a corresponding spread uplift decrease supports Hypothesis 2a. It offers evidence that after the crisis, although investors still rely on the ratings offered by CRAs to assess the qualities of ABS, the extent of this reliance has been significantly reduced.

Furthermore, the coefficient β_2, which is linked to intra-industry competition among CRAs is consistently negative in all of the four regressions. It implies that investors price an ABS higher (equivalent to a lower issuance spread) if CRAs compete more severely to rate that security (reflected by a larger number of CRAs rating it). In other words, investors 'trust' an ABS more if it is in a more competitive rating background. Although some previous research examines the impacts of CRA intra-industry competition on rating quality and issuer preference (Becker and Milbourn, 2008; Dittrich, 2007), to our knowledge, our research is the first to extend the research on impact of intra-industry competition to the field of investors' reliance.

As for the control variables, most of the estimated coefficients are consistent in MBS and non-MBS datasets and two of them are consistent with the results drawn by Fabozzi and Vink (2012). In both cases, these variables have the following interpretation:

- Paramount: consistently negative coefficients imply that investors price an ABS higher if it has a larger issuance volume (similar to Fabozzi and Vink's research).
- Coupon rate: consistently positive coefficients imply that investors price an ABS lower if it has a larger coupon rate.
- WAL: consistently positive coefficients imply that investors price an ABS lower if it has a longer weighted average length (WAL).
- Issuer size: consistently positive coefficients imply that investors price an ABS lower if its issuer owns larger market share.
- Credit support: consistently negative coefficients imply that investors price an ABS higher if that ABS has a higher degree of credit support from the issuer (similar to Fabozzi and Vink's research).

4.2.2 Transaction dataset

The results of Equations (3) and (4) are shown in Table 5. For each regression, three time-windows (1-day, 3-day and 5-day) are utilized to measure the length of observation on rating announcement dummies.

[Insert Table 5 here]

For Equation (3), designed to test Hypothesis 1b, coefficients on event-dummies $dE_{i,t}$, β_1s are significantly negative whatever the observing time-windows. This supports Hypothesis 1b by showing that compared to normal days, margin-event days see negative price returns (equal to significant price decreases). If comparing the absolute values of those negative coefficients among the three windows, we find a negative correlation between absolute values and lengths of time windows (0.43 for 1-day window, 0.36 for 3-day window and 0.20 for 5-day window). This can be explained as evidence of recovery-effects of credit rating announcements: after a negative announcement is released to the market by CRAs, investors immediately respond to it by shorting the security at once, then later when investors calm down, the prices take a few days to return to a relatively rational level. To our knowledge, this is the first research discovering such a trend of recovery effect.

For Equation (4) (Hypothesis 2b), the coefficients on interaction terms $dP_{i,t} \times dE_{i,t}$, δs are significantly positive whatever the observing time-windows are. It supports the statement of Hypothesis 2b by showing a smaller price decrease following negative rating announcements after the financial crisis compared to the pre-crisis period.

We also run Equations (3) and (4) for positive rating announcements by adjusting the setting of $dE_{i,t}$ as an indicator of whether the observation is in certain time-windows around a positive rating announcement (equal 1) or not (equal to 0). The result is displayed in Appendix Table 4. Positive β_1s indicate a trend of increasing transaction prices following (possible) rating upgrade announcements. However, it is obvious that the sizes of β_1s of Equation (3) for positive events (0.016, 0.047 and 0.032) are significantly smaller than those for negative events (0.43, 0.36 and 0.20). β_1s in Equation (4) are no longer significant for positive events. This provides evidence that indicates asymmetric shocks between positive and negative rating events: investors are much more sensitive to external bad news from CRAs.

4.3 Robustness tests

Six robustness tests are made to enhance the creditability of our empirical results. The first two tests are designed for the issuance dataset section and the remaining four are designed for the secondary dataset.

4.3.1 Issuance dataset section robustness tests

There are two robustness tests for primary market data. Robustness test 1 excludes AAA-tranches and Robustness test 2 transforms the number-format rating indicator (NR) into 20 letter-format rating indicators (LR).

Robustness test 1: Test of non-AAA tranches

In the structured finance market, AAA-rated ABS owns distinct regulatory implication from non-AAA ABS (Griffin et al. 2013). In addition, AAA-rated ABS are more than 80% of all ABS (shown in Table 6). Therefore, it may be that the significant estimated coefficients in Equations (1) and (2) are derived mainly from different situations between AAA tranches and non-AAA ones but not from the all tranche variations. To eliminate the effects of AAA tranches, we exclude them from the datasets and re-run Equations 1 and 2 to demonstrate results in non-AAA securities.

[Insert Table 6 here]

The updated regression results are shown in Table 7, excluding AAA-rated tranches from datasets and re-running Equations (1) and (2) for both MBS and non-MBS samples.

[Insert Table 7 here]

Comparing the results of Table 7 with those of Table 4, we find that for the MBS sample (Columns C and D), signs of all key variables in robustness test results are consistent with those in our original tests. However, such consistency does not hold for the non-MBS sample (Columns A and B).

The result shows that the reliance of investors on CRAs is apparent in decisions of investing securities with different ratings in the MBS market but is apparent mainly in decisions of investing AAA or non-AAA in the non-MBS market.

Robustness test 2: Substituting dummy variables for number-format variables to indicate credit rating notches

One potential shortcoming of Equations (1) and (2) is the transformation of letter-format ratings to number-format ratings. Such linear transformation is based on the assumption that the rating notch implication is linearly distributed according to the CRAs' opinion (for example, the transformation assumes that the difference in the CRAs' rating opinion difference between AAA and AA is similar to that difference between AA and A, A and BBB etc.). This assumption may not be the case in the market. Moreover, such linear transformation uses one variable representing all of the 21 rating notches and ignores how each of these notches influence the issuance spreads. Therefore, in the robustness test 2, we use 20 dummy variables (LR in Table 3), substituting the number-format rating variable (NR) and setting top rating AAA as the benchmark. The details of transformation from number-format ratings to letter-format ratings (dummies) is shown in Table 3 and the new regression equations are shown in Equations (6) and (7).

$$\ln(spread_i) = \alpha_i + \sum_{p=1}^{20} \beta_p LR_{p,i} + \beta_{21} N_i + \sum_{p=1}^{10} \beta_{p+20} C_{pi} + \varepsilon_i \qquad (6)$$

$$\ln(spread_i) = \alpha_i + \sum_{p=1}^{20} \beta_p LR_{p,i} + \beta_{21} N_i + \beta_{22} DC_i + \beta_{23} PC_i + \sum_{p=1}^{20} \beta_{p+23} (LR_{p,i} \times DC_i)$$
$$+ \sum_{p=1}^{20} \beta_{p+43} (LR_{p,i} \times PC_i) + \sum_{p=1}^{20} \beta_{p+63} C_{pi} + \varepsilon_i \qquad (7)$$

Here is the interpretation of β_1 to β_{20} in Equations (6) and (7). Each β (for example, β_1) refers to the spread difference of the corresponding rating notch (for example, AA) compared to AAA rating, the benchmark notch after controlling the tranche characteristics. The interpretation of β_{24} to β_{43} and β_{44} to β_{63} in Equation (7) is similar to the previous group of coefficients: they refer to the change of the spread difference of the corresponding rating notch (for example, AA) compared to the AAA rating, the benchmark notch before and during/after the financial crisis when controlling for the tranche characteristics.

The results of updated regressions are shown in Table 8.

[Insert Table 8 here]

Focusing on Equation (6) (Columns A and C in the Table 8) which concerns Hypothesis 1a, most of the coefficients on a series of notch dummies (from AA-dummy to C-dummy) are positive, which is consistent with positive β_1 in Equation (1). Positive LR coefficients can be interpreted in the following way: compared with benchmark notch (AAA), other notches are correlated to higher issuance spreads (lower prices). They collectively indicate a reliance of investors on issuance ratings provided by CRAs. To display the details of the coefficients with respect to different LRs, we plot the coefficients regarding different rating notches in Figure 1 (The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset). For both MBS and non-MBS lines, a rising trend of dummy coefficient values with the fall of rating notches is observed in the Figure. This means that the lower the rating, the greater the issuance spread difference between the corresponding rating and the benchmark (AAA) rating. This is consistent with Hypothesis 1a, according to which lower ratings are associated with higher spreads (lower prices).

[Insert Figure 1 here]

Focusing on Equation (7) (Columns B and D), which refers to hypothesis 2a, most of the coefficients on the interaction terms between rating-dummies and post-crisis dummy are negative, which is consistent with negative β_6 in Equation (2). They can be interpreted as average differences of β_1s after the financial crisis compared with before the crisis. Thus, negative coefficients indicate that the size of β_1s decreases after the crisis, a possible reflection of the decreased reliance of investors on CRAs.

In Figure 2, we display details of those coefficients on the interaction terms among different rating notches. It can be observed in the figure that the sizes of negative coefficients are most significant in the limit area between investment and non-investment grades, particularly Baa1 to Ba3 grades. Since investors are sensitive to ratings near the boundary between investment and non-investment grades, large negative coefficients indicate that the reliance of investors on credit ratings decreases significantly in this sensitive area. This result is contradictory to that of Wansley et al. (1992).

[Insert Figure 2 here]

4.3.2 Transaction dataset section robustness tests

For the second part of our robustness check, four tests are conducted: re-classifying pre-crisis and post-crisis observations, replacing $dE_{i,t}$ by $CD_{i,t}$, excluding 'anticipated' actual downgrades and excluding market factors.

Robustness test 3: Boundaries between pre-crisis and post-crisis periods

One of key the variables in Equation (4) is $dP_{i,t}$ which indicates whether the credit rating announcements were released before or after the financial crisis. Obviously, the definition of when the 2007/2008 global financial crisis starts determines the setting of $dP_{i,t}$. Here we set September 2007 as the assumed boundary. This is consistent with the fact that sub-prime crisis is recognized as having started in the summer of 2007 (Orlowski, 2008) as well as the fact that the Federal Reserve started to take action in response to the crisis in September 2007 (Cecchetti, 2009).

However, in general, the media did not realize there was a crisis until Lehman Brother's fall on 15th September 2008. Some claim that the 'culture crisis' started even later. Therefore, we re-set $dP_{i,t}$ by changing the boundary to September 2008 and some later time points to check whether the results are significantly reversed.

For Equation (4), we re-define $dP_{i,t}$ by resetting the boundaries of pre-and post-crisis periods. The pre-set boundary is September 2007, which is also the official boundary used in Section 4.2.2. Other boundaries are set once every two months ranging from September 2008 (Lehman Brothers' fall) to the end of 2009. The results are shown in Table 9.

The coefficient of interest, δ, remains significant if the boundary is set between September 2008 and March 2009 (see 'Significant area' in Table 9). Beyond the 'significant area' (from March 2009 to November 2009), δ becomes insignificant. In sum, it shows that our result is robust if we view any point in the period 2007.09-2009.03 as the boundary between pre-and post-crisis periods.

[Insert Table 9 here]

Robustness test 4: Substituting 'rating-change degree' for 'event dummy' to indicate effects of rating announcements

In Equations (3) and (4), we use $dE_{i,t}$, a dummy variable to discriminate observations around the rating announcements from normal observations without effects of rating announcements. However, such a setting does not imply the effective degree of those rating announcements. In other words, the event-dummy indication assumes equal effects of different downgrade degrees and even 'possible downgrade', which is a warning signal with no downgrade indeed. To address potential bias caused by the event-dummy setting, we re-run Equations (3) and (4), replacing $dE_{i,t}$ with $CD_{i,t}$ (short for 'Change Degree') indicating by how many notches they were downgraded by the rating announcements. The updated equations are shown in (8) and (9):

$$return_{i,t} = \alpha_i + \beta_1 \times CD_{i,t} + u_{i,t} \quad (8)$$

$$return_{i,t} = \alpha_i + \beta_1 \times CD_{i,t} + \beta_2 \times dP_{i,t} + \delta \times \left(dP_{i,t} \times CD_{i,t}\right) + u_{i,t} \quad (9)$$

β_1 in both Equations (8) and (9) indicate how much the average price return change is following one notch of rating downgrade from Moody's. Further, δ in Equation (9) indicates the average change of the degree of β_1 after the financial crisis compared with the pre-crisis period.

The cost of replacing $dE_{i,t}$ with $CD_{i,t}$ is that the latter can only identify 'actual downgrades' but not 'possible downgrades' because with a 'possible downgrade announcement', CRAs do not indeed downgrade the security and the degree of $CD_{i,t}$ is 0 (but $dE_{i,t}$ for the same announcement is 1 but not 0). Therefore, with $CD_{i,t}$ the 'possible downgrade' announcements are equal to the circumstance with no events occurring.

Replacing $dE_{i,t}$ by $CD_{i,t}$, we run Equations (8) and (9) (see Table 10). Our results show that except for the longest time window (5 days), results in the other two windows are robust to Equations (3) and (4).

[Insert Table 10 here]

In Equation (8), the estimated coefficients on $CD_{i,t}$ (β_1) are negative. They imply that the more notches an ABS is downgraded by CRAs, the lower the price of that ABS drops. It indicates that when making decisions on buying or selling an ABS, investors consider not only whether it is downgraded but also by how many notches it is downgraded. This finding enhances the conclusion regarding Hypothesis 2a.

In Equation (9), estimated coefficients on interaction terms (δ) are positive, which is equivalent to a lower absolute value of post-crisis β_1. It shows that the degree of $CD_{i,t}$'s effects on price returns is weaker after the crisis, consistent to the statement of Hypothesis 2b.

Robustness test 5: Excluding anticipated downgrade announcements

Creighton et al. (2007) state that an actual downgrade announcement should be categorized as 'anticipated' if it comes following a possible downgrade announcement. If a possible downgrade announcement is released on a certain security, it shows a negative signal of CRAs that they may downgrade it at some time in a near future. Receiving such signal investors have different understanding on that security compared with if there were no downgrade warnings. Therefore, it is reasonable to assume that when an actual downgrade comes, investors have already prepared for, or 'anticipated' that bad news and may have different strategies from strategies adopted in normal downgrades.

We keep only the 'unanticipated' downgrades in Robustness test 5, excluding all actual downgrade announcements which are released within 3-month time after a possible downgrade announcement is published and re-run Equations (3) and (4) to see the variation resulted from such exclusion.

Results for the re-run regressions excluding anticipated downgrades are shown in Table 11. Our results in this text are consistent with those in Table 5 except the sizes of coefficients.

[Insert Table 11 here]

If we consider the size of β_1 in Equation (3), we can view an expanded size (0.53, 0.38 and 0.22) compared to the results with anticipated downgrades in Table 5 (0.43, 0.36 and 0.20). It shows evidence to enhance the statement of Creighton et al.'s (2007) conclusions according to which 'the impact of anticipated rating revisions is normally significantly lower than that of unanticipated ones'.

Robustness test 6: Eliminating the effects of the market

The dependent variable $return_{i,t}$ is the absolute price returns without market effects considered. However, the price variations of ABS are a reaction of the combination of market variation and non-market variation (of our interest). Therefore, a significant price return reaction to negative announcements may be attributed to the market factor but not the announcements themselves.

To eliminate the market effects, we replace the dependent variable with three other indices which take the market factor into account (Index 2 and Index 3 are introduced by Brook's, 2014).

Index 1: Pure daily return excluding market return: $(p_{i,t} - p_{i,t-1}) - (M_{i,t} - M_{i,t-1})$ (M_t is the Barclays ABS market index on day t).

Index 2: Abnormal return. This is the residuals from the regression of price returns with market returns and indicates how the price at day t deviates from its expected price estimated by market index. The Abnormal return, $AR_{i,t}$ is created according to the following steps:

- For each rating event (assuming happening at day 0), run a regression of security return $Return_i$ on market return $Return_m$ for the previous 100-day observations before that event:

$Return_{i,t} = \alpha + \beta \times Return_{m,t} + \varepsilon$ (t from -100 to 0)

- Using the estimated β (if β is not significant in the regression, that observation is deleted), estimate α, and the real market return $Return_{m,t}$ to calculate the estimated return before and after the event, $Return_{i,t}$:

  $\widehat{Return}_{i,t} = \hat{\alpha} + \hat{\beta} \times Return_{m,t}$ (t from -100 to +5)

- Calculate 'AR' as the difference between the real security return and the estimated one:

  $AR_{i,t} = Return_{i,t} - \widehat{Return}_{i,t}$, (t from -100 to +5)

Index 3: Standardized abnormal return: a revised version of AR by standardizing it. $SAR_{i,t}$ is calculated as follows:

- For each rating event, collect the estimated residual terms (equal to AR):

$$\hat{\varepsilon_t} = Return_{i,t} - \hat{\alpha} - \hat{\beta} \times Return_{m,t} = Return_{i,t} - \widehat{Return}_{i,t}$$

- Calculate the variance of residual terms:

$$\sigma^2(\hat{\varepsilon}) = \frac{1}{103} \times \sum_{t=-100}^{+5} (\hat{\varepsilon_t}^2)$$

- Calculate the SAR:

  $SAR_{i,t} = \frac{AR_{i,t}}{\sqrt{\sigma^2(\hat{\varepsilon})}}$

Updated regressions (shown in Table 12) generate similar results to the original regressions of Equations (3) and (4). β_1s are significantly negative and δs are significantly positive, no matter which index and which time window we use. A recovery effect can also be observed for each index (longer time windows, smaller size of β_1).

[Insert Table 12 here]

In sum, our result for the secondary market dataset passes all four robustness tests despite some minor variations.

5 Conclusion

This paper is an empirical study on the reliance of ABS investors on CRAs. Two hypotheses are proposed. One posits the existence of ABS investors' reliance on the opinions provided by CRAs and the other proposes that such reliance has weakened since the global financial crisis. For each hypothesis, there are two sub-hypotheses, focusing separately focus on data from the primary and secondary markets. Samples for both markets are uniquely collected datasets merging market information from Bloomberg and the Thomson Database and rating information from Moody's official website. The approach to studying primary (secondary) market data is cross-sectional (panel) regression analysis.

From the data analyses, both hypotheses are supported. The empirical results showing that initial ratings impact ABS issuance spreads (prices) and that negative rating announcements from CRAs have an immediate shock on ABS transaction prices provide evidence of investors' reliance on CRAs (Hypothesis 1). In addition, the empirical results demonstrate a weaker reliance by means of a weaker relationship between ABS issuance spreads (transaction prices) and the initial ratings (rating announcements) from CRAs (Hypothesis 2). Moreover, some other related results are observed, such as the effects of intra-industry competition of CRAs on investors' confidence on ratings and investors' 'recovery-effects' of their reactions to negative rating announcements.

Several robustness tests are conducted to ensure the consistency of the above empirical results. Those checks include the following areas: excluding top-rated tranches, using 20 dummies to indicate rating notches, changing definitions on when the financial crisis started, studying the changes in degrees of ratings announced by CRAs, keeping only unanticipated rating events and eliminating the market factors from price returns.

We briefly discuss the possible theoretical reasons behind those observed empirical results. The reliance of ABS investors on CRAs can be attributed to the complexity of structured finance products, rating-based regulations and the CRAs' long-term reputations. The trend of such reliance growing weaker can be explained by the chaos of the structured finance market due to the financial crisis, regulators' efforts to remove credit ratings from regulatory activities (Dodd-Frank Act) and the damage done to the reputation disaster of CRAs due to their poor performances in the crisis. However, this paper does not cover a detailed discussion on these theoretical reasons and leaves this gap for further research.

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Tables and Figures

Table 1 Four types of rating announcements

	Real rating change	Possible rating change
Positive	*Actual upgrade*	*Possible upgrade*
Negative	*Actual downgrade*	*Possible downgrade*

Table 2 Description of variables in the issuance dataset

Category	Variable	Notation in Equations (1) and (2)	Description
Proxy to the investors' attitude	Ln(Spread)	Ln(Spread)	The logarithm of yield of the Asset-backed security (MBS or non-MBS) relative to the benchmark yield. Spread is negatively correlated to the issuance price. A higher spread is equivalent to a lower price.
Tranche characteristics (Control variables)	Par amount	C_1	The size of the tranche
	CPN	C_2	The coupon rate set before issuance
	Tranche number	C_3	The seniority number of the tranche in the whole deal: a smaller number indicates a higher seniority which means a higher priority to claim the interest/principal payment among all of the tranches in the deal.
	Length	C_4	The pre-determined life of the security, the length between the maturity date and issuance date.
	WAL	C_5	Weighted average life
	WAC	C_6	Weighted average coupon rate
	Issuer's size	C_7	Ratio of the sum of ABS issuance volume issued by the issuer to the sum of ABS issuance volume issued by all the issuers in the whole dataset. This index indicates the market share of the ABS issuer: a higher value means a larger market share.
	Credit support	C_8	Original credit support percentage for an ABS class/tranche from other subordinate classes in the same ABS deal.
	Collateral type	C_9	A series of dummy variables indicating the type of assets backing the Asset-backed security. For MBS, key types of assets include 'commercial mortgage', 'residual mortgage' and 'wholesale mortgage'; for non-MBS, key types of assets include 'CDO', 'CLO', 'student loans', 'auto loan receivables', 'credit card receivables' etc.
	Country	C_{10}	A series of dummy variables indicating the country where the security was issued. The codes used are: KY-Cayman Islands US-United States GB-Great Britain AU-Australia NL-Netherlands IE-Ireland
Credit-rating variables	Number of CRAs rating the security	N	It indicates how many CRAs among the Moody's, Standard & Pools, Fitch and DBRS offer ratings to the tranche. This variable indicates the rating-industry competition related to the ABS.
	Number-format Average rating	NR	Transform the letter-format rating to number-format based on a formula shown in Table 3. Calculate the average rating of all the ratings the security receive.
Period dummy variables	During-crisis dummy	DC	Equal to 1 if the tranche was issued during the financial crisis period (Sep.1st, 2007-Dec.31st, 2009), to 0 otherwise.
	Post-crisis dummy	PC	Equal to 1 if the tranche was issued after the financial crisis period (after Dec.31st, 2009), to 0 otherwise.

Table 3 Transformation between the actual rating notches and number-format variables (NR)

Rating notch (Moody's)	Value of number-format variable in Equations (1) and (2)	Letter-format dummy variable in Equations (3) and (4)
Aaa	1	N/A (Benchmark notch)
Aa1	2	LR_1
Aa2	3	LR_2
Aa3	4	LR_3
A1	5	LR_4
A2	6	LR_5
A3	7	LR_6
Baa1	8	LR_7
Baa2	9	LR_8
Baa3	10	LR_9
Ba1	11	LR_{10}
Ba2	12	LR_{11}
Ba3	13	LR_{12}
B1	14	LR_{13}
B2	15	LR_{14}
B3	16	LR_{15}
Caa1	17	LR_{16}
Caa2	18	LR_{17}
Caa3	19	LR_{18}
Ca	20	LR_{19}
C	21	LR_{20}

Table 4 Regression result of Equations (1) and (2)

Dependent variable: ln(spread)				
	Non-MBS		MBS	
Column	A	B	C	D
Equation	(1)	(2)	(1)	(2)
Intercept	4.39**	2.59**	3.55**	2.56**
	(16.52)	(12.31)	(23.59)	(21.77)
Key variables				
Number-format Average rating (NR)	0.043**	0.172**	0.171**	0.200**
	(2.97)	(10.48)	(29.37)	(40.91)
Number of CRAs rating the security (N)	-0.241**	-0.025	-0.25**	-0.073**
	(-3.78)	(-0.52)	(-8.84)	(-3.29)
during_crisis (DC)	--	1.472**	--	1.58**
		(12.75)		(16.34)
post_crisis (PC)	--	1.742**	--	2.06**
		(17.16)		(35.16)
average_rating× post_crisis	--	-0.143**	--	-0.146**
		(-7.51)		(-13.92)
Control variables				
Par_amount($\times 10^8$)	-0.029**	-0.036**	-0.0078	-0.0049
	(-2.63)	(-4.67)	(-1.48)	(-1.19)
CPN (%)	0.290**	0.242**	0.112**	0.095**
	(11.10)	(12.41)	(12.51)	(13.95)
Tranche_num	0.024	-0.0251*	0.0018	0.000085
	(1.34)	(-1.71)	(0.72)	(0.43)
Length (year)	0.0002	0.0031	-0.0068**	-0.0063**
	(0.05)	(0.94)	(-3.36)	(-3.99)
WAL (year)	0.024	0.044**	0.059**	0.067**
	(1.33)	(3.31)	(8.83)	(12.88)
WAC (%)	-0.03*	-0.0045	-0.081**	0.047**
	(-1.92)	(-0.35)	(-5.60)	(3.8)
Issuer Size (%)	2.450**	3.005**	0.701**	0.194
	(3.49)	(6.02)	(3.23)	(1.14)
Credit_support (%)	-0.0053**	-0.0051**	0.0009	-0.0043**
	(-2.46)	(-3.38)	(0.73)	(-4.66)
CLO_dummy	-0.715**	-0.711**	--	--
	(-4.80)	(-6.76)		
Auto_dummy	0.153	-0.274**	--	--
	(1.15)	(-2.78)		
Collateral_CMBS_dummy	--	--	-0.419**	-0.145**
			(-7.06)	(-3.07)
Collateral_RMBS_dummy	--	--	-0.697**	-0.316**
			(-6.52)	(-3.75)
Collateral_Wholesale_dummy	--	--	-0.324**	-0.487**
			(-3.84)	(-7.38)
Country_KY	0.667**	0.491**	--	--
	(3.38)	(3.52)		
Country_US	-0.130	0.052	0.780**	0.147*
	(-0.85)	(0.48)	(9.37)	(2.15)
Country_GB	0.457*	0.074	1.051**	0.326**
	(2.57)	(0.58)	(13.25)	(4.69)
Country_AU	-0.039	-0.273*	0.692**	0.058
	(-0.17)	(-1.67)	(5.20)	(0.55)
Country_NL	0.374*	0.135	1.018**	0.360**
	(2.19)	(0.12)	(16.53)	(7.1)
Country_IE	-0.75**	-0.48**	0.795**	0.512**
	(-4.29)	(-3.62)	(10.44)	(8.52)
Adjusted R^2	51.81%	76.56%	51.20%	70.65%
Observations	17077	17077	7391	7391

The dependent variable is logarithm of issuance spreads. Regressions are estimated using OLS method. Independent variables are introduced in Table 2.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 5 Regression result of Equations (3) and (4)

		Time windows					
		1 day		3 days		5 days	
Variables	Coefficient Descriptor	Eq (3)	Eq (4)	Eq (3)	Eq (4)	Eq (3)	Eq (4)
Intercept	--	-0.0028 (-0.02)	0.0016 (0.10)	-0.0005 (-0.02)	0.00192 (0.12)	-0.00009 (-0.01)	0.00239 (0.14)
Event dummy (dE)	β_1	-0.43** (-6.38)	-0.60** (-7.40)	-0.36** (-6.93)	-0.32** (-6.71)	-0.20** (-6.42)	-0.27** (-7.36)
Post-crisis dummy (dP)	β_2	--	-0.003 (-0.64)	--	-0.0031 (-0.77)	--	-0.0036 (-0.89)
dP × dE	δ	--	0.56** (3.74)	--	0.36** (4.11)	--	0.24** (3.59)
No. of ID		72	72	72	72	72	72
No. of days		3915	3915	3915	3915	3915	3915

The dependent variable is daily price return (price at exact day minus price at one day before) .Regressions are estimated using fixed-effect panel method. dE is equal to 1 if the observation happens in certain days (1, 3 or 5) after a negative rating event happens and 0 otherwise. dP is equal to 1 if the observation happens after Sep 15th 2007 and 0 otherwise.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 6 Volume proportion of AAA and non-AAA tranches

	MBS dataset	Non-MBS dataset
Proportion of AAA tranches volume	82.45%	80.72%
Proportion of non-AAA tranches volume	17.55%	19.23%

Table 7 Updated regression result of Equations (1) and (2) excluding AAA notches

Dependent variable: ln(spread)				
Column	A	B	C	D
	Non-MBS		MBS	
Equation	(1)	(2)	(1)	(2)
Intercept	3.79**	2.05**	4.06**	2.81**
	(12.75)	(7.83)	(22.68)	(18.28)
Key variables				
Number-format Average rating (NR)	-0.0056	0.132**	0.117**	0.159**
	(-0.46)	(7.8)	(18.54)	(27.41)
Number of CRAs rating the security (N)	-0.045	0.061	-0.165**	-0.035
	(-0.75)	(1.32)	(-5.71)	(-1.44)
during_crisis (DC)	--	1.200**	--	1.582**
		(6.35)		(9.68)
post_crisis (PC)	--	1.796**	--	2.056**
		(13.89)		(24.71)
average_rating× post_crisis	--	-0.154**	--	-0.142**
		(-8.26)		(-12.2)
Control variables				
Par_amount($\times 10^8$)	0.012	-0.023**	0.0014	-0.004**
	(1.03)	(-2.87)	(0.09)	(-3.06)
CPN (%)	0.445**	0.372**	0.223**	0.171**
	(16.15)	(17.19)	(21.89)	(20.02)
Tranche_num	0.037*	-0.030*	-0.0031	-0.025
	(2.09)	(-2.02)	(-1.31)	(-1.26)
Length (year)	-0.0025	0.011*	-0.005*	-0.0009
	(-0.39)	(2.22)	(-2.07)	(-0.41)
WAL (year)	0.048**	0.021	0.02*	0.036*
	(2.68)	(1.51)	(2.30)	(4.86)
WAC (%)	-0.005*	0.016	-0.057*	0.056**
	(-2.13)	(0.9)	(-3.88)	(4.16)
Issuer Size (%)	0.462	1.242*	0.98*	0.242
	(0.66)	(2.43)	(4.22)	(1.26)
Credit_support (%)	-0.005	-0.0054*	-0.004*	-0.0074***
	(-1.95)	(-2.8)	(-2.19)	(-4.61)
CLO_dummy	-0.002	-0.047	--	--
	(-0.01)	(-0.38)		
Auto_dummy	0.378*	0.192	--	--
	(2.55)	(1.79)		
Collateral_CMBS_dummy	--	--	-0.494**	-0.098
			(-7.64)	(-1.77)
Collateral_RMBS_dummy	--	--	-0.332**	-0.091
			(-2.91)	(-0.97)
Collateral_Wholesale_dummy	--	--	-0.434	-0.484**
			(-4.94)	(-6.68)
Country_KY	0.534**	0.447**	--	--
	(3.25)	(3.76)		
Country_US	0.109	0.426**	0.359**	-0.026
	(0.69)	(3.69)	(3.87)	(-0.33)
Country_GB	0.534*	-0.091	0.446**	0.046
	(2.56)	(-0.58)	(5.15)	(0.62)
Country_AU	-0.223	-0.705*	0.004	-0.353**
	(-0.45)	(-1.98)	(0.03)	(-2.69)
Country_NL	0.473*	0.177	0.294**	-0.034
	(2.32)	(1.19)	(4.07)	(-0.56)
Country_IE	-0.73**	-0.558**	0.521**	0.371**
	(-4.61)	(-4.86)	(6.55)	(5.66)
Adjusted R^2	71.7%	85.53%	50.30%	66.71%
Observations	10333	10333	4759	4759

The dependent variable is logarithm of issuance spreads .Regressions are estimated using OLS method. Independent variables are introduced in Table 2.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 8 Regression result of Equations (6) and (7)

Dependent variable: ln(spread)				
Column	A	B	C	D
	Non-MBS		MBS	
Equation	(6)	(7)	(6)	(7)
Intercept	4.193** (14.13)	2.740** (11.58)	3.075** (19.06)	2.682** (20.96)
Key variables				
Aa1_dummy (LR1)	-0.052 (-0.28)	0.128 (0.77)	0.453** (5.73)	0.374** (5.58)
Aa2_dummy (LR2)	0.0052 (0.03)	0.406** (2.96)	0.593** (8.44)	0.540** (9.27)
Aa3_dummy (LR3)	-0.144 (-0.82)	0.266 (1.65)	0.665** (9.38)	0.683** (11.88)
A1_dummy (LR4)	0.202 (1.37)	0.606** (3.98)	0.970** (12.10)	0.958** (14.32)
A2_dummy (LR5)	0.321 (1.80)	0.878** (5.49)	1.108** (15.46)	1.197** (20.94)
A3_dummy (LR6)	0.204 (1.14)	0.851** (5.51)	1.209** (15.06)	1.277** (19.32)
Baa1_dummy (LR7)	0.266 (1.08)	1.032** (4.8)	1.480** (18.05)	1.637** (25.18)
Baa2_dummy (LR8)	0.646** (3.02)	1.538** (8.27)	1.635** (21.80)	1.787** (30.31)
Baa3_dummy (LR9)	0.750** (3.74)	1.598** (8.53)	1.812** (23.58)	1.876** (30.3)
Ba1_dummy (LR10)	0.455 (1.16)	1.860** (3.75)	2.167** (17.05)	2.305** (22.67)
Ba2_dummy (LR11)	1.152 (1.63)	0.930 (1.89)	2.368** (19.14)	2.513** (25.15)
Ba3_dummy (LR12)	0.989 (1.82)	1.645** (3.43)	2.570** (12.96)	2.694** (15.19)
B1_dummy (LR13)	--	--	1.413** (4.30)	1.434** (5.12)
B2_dummy (LR14)	1.360 (1.94)	1.050* (2.17)	1.021* (2.42)	1.231** (3.84)
B3_dummy (LR15)	0.232 (0.45)	0.262 (0.74)	1.824** (6.57)	1.920** (6.86)
Caa1_dummy (LR16)	0.922 (1.83)	0.608 (1.75)	1.582** (3.06)	1.845** (4.69)
Caa2_dummy (LR17)	--	--	--	--
Caa3_dummy (LR18)	--	--	1.517* (2.10)	1.743** (3.16)
Ca_dummy (LR19)	1.633** (3.17)	3.191** (6.53)	2.268** (4.42)	2.288** (5.86)
C_dummy (LR20)	--	--	--	--
Number of CRAs rating the security (N)	-0.210** (-3.00)	-0.037 (-0.69)	-0.254** (-8.98)	-0.116** (-5.27)
during_crisis	--	1.430** (13.04)	--	1.399** (15.56)
post_crisis	--	1.423** (13.46)	--	1.800** (29.94)
Aa1_dummy× post_crisis	--	0.107 (0.4)	--	-0.076 (-0.51)
Aa2_dummy × post_crisis	--	-0.092 (-0.42)	--	0.211 (1.38)
Aa3_dummy × post_crisis	--	0.344 (1.34)	--	-0.0048 (-0.03)
A1_dummy× post_crisis	--	-0.186 (-0.93)	--	-0.403* (-2.7)
A2_dummy× post_crisis	--	-0.253 (-1.01)	--	-0.465** (-2.73)
A3_dummy× post_crisis	--	-0.320 (-1.11)	--	-0.830** (-4.77)
Baa1_dummy× post_crisis	--	-1.041* (-2.5)	--	-1.519** (-7.52)
Baa2_dummy× post_crisis	--	-1.129** (-3.71)	--	-1.846** (-8.32)
Baa3_dummy× post_crisis	--	-0.998** (-3.72)	--	-0.898* (-5.01)

Ba1_dummy× post_crisis	--	-1.262* (-2.22)	--	-1.359** (-4.06)
Ba2_dummy× post_crisis	--	--	--	-1.285** (-4.35)
Ba3_dummy× post_crisis	--	-0.845 (-1.24)	--	-1.461** (-3.98)
B1_dummy× post_crisis	--	--	--	-0.053 (-0.09)
B2_dummy× post_crisis	--	--	--	--
B3_dummy× post_crisis	--	--	--	-0.910 (-1.89)
Caa1_dummy× post_crisis	--	--	--	--
Caa2_dummy× post_crisis	--	--	--	--
Caa3_dummy× post_crisis	--	--	--	--
Ca_dummy× post_crisis	--	-1.934** (-2.87)	--	--
C_dummy× post_crisis	--	--	--	--
Control variables				
Par_amount($\times 10^8$)	-0.025* (-2.13)	-0.022** (-2.63)	0.0080 (1.45)	0.0093* (2.21)
CPN (%)	0.240** (8.62)	0.174** (8.37)	0.076** (8.05)	0.067** (9.14)
Tranche_num	0.011 (0.53)	-0.03 (-1.52)	-0.0017 (-0.64)	-0.0004 (-0.18)
Length (year)	-0.0002 (-0.04)	0.0034 (0.97)	0.0015 (0.69)	-0.0023 (-1.43)
WAL (year)	0.028 (1.45)	0.036* (2.39)	0.047** (6.90)	0.066** (12.48)
WAC (%)	-0.0069 (-0.36)	0.013 (0.96)	-0.052** (-3.41)	0.037** (2.83)
Issuer Size (%)	3.113** (4.06)	3.265** (5.82)	1.130** (5.02)	0.380* (2.15)
Credit_support (%)	-0.0042 (-1.82)	-0.0042* (-2.62)	0.007** (5.37)	0.0002 (0.21)
CLO_dummy	-0.802** (-4.95)	-0.787** (-6.68)	--	--
Auto_dummy	0.047 (0.33)	-0.361** (-3.4)	--	--
Collateral_CMBS_dummy	--	--	-0.432** (-6.72)	-0.303** (-5.95)
Collateral_RMBS_dummy	--	--	-0.786** (-6.96)	-0.468** (-5.35)
Collateral_Wholesale_dummy	--	--	-0.227** (-2.47)	-0.557** (-7.72)
Country_KY	0.729* (2.33)	0.591** (2.7)	--	--
Country_US	-0.239 (-1.37)	0.0058 (0.05)	0.767** (8.39)	0.162* (2.19)
Country_GB	0.460* (2.48)	0.069 (0.52)	1.091** (12.99)	0.388** (5.65)
Country_AU	-0.0088 (-0.03)	-0.073 (-0.4)	0.580** (4.19)	0.103 (0.95)
Country_NL	0.468** (2.62)	0.242 (1.93)	1.036** (16.67)	0.396** (7.78)
Country_IE	-0.672** (-3.53)	-0.465** (-3.41)	0.571** (6.54)	0.476** (7.09)
Adjusted R^2	47.81%	75.77%	54.76%	73.82%
Observations	17077	17077	7391	7391

The dependent variable is logarithm of issuance spreads .Regressions are estimated using OLS method. Independent variables except LR1-LR20 are introduced in Table 2. The introduction of LR1-LR20 is in Table 3.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 9 Results of regressions of Equation (4) setting different boundaries of crisis/non-crisis periods

		Time windows					
		1 day		3 days		5 days	
	Boundary	dE	dP × dE	dE	dP × dE	dE	dP × dE
‘Significant’ Area	2007.9.15	-0.60**	0.56**	-0.32**	0.36**	-0.27**	0.24**
		(-7.40)	(3.74)	(-6.71)	(4.11)	(-7.36)	(3.59)
	2008.9.15	-0.54**	0.50**	-0.40**	0.28	-0.24**	0.20**
		(-7.02)	(2.98)	(-7.10)	(1.86)	(-6.92)	(2.71)
	2008.11.15	-0.53**	0.47**	-0.45**	0.41**	-0.25**	0.23**
		(-6.93)	(2.78)	(-7.63)	(3.28)	(-7.02)	(2.96)
	2009.1.15	-0.52**	0.45**	-0.44**	0.41**	-0.24**	0.22**
		(-6.86)	(2.60)	(-7.61)	(3.20)	(-6.99)	(2.87)
	2009.3.15	-0.49**	0.39*	-0.42**	0.34*	-0.23**	0.21*
		(-6.67)	(2.10)	(-7.28)	(2.43)	(-6.85)	(2.54)
‘Insignificant’ Area	2009.5.15	-0.47**	0.35	-0.38**	0.24	-0.22**	0.18
		(-6.53)	(1.68)	(-6.96)	(1.48)	(-6.60)	(1.89)
	2009.7.15	-0.47**	0.33	-0.38**	0.21	-0.22**	0.17
		(-6.49)	(1.53)	(-6.91)	(1.27)	(-6.55)	(1.71)
	2009.9.15	-0.45**	0.27	-0.37**	0.16	-0.21**	0.13
		(-6.40)	(1.07)	(-6.86)	(0.82)	(-6.43)	(1.16)
	2009.11.15	-0.52**	0.47**	-0.37**	0.12	-0.21**	0.11
		(-6.89)	(2.66)	(-6.82)	(0.60)	(-6.37)	(0.94)
	No. of ID	72	72	72	72	72	72
	No. of days	3915	3915	3915	3915	3915	3915

The dependent variable is daily price return (price at exact day minus price at one day before). Regressions are estimated using fixed-effect panel method. dE is equal to 1 if the observation happens in certain days (1, 3 or 5) after a negative rating event happens and 0 otherwise. dP is equal to 1 if the observation happens after the date in the ‘boundary’ column and 0 otherwise.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 10 Regression result of Equations (8) and (9)

		Time windows					
		1 day		3 days		5 days	
Variables	Coefficient Descriptor	Eq (8)	Eq (9)	Eq (8)	Eq (9)	Eq (8)	Eq (9)
Intercept	--	-0.00042	0.0081	-0.00066	0.0015	-0.0002	-0.00433
		(-0.03)	(0.36)	(-0.03)	(0.09)	(-0.01)	(-0.71)
Change degree (CD)	β_1	-0.10**	-0.14**	-0.06**	-0.08**	-0.019	0.00453
		(-3.58)	(-4.14)	(-3.74)	(-4.13)	(-0.68)	(0.42)
Post-crisis dummy (dP)	β_2	--	-0.012*	--	-0.00025	--	0.00136
			(-2.07)		(-0.6)		(0.87)
dP × CD	δ	--	0.128*	--	0.074	--	0.193**
			(1.99)		(1.73)		(12.12)
No. of ID		72	72	72	72	72	72
No. of days		3915	3915	3915	3915	3915	3915

The dependent variable is daily price return (price at exact day minus price at one day before). Regressions are estimated using fixed-effect panel method. CD is the number of notches the security is downgraded if the observation is in certain days (1, 3 or 5) after a negative rating event happens and 0 otherwise. dP is equal to 1 if the observation happens after Sep 15th 2007 and 0 otherwise.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 11 Result of regressions of Equations (3) and (4) excluding anticipated downgrades

		Time windows					
		1 day		3 days		5 days	
Variables	Coefficient Descriptor	Eq (3)	Eq (4)	Eq (3)	Eq (4)	Eq (3)	Eq (4)
Intercept	--	-0.00025	-0.0022	-0.00047	0.01	-0.00006	0.0025
		(-0.02)	(-0.13)	(-0.02)	(0.43)	(-0.00)	(0.15)
Event dummy (dE)	β_1	-0.53**	-0.68**	-0.38**	-0.62**	-0.22**	-0.30**
		(-7.07)	(-7.85)	(-6.59)	(-8.86)	(-6.34)	(-7.39)
Post-crisis dummy (dP)	β_2	--	0.0026	--	-0.014**	--	-0.0038
			(0.66)		(-2.45)		(-0.92)
dP × dE	δ	--	0.62**	--	0.74**	--	0.28**
			(3.45)		(5.99)		(3.78)
No. of ID		72	72	72	72	72	72
No. of days		3915	3915	3915	3915	3915	3915

The dependent variable is daily price return (price at exact day minus price at one day before). Regressions are estimated using fixed-effect panel method. dE is equal to 1 if the observation happens in certain days (1, 3 or 5) after a negative rating event happens (except anticipated downgrades which happens within 3 months after a possible downgrade announcement is released) and 0 otherwise. dP is equal to 1 if the observation happens after Sep 15th 2007 and 0 otherwise.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic

Table 12 Result of regressions of Equations (3) and (4) replacing dependent variables

		Time windows								
		1 day			3 days			5 days		
Variables	Coefficient Descriptor	Index 1	Index 2	Index 3	Index 1	Index 2	Index 3	Index 1	Index 2	Index 3
$Index_{i,t} = \alpha_i + \beta_1 \times dE_{i,t} + u_{i,t}$										
Intercept	--	-0.0017	0.00009	0.00007	-0.0035	0.0001	0.0001	-0.001	0.0001	0.0001
		(-0.10)	(0.05)	(0.03)	(-0.16)	(0.06)	(0.05)	(-0.09)	(0.07)	(0.07)
Event dummy	β_1	-0.45**	-0.35**	-0.26**	-0.37**	-0.13**	-0.14**	-0.19**	-0.10**	-0.11**
(dE)		(-6.54)	(-39.92)	(-25.33)	(6.97)	(-26.04)	(-23.57)	(-6.22)	(-25.05)	(-23.98)
$Index_{i,t} = \alpha_i + \beta_1 \times dE_{i,t} + \beta_2 \times dP_{i,t} + \delta \times (dP_{i,t} \times dE_{i,t}) + u_{i,t}$										
Intercept	--	0.0034	-0.00015	-0.00012	0.00368	-0.0001	0.00021	0.00415	0.0000	0.00009
		(0.20)	(-0.08)	(-0.06)	(0.22)	(-0.06)	(0.09)	(0.25)	(-0.03)	(0.04)
Event dummy	β_1	-0.62**	-0.52**	-0.38**	-0.30**	-0.36**	-0.31**	-0.26**	-0.15**	-0.16**
(dE)		(-7.59)	(-49.48)	(-31.24)	(-6.36)	(-57.28)	(-40.36)	(-7.07)	(-31.22)	(-29.13)
Post-crisis	β_2	-0.007	0.000248	0.000199	-0.0073	0.00017	-0.0003	-0.0077	0.00005	-0.00017
dummy (dP)		(-1.66)	(0.58)	(0.4)	(-1.76)	(0.38)	(-0.54)	(-1.88)	(0.12)	(-0.35)
dP × dE	δ	0.57**	0.57**	0.41**	0.34**	0.378**	0.26**	0.22**	0.166**	0.169**
		(3.82)	(29.77)	(18.36)	(3.92)	(32.99)	(18.35)	(3.30)	(18.77)	(16.56)
No. of ID		72	72	72	72	72	72	72	72	72
No. of days		3915	3915	3915	3915	3915	3915	3915	3915	3915

The dependent variable index 1 is the daily price return minus daily market return: $(p_{i,t} - p_{i,t-1}) - (M_{i,t} - M_{i,t-1})$ (M_t is the Barclays ABS market index on day t). Index 2 is abnormal return, $AR_{i,t} = Return_{i,t} - \widehat{Return}_{i,t}$. Index 3 is standardized abnormal return, $SAR_{i,t} = \frac{AR_{i,t}}{\sqrt{\sigma^2(\hat{\varepsilon})}}$.

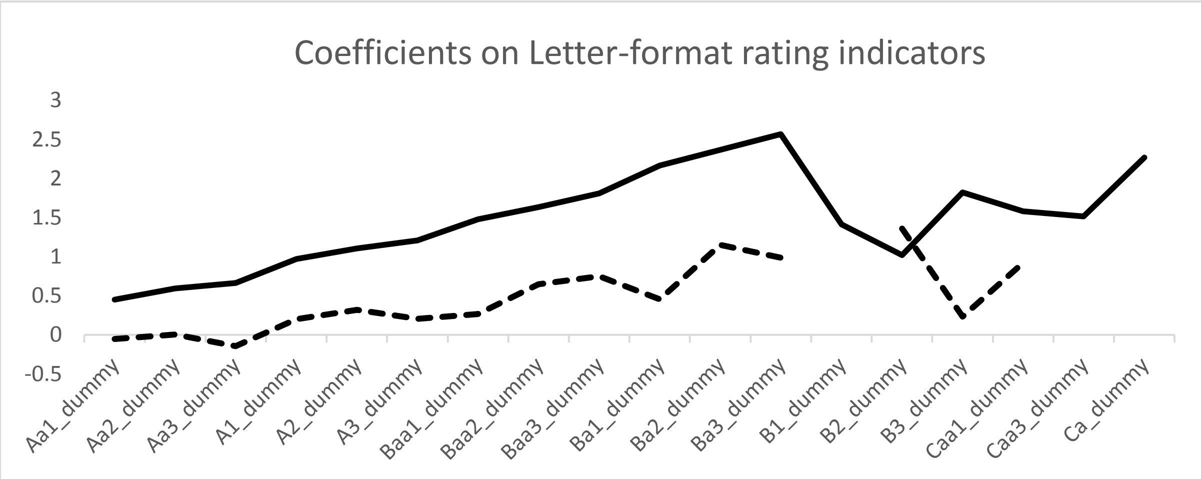
Regressions are estimated using fixed-effect panel method. dE is equal to 1 if the observation happens in certain days (1, 3 or 5) after a negative rating event happens and 0 otherwise. dP is equal to 1 if the observation happens after Sep 15th 2007 and 0 otherwise.

**the coefficient is significant at 1% level

* the coefficient is significant at 5% level

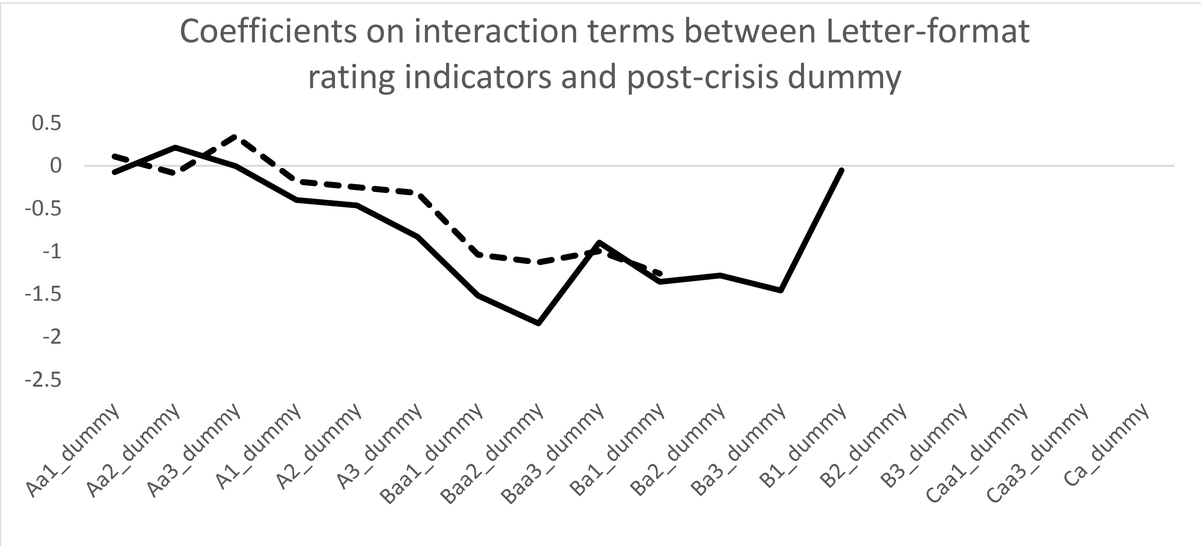
The figures in the bracket show the corresponding t-statistic

Figure 1



This figure demonstrates the regression coefficients on letter-format rating indicator (LRs) dummies in Equation (6). The horizontal axis shows the LR in Equation (6) and the vertical axis shows the corresponding regression coefficients on the LR (the values of those coefficients are shown in Columns A and C of Table 8). The full line and the dashed line are for the non-MBS and MBS datasets respectively. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset

Figure 2



This figure demonstrates the regression coefficients on interaction terms between letter-format rating indicator (LR) dummies and post-crisis dummy in Equation (7). The horizontal axis shows the LR in Equation (7) and the vertical axis shows the corresponding regression coefficients on the interaction terms between the LR and post-crisis dummy (the values of those coefficients are shown in Columns B and D of Table 8). The full line and the dashed line are for the non-MBS and MBS datasets respectively. The coefficients for some rating notches are missing due to no securities being rated to those notches in the dataset.

Appendix

Appendix Table 1 Distributions of tranche numbers and deal numbers and issuance of MBS and non-MBS in three periods

	MBS			**Non-MBS**		
Period	Pre-crisis	During crisis	Post-crisis	Pre-crisis	During crisis	Post-crisis
Number of tranches	6123	291	967	12409	1051	3617
Number of deals	1133	83	268	2886	383	949

Appendix Table 2 Number of negative/positive events in two periods

Period	Positive events	Negative events	Total
Pre-crisis (2001.02-2007.09)	143	273	415
Post-crisis (2007.09-2016.02)	205	274	479
Total (2001.02-2016.02)	348	547	894

Appendix Table 3 T-test result of the price return reactions around rating events

Events category/ Time period	Time windows								
	(-1,0)	(0,+1)	(-1,+1)	(-3,0)	(0,+3)	(-3,+3)	(-5,0)	(0,+5)	(-5,+5)
Price return									
Negative events/Pre-crisis	-0.41033	-0.190	-0.54819**	-0.577*	-0.345	-0.922**	-0.715**	-0.510*	-1.26**
	(-1.7205)	(-1.043)	(-2.8594)	(-2.354)	(-1.684)	(-4.366)	(-2.975)	(-2.831)	(-4.971)
Negative events/Post-crisis	-0.042	0.211	0.170	0.131	0.238	0.369	0.189	0.074	0.201
	(-0.434)	(0.724)	(0.596)	(0.935)	(0.818)	(1.109)	(1.286)	(0.423)	(0.906)
Positive events/Pre-crisis	-0.046	0.028	0.009	-0.048	0.065*	0.017	-0.066	0.074*	0.039
	(-1.549)	(0.994)	(0.264)	(-1.402)	(2.067)	(0.398)	(-1.729)	(2.233)	(0.787)
Positive events/Post-crisis	0.130	-0.004	0.085	0.190	0.029	0.219	0.231	0.068	0.285
	(0.348)	(-0.076)	(0.224)	(0.470)	(0.325)	(0.464)	(0.608)	(0.760)	(0.637)

**the coefficient is significant at 1% level

* the coefficient is significant at 5% level

The figures in the bracket show the corresponding t-statistic

Appendix Table 4 Panel regressions result of Equations (3) and (4) for positive rating announcements

		Time windows					
		1 day		3 days		5 days	
Variables	Coefficient Descriptor	Eq 3	Eq 4	Eq 3	Eq 4	Eq 3	Eq 4
Intercept	--	-0.0032	-0.0045	-0.004	-0.0047	-0.0034	-0.0047
		(-0.55)	(-0.72)	(-0.55)	(-0.76)	(-0.56)	(-0.76)
Event dummy (dE)	β_1	0.016	0.0013	0.047**	0.0015	0.032**	0.0015
		(0.55)	(0.85)	(2.76)	(0.95)	(2.39)	(0.94)
Post-crisis dummy (dP)	β_2	--	-0.0327	--	0.029	--	0.015
			(-0.98)		(1.51)		(1.03)
dP × dE	δ	--	0.25**	--	0.12**	--	0.088**
			(3.36)		(2.80)		(2.63)
No. of ID		73	73	73	73	73	73
No. of days		3915	3915	3915	3915	3915	3915

The dependent variable is daily price return (price at exact day minus price at one day before). Regressions are estimated using fixed-effect panel method. dE is equal to 1 if the observation happens in certain days (1, 3 or 5) after a positive rating event happens and 0 otherwise. dP is equal to 1 if the observation happens after Sep 15th 2007 and 0 otherwise.
**the coefficient is significant at 1% level
* the coefficient is significant at 5% level
The figures in the bracket show the corresponding t-statistic