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Do credit ratings affect spread and return? A study of structured finance products

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Fernando Moreira
University of Edinburgh Business School
Fernando.Moreira@ed.ac.uk

Sheng Zhao
University of Edinburgh Business School
s1402430@sms.ed.ac.uk

Abstract

Whilst the previous studies investigating the relationship between credit ratings and spread or return in the financial market are normally restricted to non-causal measures, this paper uses Structural Equation Modelling (SEM) to test the possibility of causal links from ratings to spread and return in the context of structured finance products. Our analyses are split into two stages: first, we search for causality between ratings and spread at the issuance stage (primary market) based on a sample comprising all tranches of asset-backed securities (ABS) issued in the US from December 1999 to December 2015. Then, we consider all ABS rating changes from February 2001 to December 2015 to check whether the assumption of causal connection between ratings and return at the trading stage (secondary market) is reasonable. After testing all pertinent combinations among the variables in our database, we find evidence of causality at the issuance stage but very little support to causality at the trading stage. This study contributes to the debate on the regulation of credit rating agencies (CRAs) as our findings suggest that ratings may have an effective influence on decisions made by investors at the time structure finance products are issued. As this effect is very weak when those assets are traded in the secondary market, in principle, regulators should focus their attention on the CRAs' activities regarding the issuance of new structured products.

1. Introduction

Credit ratings play a vital role in the structured finance market not only due to regulatory requirements but also because the instruments issued are more complex than conventional securities, which makes most of the investors unable to evaluate the risks involved in the transactions.

Especially after the events observed in the US Subprime Mortgage Crisis in 2007 and the Global Financial Crisis (GFC) in 2008, credit rating agencies (CRAs) have been highly criticised for assigning inaccurate and biased ratings to structured finance products (Griffin and Tang., 2011; He et al., 2011; Kraft, 2015). Investments on mortgage-backed securities (MBS) and other types of asset-backed securities (ABS) that became worthless during the financial crisis were presumably based on credit ratings provided by CRAs (Friedman and Posner, 2011). This has stimulated a debate on the regulation of CRAs as they are believed to have the potential for misleading investors (in particular, the less informed ones), which can result in a financial turmoil and/or in the benefit to a few agents at the expense of many others.

In this context, the literature has studied the relationship between credit ratings and spread or return of the assessed instruments with a view to find evidence of the impact of rating announcements on investors' decisions. Spread and return are seen as proxies for investors' reactions in the primary (issuance) and the secondary (trading) markets, respectively. Alas, such investigations have typically been restricted to *associative* measures that tell us virtually nothing about the actual (if any) impact of ratings on the performance of financial products, which would reflect corresponding actions taken by investors. Even if a strong association between ratings and spread or return is found, it would not necessarily mean that the latter is a consequence of the former. It could be the case that spread or return movements happening just after rating announcements are simultaneously caused by, for example, other factors taking place in the same period.

In order to make a more precise judgement about the impact of ratings on financial products' spread and return (i.e. on investors' reactions) we should use a method that allows us to verify the feasibility of possible causal relation between rating changes and spread or return. Following a growing body of literature (e.g. Glymour et al., 1987; Morgan and Winship, 2007; Pearl, 2009; Mulaik, 2009), we use Structural Equation Modelling (SEM) by means simultaneous linear equations to test hypothetical models about the potential causal impact of ABS ratings on those assets' spread and return.

It is worth noting that we focus on ABS because, besides their deterioration that contributed to the GFC, it is argued that ABS investors tend to follow ratings more than investors in other types of products do (Fender and Mitchell, 2005; Coval et al., 2009).

We add to the existing knowledge in this field by running causality tests from ratings to spread and return and by including analyses on the secondary market rather than, as the existing literature has typically done, relying on techniques that only show simultaneous occurrences and only focusing on the primary market.

In addition to contribute to the academic literature, this paper is also important as a tool to support decisions concerning the regulation of CRAs. Simply identifying co-movements between credit ratings and spread (at issuance) or return (at the trading stage) does not give regulators and policy-makers enough information to decide on the needs of controlling CRAs more or less. For example, if ratings and spread/return move hand in hand but the former do not cause changes in the latter, intervening on CRAs will likely not bring the expected results. Causal evaluations are much more appropriate to guide actions by regulators and policy-makers.

The remainder of this paper is organised as follows. In Section 2, we review other studies related to the association between credit ratings and financial instruments' spread and return. Section 3 is concerned with the method (SEM) used in our analyses. In Sections 4 and 5, we present our empirical results regarding the primary and the second markets, respectively. Section 6 concludes.

2. Credit ratings and financial instruments' performance

The empirical research dealing with the performance of financial products and their credit ratings initially focuses on the bond market. West (1973), for instance, finds a significant association between bond ratings and yields. Weinstein (1977), however, concludes that bond returns are not related to rating changes in a period of up to six months after the announcements. Later, other authors have identified links between rating announcements and issuance spread (e.g. Iannotta et al., 2013) and return (e.g. Liu and Thakor, 1984; Stover, 1991; Abad and Robles, 2015).

Aside from bonds, other instruments have been considered in studies related to rating changes. Hand et al. (1992) and Dichev and Piotroski (2001), for example, investigate the behaviour of stock returns after announcements on ratings of bonds issued by the respective companies. Both studies conclude that bond downgrades are followed by stock abnormal negative returns

although such association is not observed for positive events. Hull et al. (2004) show that, in the Credit Default Swap (CDS) market, downgrades are related to increasing return.

The relationship between structured finance products and rating changes is considered in the following studies. Regressing mortgage-backed securities (MBS) ratings and prices on a set of control variables, Ashcraft et al. (2011) find a negative relation between ratings and yields. That is, as expected, their findings indicate that worse MBS ratings are associated with higher yields. Mählmann (2012) predicts losses in asset-back securities (ABS) investments using issuance yields and controlling for ratings at the issuance stage. The author concludes that issuance ratings have predictive power on yield spread. Fabozzi and Vink (2012) use data on AAA tranches of European ABS to try to identify potential links between issuance spreads and ratings. They find that investors, when pricing ABS spread at issue, rely not only on ratings but also on other factors, such as credit enhancement and creditor protection.

Fender and Mitchell (2005) and Coval et al. (2009) state that ABS ratings impact investors (and therefore ABS spread and returns) via three channels: information intermediate function, historical behavioural reliance and regulatory demands. The first channel exists because investors typically do not have access to the necessary information to evaluate financial products while CRAs, being able to collect such information, are in a better position to assess the risk of investments (Cantor and Packer, 1994). The reliance channel is explained by the fact that CRAs were created around seven decades before structured finance products. Thus, the early investors in this market used ratings as a natural support to their decisions and this has historically been replicated by new participants in the market (Servigny and Jobst, 2007). The third channel (regarding regulation) gained importance in the 1970s since when the Securities and Exchange Commission of US (SEC) and international regulators have been linking regulatory requirements to ratings provided by CRAs (Darbellay, 2013).

In short, studies dealing with credit ratings and spread/return have been focused on conventional financial instruments such as bonds and stocks while less attention has been given to structure finance products. Among the authors investigating structured finance ratings, most restrict their samples to the primary market (issuance stage) and analyse associative relationships while causal linkages are not explored by means of techniques specially designed to that end.

We overcome these limitations by using a sample of structured finance products that includes data on the secondary market to search for evidence of causal relationships between ABS ratings and spread/return.

3. Structural Equation Modelling (SEM) and causality

3.1. SEM: definition and key steps

Structural Equation Modelling (SEM) is a statistical technique used to analyse direct and indirect relationships across variables. For an introduction to SEM, see, for example, Schumacker and Lomax (2016) or Kline (2005). It is worth noting that although this approach is often associated with questions involving latent variables it can also be used to study observed variables alone (see, e.g., Acock, 2013, Chapter 2).

In sum, when using SEM, we test whether a sample variance-covariance matrix is similar (i.e. has a close fit) to the variance-covariance matrices of theoretical (hypothesised) models. That is, we check if the data we have in hand support assumed models regarding the association among variables of interest.

The aforementioned test is conducted in a sequence of steps (see, e.g., Schumacker and Lomax, 2016, Chapter 7 and Acock, 2013). First, models are specified (assumed) based on previous investigations or conjectures to be evaluated. Second, it should be certified that the models are over-identified (i.e. have degrees of freedom > 0). This is a necessary condition for SEM estimation because over-identification means that the models assumed may not be a good fit to the sample data. If such models fit well, this adds evidence to the hypothesis that those models are adequate to represent the presumed relationships among variables.

Third, the model parameters are estimated. Some of the estimation methods rely on distribution assumptions (e.g. Unweighted Least Squares approach, which is based on the assumption of normality). In this paper, we opt for a Maximum Likelihood approach in order to relax parametric assumptions. The fourth step in SEM analyses is concerned with goodness-of-fit tests. A number of measures serve this purpose. Table 1 presents four criteria used in this paper and the respective values that indicate good fit.

[Insert Table 1 here]

If no model is suitable or if the fit is considered poor (e.g. if the results are too close to the boundary values shown in Table 1 or if the models only pass few of the tests), alternative models should be tested. If more than one model pass the goodness-of-fit tests, the best-fit model can be selected by means of the Alkaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) measures, where the lower the values, the better the fit.

3.2. SEM and causality

Causal analyses based on SEM go back to Wright (1921) and Haavelmo (1943) and were disseminated by the Cowles Commission shortly after (see, e.g. Koopmans, 1950; Hood and Koopmans, 1953). Although this interpretation had not normally been adopted for a number of years, it has recently gained more and more followers in the academic community (Mulaik, 2009; Morgan and Winship, 2007) and this approach's soundness has been corroborated by links built with graph theory (Pearl, 2009; Glymour et al., 1987).

However, it is essential to make clear that SEM does *not* prove causal relationships. It is simply a way of testing the feasibility of assumed connections among potential causes and their respective effects. As pointed out by Bollen and Pearl (2013), this fact was made clear at least half a century ago by Ducan (1966) but still many researchers have mistaken SEM as a tool to find causes by means of regressions. Parameters in structural equations are interpreted differently from parameters of conventional regressions, which measure the expected value of the dependent variable conditional on values observed for the independent variables. Given a set of pre-defined paths among variables, SEM provides statistical evidence in favour or against of models that result in a particular expected value of the dependent variable when the values of the independent variables are controlled (instead of being left free to vary).

The order of the presumed links from causes to effects dictates the set-up of the equations (regressions), i.e., in each of the regressions, cause and effect become dependent and independent variables, respectively. This, in turn, determines the variance-covariance matrix of the variables included in the model. Therefore, when we compare such matrix with that of actual data, we are implicitly incorporating the assumed causal links into the analyses. If those matrices are close enough to each other (according to the goodness-of-fit statistics mentioned in the previous section), we understand that the theoretical causal paths used to build the models (equations) might represent the relationship in the sample that generated the data. In this case, at least we cannot reject the fact that the variables studied may be causally related.

As said above, the causal arguments in the SEM approach should be grounded in theoretical assumptions or predictions. Hence, the hypotheses tested are accepted *a priori* as feasible scenarios. Then, for a set of equations to corroborate the possibility of causality, the goodness-of-fit tests cited in the previous section and shown in Table 1 should be compatible with the model as a whole and the specific variables of interest should be statistically significant in the respective equations.

Lastly, in order to avoid any confusion and to stress what we can conclude based on SEM results, we emphasise that if SEM supports causality in a model, this finding gives credibility

to the hypothetical model evaluated but it does not attest causality. As we explain throughout the paper, our objectives are aligned with the features of this approach and we see this study as an initial step to stimulate further investigations on the processes linking credit ratings to the ABS performance, which might include the use of alternative approaches.

4. Testing for the possibility of causality in the primary market

4.1. Data

Taking into consideration data availability, we analyse all (24,637) tranches of asset-backed securities (ABS) issued from 28 December 1999 to 31 December 2015 and traded in the US (in American dollars).

We test for possible causal relationships from (i) a set of selected variables to credit ratings and to the spread of newly issued structured finance products and (ii) from ratings to spread.

Two types of variables are included in this study. The first one is assumed to potentially impact on both ratings and spread. These variables are related to the products themselves: number of tranches in the products (*Tranche_Number*), tranche's weighted average life (*WAL*), tranche's weighted average coupon rate (*WAC*), issuer's market share calculated as the ratio between the volume issued by an issuer and total volume issued in the respective market (*Market_Share*), the percentage of credit support from other subordinate classes in the same deal (*Credit_Support*), type of collateral such as mortgages, auto loans or student loans (*Collateral_Type*), and country where the security was issued (*Country*). This information is retrieved from Bloomberg database.

The second type of variables assumed to possibly affect spread (but not ratings) are concerned with financial information regarding returns in another three financial markets – stock, government bond and corporate bond – which are respectively proxied by the following indexes: S&P 500, US Benchmark 5 Year DS Government index, and Thomson Reuters United States Corporate Benchmark AAA 5 year yield. We use 5-Year indexes for the government and the corporate bond markets because this maturity is the closest one to the weighted average life (*WAL*) across all tranches in our issuance database (5.86 years). These returns are collected for the issuance dates of ABS and therefore they cannot impact on credit ratings because ratings are defined before the issuance dates whilst we assume that investors *may* make their investment decisions according to the market conditions on the respective issuance dates (apart from taking ABS characteristics into consideration as well). The source of the financial market data is Datastream.

Spread is analysed as the natural logarithm of the spread observed (*Ln_spread*). The credit ratings are originally in letter format and are converted into a numerical format as shown in Table 2. Since we collect ratings from four credit rating agencies (Moody's, Standard & Poor's, Fitch and DBRS) and ratings are not always the same when they are available for more than one agency, we use the average rating (based on the numeric format). The sources of the information regarding the ratings are Bloomberg and the Moody's website (https://www.moodys.com/).

Table 3 – Panel A displays the summary statistics of all numerical variables included in our analyses while Panel B shows the frequency of the categorical variables.

[Insert Tables 2 and 3 here]

4.2. Modelling procedures

In order to estimate the model that best represents the (potentially) causal relationship between ABS ratings and spread at issuance, we follow the steps described in Section 3.1. As discussed in that section, models should be over-identified in order to allow the comparison of different possible alternatives. We test all plausible combinations of the variables considered in our study (see Section 4.1) that satisfy the constraint related to the over-identification of the models. More specifically, the models should comply with (see, e.g. Schumacker and Lomax, 2016, Chapter 5; Rigdon, 1994):

$$\left(\frac{a(a+1)}{2}\right)-\left(\frac{b(b+1)}{2}\right)-c-d > 0 \qquad (1)$$

where *a* is the total number of variables in the model, *b* is the number of exogenous (independent) variables that are not also endogenous, *c* is the number of regression coefficients to be estimated and *d* is the number of endogenous variables (which is the number of error terms in the model).

Given that our database has missing values, the regression coefficients are estimated by means of the 'Maximum Likelihood with missing values' method in STATA.

Then, among the models that confirm causality in the light of the measures presented in Section 3.1 (Chi-square test, RMSE, CFI and TLI), we look for the one with best-fit according to the AIC and BIC measures.

Focusing on plausible combinations means ignoring counterintuitive models. For instance, it is known that credit ratings are provided before the issuance date when spread is determined. Thus, we do not test models in which spread would cause the assignment of credit ratings due to the temporal aspect (in principle, an event occurring at time t cannot cause an event at time $t-1$).

4.3. Results

Among the models that comply with the condition in expression (1), only in three cases causality is not rejected. For a security i, the first model (M1) is written as:

$$Rating_i = \alpha_1 + \beta_{11}Tranche\_Number_i + \beta_{12}WAL_i + \beta_{13}WAC_i + \beta_{14}Market\_Share_i + \beta_{15}Credit\_Support_i + \varepsilon_{1i}$$

and

$$Ln\_spread_i = \alpha_2 + \beta_{21}Tranche\_Number_i + \beta_{22}WAL_i + \beta_{23}Market\_Share_i + \beta_{24}Credit\_Support_i + \beta_{25}Rating_i + \varepsilon_{2i}.$$

The second model (M2) is given by the following equations:

$$Rating_i = \alpha_3 + \beta_{31}Tranche\_Number_i + \beta_{32}WAL_i + \beta_{33}WAC_i + \beta_{34}Market\_Share_i + \beta_{35}Credit\_Support_i + \beta_{36}Country_i + \varepsilon_{3i}$$

and

$$Ln\_spread_i = \alpha_4 + \beta_{41}Tranche\_Number_i + \beta_{42}WAL_i + \beta_{43}Market\_Share_i + \beta_{44}Credit\_Support_i + \beta_{45}Country_i + \beta_{46}Rating_i + \varepsilon_{4i}.$$

The third model (M3) is represented by:

$$Rating_i = \alpha_5 + \beta_{51}Tranche\_Number_i + \beta_{52}WAL_i + \beta_{53}WAC_i + \beta_{54}Market\_Share_i + \beta_{55}Credit\_Support_i + \beta_{56}Country_i + \beta_{57}Collateral\_Type + + \varepsilon_{5i}$$

and

$$Ln\_spread_i = \alpha_6 + \beta_{61}Tranche\_Number_i + \beta_{62}WAL_i + \beta_{63}Market\_Share_i + \beta_{64}Credit\_Support_i + \beta_{65}Country_i + \beta_{66}Collateral\_Type + \beta_{67}Rating_i + \varepsilon_{6i}.$$

The variables appearing in the six equations above are explained in Section 4.1. The three aforementioned models are respectively represented in Figures 1 to 3, where the arrows indicate the direction of potential impact across the variables studied. The statistical results are shown in Table 4. Note that Prob $> \chi^2$ is greater than 0.10 in all models (i.e. the null hypothesis assuming the respective causal structures is not rejected) and CFI and TLI are equal or very near to 1 (also indicating that those causal models are statistically feasible as explained in Section 3.1 and in accordance with the values presented in Table 1). RMSEA is equal or very close to zero, which is below its acceptable level, from 0.05 to 0.08 (see Table 1). Nonetheless, this relatively small value should not be seen as a problem. It results from the small χ^2 statistics shown in Table 4 (an essential condition for supporting the hypothetical causal models tested), which, in turn, makes RMSEA approach zero (see RMSEA formula in Acock, 2013, p. 24 or Schumacker and Lomax, 2016, p. 111).

[Insert Figures 1 to 3 and Table 4 here]

In the three models, the positive coefficient for *Rating* in the regressions that have *Ln_spread* as the dependent variable indicates that lower ratings (i.e. increase in the number-format ratings listed in Table 2) are associated with higher spread. Following the causal interpretation advocated by the literature presented in Section 3, we interpret this relationship as evidence of causality from the ratings assigned by CRAs to ABS spread at their issuance.

Even though we have already found evidence of causality, we can still be more specific and find which model better represents the data analysed. A comparison across the three aforementioned models reveals that Model M1 (see Figure 1) is the best-fit to the data because it has the lowest AIC and BIC measures as shown in the last two rows in Table 4. That best-fit model is also assessed by replacing *Ln_spread* with spread and the results[1] confirm that the possibility of causality is not rejected.

Additionally, as a robustness test, we consider a model according to which spread has no link with ratings, indicating that investors would only consider the same information used by CRAs but not the ratings themselves. This is illustrated in Figure 4. According to our results, that causal structure does not hold as the null hypothesis suggesting causality is rejected (Prob $> \chi^2$ = 0). Therefore, this finding reinforces the evidence that there is a causal connection from the ratings given by CRAs to the spread of finance structured products at issuance.

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[1] For the sake of brevity, these results are not displayed here but are available upon request.

[Insert Figure 4 here]

With regard to the channels linking ratings to investors (see Section 2), our findings suggest that both the CRAs' information intermediate and regulatory compliance functions are valued by ABS investors as these agents can use the ratings to compensate for the absence of public information on the instruments issued or on the issuers and to comply with ABS regulations based on their initial ratings.

It is important to note that we do not claim that ratings are the only factor driving spread. The significance of other variables included in the models (Table 4) indicate that those factors also impact on spread, which corroborates the findings in, for example, Fabozzi and Vink (2012) although that study deals with associative relationships rather than causal ones. Our objective here is to provide evidence regarding the possible causal effect of ratings on ABS spread. Whether or not ratings influence spread is a relevant piece of information in itself because we can predict if controlling ratings would result in different spread while, in this case, associative measures do not allow us to conclude that (intentionally) changing ratings would lead to different spread.

5. Testing for the possibility of causality in the secondary market

5.1. Data

Our trading sample is composed of all effective and possible rating changes for structured finance products traded in the US from February 2001 to December 2015. In total, we observe 895 rating-change events for 328 securities. The information on credit ratings is retrieved from Moody's website.

We consider two scenarios. At first, we classify possible and actual changes as the same type of events. Then, in an alternative scenario, we distinguish between possible and actual changes. Possible changes refer to rating outlook (i.e. possible direction of a rating in the near future) and actual changes denote effective changes announced by CRAs. Table 5 shows the numbers of downgrades and upgrades according to both criteria.

[Insert Table 5 here]

While at the issuance stage (Section 4) we focus on the spread paid by investors, the trading analyses deal with (log) return calculated from structured finance products' price downloaded

from Bloomberg. In this context, three windows are tested: up to one, three and five days after the respective events. The summary statistics of the returns are presented in Table 6.

[Insert Table 6 here]

As for factors other than rating changes that can potentially impact ABS returns, we consider returns in another three financial markets – stock, government bond and corporate bond – as mentioned in Section 4.1.

The other variables fixed at the issuance time and included in our previous analysis are not used in this part of the study (secondary market) because, although they may influence investors' decisions about trading structured finance products over the securities' lifetime, they tend to do so in a similar way regardless of the occurrence of changes in ratings. That is, those factors (e.g. Tranche_Number, WAL, WAC and Collateral_Type, defined in Section 4.1) are permanent or have negligible variations in the short term. Therefore, such variables would have the same effect (if any) on ABS returns throughout their whole trading period in the secondary market. Given that we aim at disentangling the impact of downgrades and upgrades on return, we concentrate on factors that are specific for the periods when ratings are changed.

5.2. Procedures and results

In this part of the study, we follow the steps described in Section 4.2. For each of the two scenarios regarding the treatment of the rating changes explained in Section 5.1, we test returns in three time windows: one, three and five days after the changes in the ratings. Four models comply with the condition stablished in equation (1). Three of these models (M4 to M6) have a single expression each[2]:

$$Ln\_return_i = \alpha_7 + \beta_{71}Rating\_change_i + \beta_{72}Ln\_ret\_gov + \beta_{73}Ln\_ret\_corp + \varepsilon_{7i},$$

$$Ln\_return_i = \alpha_8 + \beta_{81}Rating\_change_i + \beta_{82}Ln\_ret\_SP500 + \beta_{83}Ln\_ret\_corp + \varepsilon_{8i},$$

and

$$Ln\_return_i = \alpha_9 + \beta_{91}Rating\_change_i + \beta_{92}Ln\_ret\_SP500 + \beta_{93}Ln\_ret\_gov + \varepsilon_{9i}.$$

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[2] For the sake of brevity, the diagrams concerning the models presented in this section are omitted. They follow the same idea of the diagrams shown in Figures 1 to 4, where dependent and independent variables are respectively associated with incoming and outgoing arrows.

where *Rating_change* is a dummy variable indicating downgrade or upgrade in the first scenario considered and potential/effective downgrade/upgrade in the second scenario. *Ln_ret_gov*, *Ln_ret_corp* and *Ln_ret_SP500* are the natural logarithmic returns of the government bond, the corporate bond and the stock markets, respectively, proxied by the variables mentioned in Section 4.1. For each scenario, these returns are calculated in three periods: one, three and five days after the respective rating change events.

M7 is composed of two equations:

$$Ln\_ret\_corp_i = \alpha_{10} + \beta_{101}Ln\_ret\_gov + \varepsilon_{10i},$$

and

$$Ln\_return_i = \alpha_{11} + \beta_{111}rating\_change_i + \beta_{112}Ln\_ret\_SP500 + \beta_{113}Ln\_ret\_gov + \beta_{114}Ln\_ret\_corp_i + \varepsilon_{11i}.$$

where the variables follow the same notation as above. We also run a model (M8) in which rating down/upgrades are not included as a potential cause of changes in ABS returns:

$$Ln\_return_i = \alpha_{12} + \beta_{121}Ln\_ret\_SP500 + \beta_{123}Ln\_ret\_gov + \beta_{124}Ln\_ret\_corp_i + \varepsilon_{12i}.$$

Table 7 shows the results of models M4 to M8 for Scenario 1 (i.e. assuming that potential and effective rating changes are perceived as the same by investors) with one-day ABS returns. According to the models' χ^2 statistics, we cannot reject causality in models M4 to M7 when evaluating one-day return. Checking their AIC/BIC measures (see the two last rows in Table 7), we conclude that M7 is the best-fit model among the four options and rating change is the only variable that (causally) affects return in the periods when CRAs' announcements take place[3]. Following the causal interpretation of SEM presented in Section 3 and supported by the growing body of literature in this area, the positive coefficient for *Rating_change* indicates the possibility that, as expected, upgrades (downgrades) contribute to higher (lower) ABS returns. Nonetheless, the statistical significance of the rating changes is only 10%, which can be seen as relatively weak.

[Insert Table 7 here]

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[3] Note also that the TLI values for M4 to M6 are outside the expected range. This is evidence against the good fit of those three models (even though the other three goodness-of-fit tests are at the acceptable level). M7, on the other hand, passes the four goodness-of-fit tests and this corroborates its superiority over the other models.

ABS returns in other time windows are not affected by rating changes. For three- and five-day returns, M6 is the best-fit model. In the former case, only the returns at the stock (S&P500) and the government bond markets may causally impact ABS returns on dates around rating changes. In the latter case (five-day return), only the stock market return might affect ABS returns in periods when we observe rating events[4]. Altogether, these findings reveal that in the shortest term analysed here (one day after a new outlook or actual rating changes are announced), investors factor in CRAs' announcements when trading ABS but, a few more (another two) days later, their attention moves to the returns in the stock and the government bond markets, and, by the fifth day after the announcements, investors tend to focus on the stock market alone (among the variables included in this study).

In Scenario 2 (i.e. distinguishing potential and effective rating movements), for all time-windows of ABS returns, rating changes are not significant in any of the models tested (i.e. considering models that comply and do not comply with the causality hypothesis)[5]. Therefore, in this context, rating changes are not even *associated* with ABS returns. We interpret this as a signal showing that ABS investors do not discriminate actual changes in ratings from outlook.

6. Conclusions

Our findings show that the impact of credit ratings in the ABS market is potentially much stronger in the primary market (issuance stage) than in the secondary market (trading stage). This suggests that, when ABS are issued, investors would rely on credit ratings due to the lack of information on the respective products and on their issuers. The uncertainty involved in the new investments is thus offset by the use of ratings provided by CRAs. As expected, lower ratings lead to higher spreads (i.e. lower issue prices).

Nevertheless, after these securities start being traded in the secondary market, investors become more concerned about comparing their performance to the return of alternative investments. At this stage, the possibility of causality is only confirmed for ratings to one-day return when actual and potential changes in ratings are treated as the same (scenario 1). This causal connection is not identified when actual and potential rating changes are assumed to be perceived by investors in different ways (scenario 2). These results indicate that, if investors see actual and potential changes in ratings as similar (scenario 1), the latter may impact ABS

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[4] Due to space constraints, we do not present detailed results regarding the three- and the five-day windows but they are available upon request.

[5] These results are available upon request.

returns one day after the announcements made by CRAs. We also show that the drivers of these securities' return alter over time: stock market and government bond returns seem to lead ABS returns in a three-day time window and only the impact of the stock market remains relevant until the fifth day after CRAs' announcements. Therefore, changes in ratings (effective or just potential) would affect structured finance products' return in a very short period (one day) and such influence vanishes soon after that.

Bearing in mind that changes in spread reflect decisions made by investors, we can infer that our findings support the possibility that ratings directly affect investors' actions in the primary market. Hence, our research has potential implications for regulators, whose missions include protecting investors (in particular, the non-professional ones) and striving for financial stability. In this context, the latter can be negatively influenced by ratings when investors are misled to alike trading behaviour that can bring about sudden massive changes in prices. Given our results described above, regulations seem to be more important at the issuance stage than at the trading stage.

It is important to recall that our conclusions are based on previously assumed hypothetical models. Our main objective is to test whether or not causality between ratings and ABS performance is plausible. We look for evidence in favour or against the assumed models and, even when our results do not reject the models, they cannot prove the causal associations analysed; they just assure the possibility of causality. This should be seen as an initial effort to stimulate other researchers to delve into the (possibly) complex causal mechanisms that connect credit ratings with ABS spread and return.

Moreover, we face the risk of omitted variables bias, which would be a problem especially when common factors may drive both credit ratings and spread or return. Hence, our conclusions are limited to the sample of models assumed as reasonable *a priori* and to the variables present in our data set. When other pertinent variables are available, models including those variables should be taken into account. Additional possible extensions of this study refer, for instance, to the application of SEM to different types of financial products and the use of other econometric techniques designed to evaluate causality, such as the methods described in Angrist and Pischke (2015).

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Table 1: Model goodness-of-fit criteria

Criteria		Acceptable level	Interpretation
Chi-square	χ^2	> 0.10 (for 10% confidence level)	For values greater than 0.10, the null hypothesis in favour of fit cannot be rejected
Root Mean Square Error of Approximation	RMSEA	0.05 to 0.08	Values in this range indicate close fit
Comparative Fit Index	CFI	0 (no fit) to 1 (perfect fit)	At least 0.90 indicates good fit
Tucker-Lewis Index	TLI	0 (no fit) to 1 (perfect fit)	At least 0.90 indicates good fit

Note: based on Schumacker and Lomax (2016, pp. 112) and Acock (2013, pp. 23-24).

Table 2: Conversion of rating notches into number-format variables

Rating notch (Moody's)	Number-format
Aaa	1
Aa1	2
Aa2	3
Aa3	4
A1	5
A2	6
A3	7
Baa1	8
Baa2	9
Baa3	10
Ba1	11
Ba2	12
Ba3	13
B1	14
B2	15
B3	16
Caa1	17
Caa2	18
Caa3	19
Ca	20
C	21

Table 3: Summary statistics

Panel A – Summary statistics of numerical variables

Variable	Mean	Standard deviation	1st quartile	Median	3rd quartile	Min	Max
Rating	3.6717	3.1426	1.0000	3.0000	6.0000	1.0000	21.0000
Ln_spread	4.1674	1.4505	3.3673	4.2485	5.1930	-0.6931	8.2260
Tranche_Number	4.2655	4.0635	2.0000	3.0000	5.0000	1.0000	68.0000
WAL	5.8648	3.0678	3.2500	5.5000	7.9000	0.2000	41.0000
WAC	6.1509	2.4627	4.4576	5.5400	7.7000	1.2000	23.8850
Market_Share	0.2339	0.7480	0.0160	0.0427	0.1241	0.0002	4.6808
Credit_Support	3.3815	9.7173	0.0000	0.0000	0.0000	0.0000	126.9787
Ln_ret_SP500	0.0004	0.0095	-0.0039	0.0008	0.0052	-0.0920	0.1024
Ln_ret_gov	0.0001	0.0025	-0.0014	0.0000	0.0016	-0.0128	0.0217
Ln_ret_corp	0.0002	0.0236	-0.0064	0.0000	0.0057	-0.4055	0.4055

Ratings are expressed in numerical format as described in Table 2. Ln_spread is the natural logarithm of spread. Tranch_Number is the number of tranches in the deal. WAL is the tranches' weighted average life. WAC is the tranches' weighted average coupon rate. Market_Share is the issuers' market share. Credit_Support is the percentage of credit support from other subordinate classes in the same deal. Ln_ret_SP500 is natural logarithm of the S&P 500 index return. Ln_ret_Gov is the natural logarithm of the US Benchmark 5 Year DS Government index. Ln_ret_Corp is the natural logarithm of the Thomson Reuters United States Corporate Benchmark AAA 5 year yield.

Panel B – Frequency of categorical variables

Collateral Type	Number of obs	Frequency	Issuance country	Number of obs	Frequency
Auto	977	3.97%	AU	996	4.04%
Card	1072	4.35%	GB	2432	9.87%
CDO	4665	18.93%	IE	1810	7.35%
CLO	6995	28.39%	KY	9176	37.24%
CMBS	2009	8.15%	NL	1568	6.36%
RMBS	1862	7.56%	US	5961	24.20%
Student	1619	6.57%	n/a	2694	10.93%
Whole	1757	7.13%			
n/a	3681	14.94%			
TOTAL	24637	100.00%		24637	100.00%

As for collateral types, Auto refers to auto loans. Card: credit card loans. CDO: collateralised debt obligations. CLO: collateralised loan obligations. CMBS: commercial mortgage-backed securities. RMBS: residential mortgage-backed security. Student: student loans. Whole: whole business, including franchise and royalty agreements. With regard to issuance country, AU is Australia, GB: Great Britain., IE: Ireland, NL: the Netherlands, US: the United States. For both variables, n/a stands for not available (data missing in our database).

Table 4: Parameter estimation for Models 1 to 3

	M1	M2	M3
→ *Rating*			
constant	2.168***	2.027***	2.093***
	(0.113)	(0.139)	(0.139)
Tranche_Number	0.287***	0.286***	0.287***
	(0.004)	(0.005)	(0.005)
WAL	0.129***	0.129***	0.128***
	(0.007)	(0.007)	(0.007)
WAC	-0.047***	-0.041***	-0.041***
	(0.015)	(0.016)	(0.016)
Market_Share	-0.532***	-0.527***	-0.529***
	(0.025)	(0.025)	(0.025)
Credit_Support	-0.028***	-0.028***	-0.029***
	(0.002)	(0.002)	(0.002)
Country		0.028*	0.052***
		(0.014)	(0.015)
Collateral_Type			-0.050***
			(0.010)
→ *Ln_spread*			
constant	3.388***	3.780***	3.668***
	(0.020)	(0.027)	(0.027)
Tranche_Number	0.348***	0.037***	0.036***
	(0.002)	(0.002)	(0.002)
WAL	0.055***	0.057***	0.059***
	(0.003)	(0.003)	(0.003)
Market_Share	-0.307***	-0.319***	-0.316***
	(0.009)	(0.009)	(0.009)
Credit_Support	-0.013***	-0.012***	-0.011***
	(0.001)	(0.001)	(0.001)
Country		-0.101***	-0.146***
		(0.005)	(0.005)
Collateral_Type			0.086***
			(0.003)
Rating	0.156***	0.157***	0.159***
	(0.002)	(0.002)	(0.002)
N	24,637	24,637	24,637
χ^2	2.600	0.080	0.070
Prob > χ^2	0.107	0.779	0.797
RMSEA	0.008	0.000	0.000
CFI	1.000	1.000	1.000
TLI	0.999	1.000	1.000
AIC	654761.039	732041.892	821389.241
BIC	655036.847	732390.708	821819.177

Rating is expressed in numerical format as described in Table 2. *Ln_spread* is the natural logarithm of spread. *Tranch_Number* is the number of tranches in the deal. *WAL* is the tranches' weighted average life. *WAC* is the tranches' weighted average coupon rate. *Market_Share* is the issuers' market share. *Credit_Support* is the percentage of credit support from other subordinate classes in the same deal. *Country* is the issuer's country (AU = Australia is the omitted category). *Collateral_Type* is the type of asset that supports the security (Auto is the omitted category). Standard errors are in parentheses. The goodness-of-fit tests RMSEA, CFI and TLI are listed in Table 1. AIC and BIC are the Alkaike Information Criteria and the Bayesian Information Criteria measures, respectively. *** and * indicate 1% and 10% significance levels, respectively.

Table 5: Number of downgrades and upgrades in the trading data

Scenario 1 – Effective and potential changes treated as the same importance	
Downgrades	545
Upgrades	350
Total – Scenario 1	895
Scenario 2 – Effective and potential changes distinguished	
Effective downgrades	258
Potential downgrades	287
Potential upgrades	44
Effective downgrades	306
Total – Scenario 2	895

Table 6: Returns at the trading stage - summary statistics

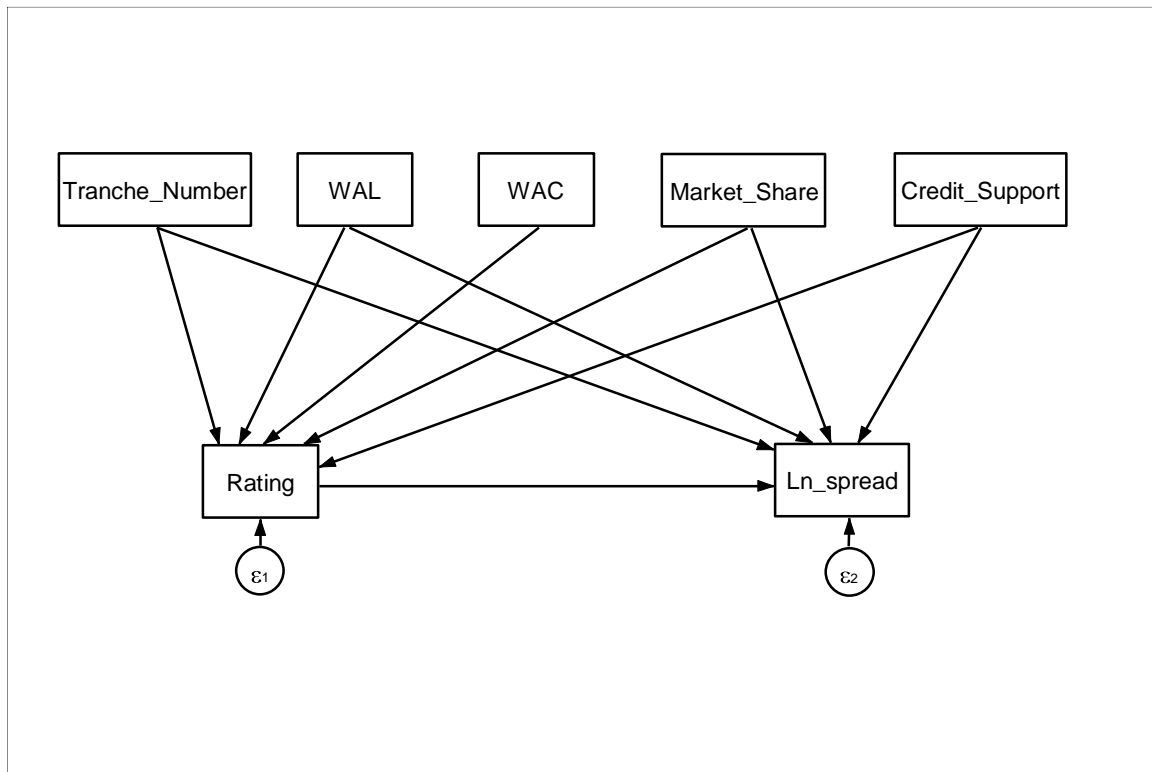| Time window	Mean	Standard deviation	1st quartile	Median	3rd quartile	Min	Max
1 day	-0.00092	0.01523	0	0.00007	0.00182	-0.31245	0.14388
3 days	-0.00073	0.02990	0	0.00081	0.00281	-0.31245	0.44891
5 days	-0.00067	0.03125	0	0.00091	0.00331	-0.31474	0.44891

Note: Returns are calculated as the natural logarithmic price change (i.e. log returns).

Table 7: Parameter estimation for Models M4 to M8

|	M4	M5	M6	M7	M8
→ *Ln_return*					
constant	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rating_change	0.001*	0.001	0.001*	0.001*	
	(0.0006)	(0.001)	(0.0006)	(0.0006)	
Ln_ret_SP500		-0.035	-0.049	-0.046	-0.053
		(0.517)	(0.052)	(0.052)	(0.052)
Ln_ret_gov	-0.476		-0.519***	-0.536	-0.487
	(0.332)		(0.202)	(0.334)	(0.337)
Ln_ret_corp	-0.007	0.088**		-0.005	0.004
	(0.720)	(0.042)		(0.072)	(0.727)
→ *Ln_ret_corp*					
constant				-0.001**	
				(0.0006)	
Ln_ret_gov				-3.597***	
				(0.195)	
N	895	895	895	895	895
χ^2	0.800	2.370	0.000	2.100	2.910
Prob > χ^2	0.372	0.124	0.999	0.350	0.088
RMSEA	0.000	0.039	0.000	0.007	0.046
CFI	1.000	0.729	1.000	1.000	0.622
TLI	1.161	-0.083	1.791	0.999	-0.510
AIC	-18647.824	-18646.251	-18648.620	-18666.522	
BIC	-18556.685	-18555.111	-18557.481	-18623.351	

Ln_return is the natural logarithm return of ABS. *Rating_change* is a dummy variable indicating downgrade or upgrade (either potential or actual). *Ln_ret_SP500*, *Ln_ret_gov* and *Ln_ret_corp* are the natural logarithm returns of the stock, the government bond, and the corporate bond markets, respectively (represented by the variables mentioned in Section 4.1). Standard errors are in parentheses. The goodness-of-fit tests RMSEA, CFI and TLI are listed in Table 1. AIC and BIC are the Alkaike Information Criteria and the Bayesian Information Criteria measures, respectively. ***, ** and * indicate 1%, 5% and 10% statistical significance levels, respectively. AIC and BIC measures for M8 are not reported because the null hypothesis in favour of causality in that model is rejected (χ^2 statistic < 0.10).

Figure 1: Model 1 – Potential causal relationship from five control variables to rating and to spread and from rating to spread
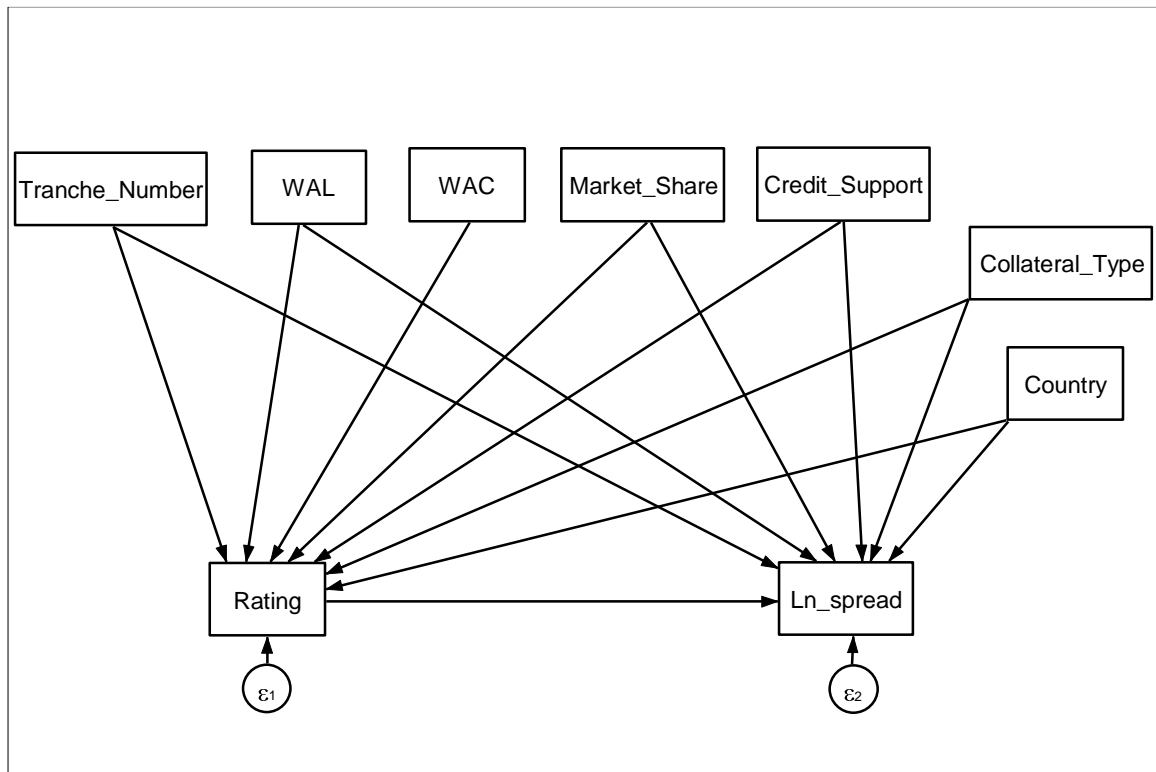

Ratings are expressed in numerical format as described in Table 2. Ln_spread is the natural logarithm of spread. Tranch_Number is the number of tranches in the deal. WAL is the tranches' weighted average life. WAC is the tranches' weighted average coupon rate. Market_Share is the issuers' market share. Credit_Support is the percentage of credit support from other subordinate classes in the same deal. Arrows indicate the direction of the potential impact.

Figure 2: Model 2 – Potential causal relationship from six control variables to rating and to spread and from rating to spread
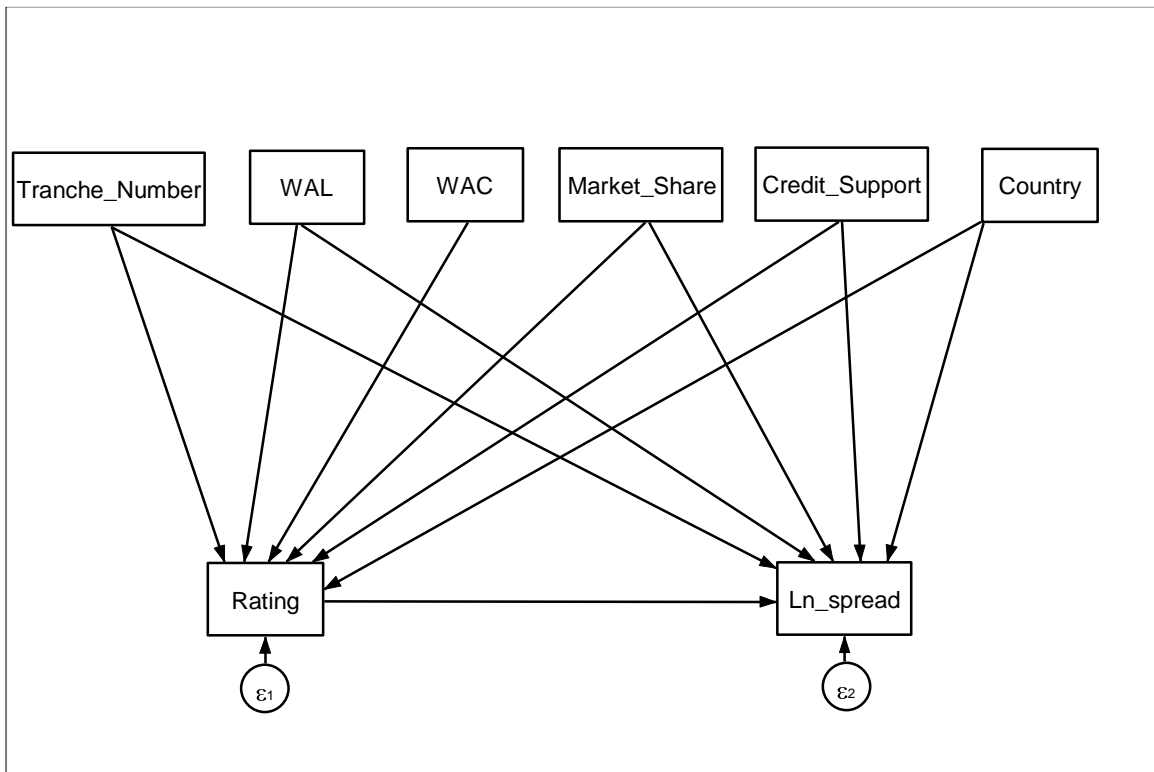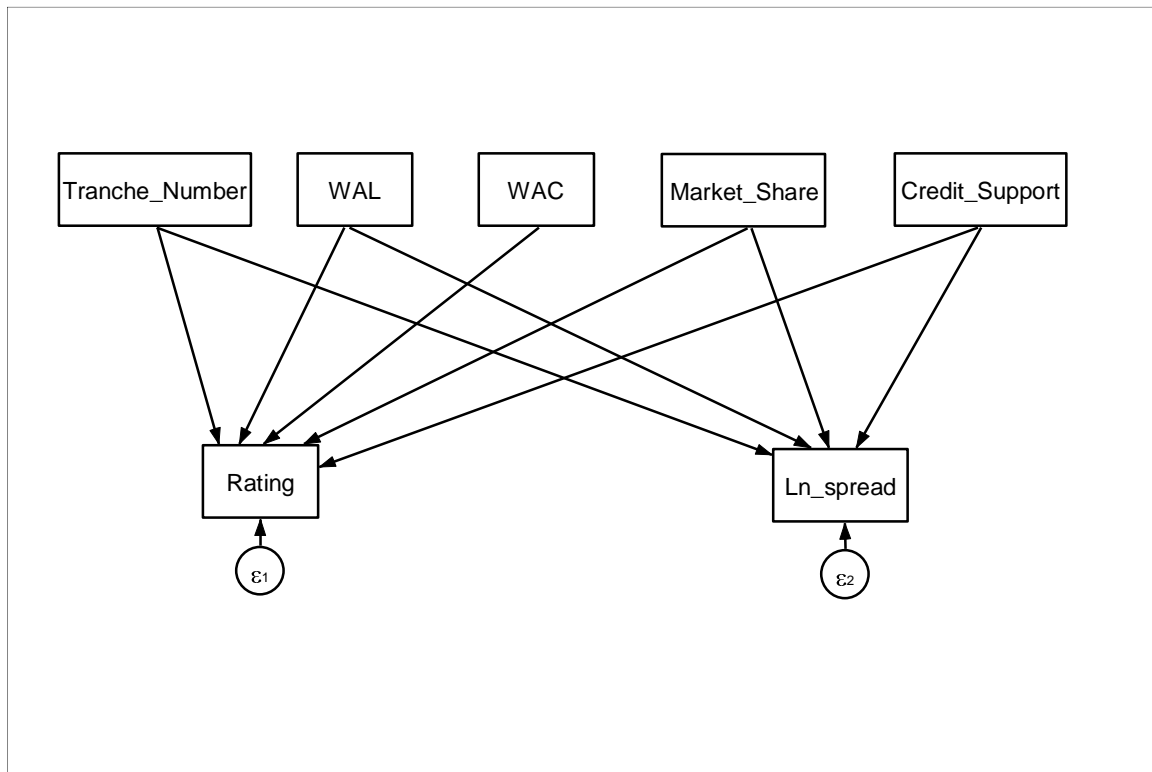

Ratings are expressed in numerical format as described in Table 2. Ln_spread is the natural logarithm of spread. Tranch_Number is the number of tranches in the deal. WAL is the tranches' weighted average life. WAC is the tranches' weighted average coupon rate. Market_Share is the issuers' market share. Credit_Support is the percentage of credit support from other subordinate classes in the same deal. Country is the issuer's country. Arrows indicate the direction of the potential impact

Figure 3: Model 3 – Potential causal relationship from seven control variables to rating and to spread and from rating to spread

Ratings are expressed in numerical format as described in Table 2. Ln_spread is the natural logarithm of spread. Tranch_Number is the number of tranches in the deal. WAL is the tranches' weighted average life. WAC is the tranches' weighted average coupon rate. Market_Share is the issuers' market share. Credit_Support is the percentage of credit support from other subordinate classes in the same deal. Collateral_Type is the type of asset supporting the ABS. Country is the issuer's country. Arrows indicate the direction of the potential impact

Figure 4: Model 4 – Potential causal relationship from five control variables to rating and to spread (without assuming that rating impacts on spread).

Ratings are expressed in numerical format as described in Table 2. Ln_spread is the natural logarithm of spread. Tranch_Number is the number of tranches in the deal. WAL is the tranches' weighted average life. WAC is the tranches' weighted average coupon rate. Market_Share is the issuers' market share. Credit_Support is the percentage of credit support from other subordinate classes in the same deal. Arrows indicate the direction of the potential impact.