Split credit ratings of banks in times of crisis

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Abstract

This paper analyses whether opacity of bank creditworthiness increases during crisis periods and if the conservativeness of CRAs changes through business cycles. Univariate and multivariate methodologies are used: data from Moody's and S&P on credit ratings and watch status for 133 commercial banks across 17 developed countries from 2007 to 2015 is employed. The univariate analysis is a unique technique that provides a new perspective to assess whether splits between CRAs are defined as permanent or temporary. The evidence demonstrates that Moody's and S&P frequently disagree. S&P is shown to be the more conservative CRA overall, however, the extent to which Moody's issues higher ratings decreases over time until it becomes the more conservative CRA. The paper is the first of its kind to establish that the conservativeness of Moody's and S&P changes throughout business cycles, which should impact on the strategic decision making of investors.

Introduction

'Credit rating agencies play a crucial role in providing information about the ability and willingness of issuers, including governments and private firms, to meet their financial obligations' (Almeida et al [2016] p.255). Credit ratings agencies (CRAs) played a large role in the 2007-09 financial crisis, whereby 'the crisis was exacerbated by a combination of faulty ratings methodologies, conflicts of interest, and overreliance on ratings by banks, investors and regulators' (Deb et al [2011, p.3]).

The vast majority of debt issuers have ratings assigned by more than one CRA. Mahlmann [2009] suggests that in order for firms to have access to a broader pool of investors it is necessary for issuers to have ratings from the two major CRAs (Moody's and S&P). Differences of opinion across CRAs have become more prevalent during and since the financial crisis. For example, Alsakka et al [2017] show that at least 40% of European sovereign rating observations reflect different opinions across Fitch, Moody's and S&P.

The main aim of this paper is to investigate whether banks' opacity, and therefore rating disagreement between CRAs, increases during crisis periods. The second aim is to consider whether the relative conservativeness of CRAs changes during crisis periods. Compared to prior related literature, further insights are possible due to the inclusion of watchlist status within the dataset. Morgan [2002] and Iannotta [2006] find that banks are more opaque than non-bank debt issuers, and that this leads to more disagreements in ratings between CRAs. In addition, this paper extends the work of Livingston et al [2010] who find that Moody's is the more conservative CRA when issuing corporate rating opinions, whereas Vu et al [2015] find the opposite result for sovereigns.

Split ratings arise when different ratings are assigned to the same issuer by more than one CRA. When CRAs are assigning a solicited bank rating,[1] a common perception might be that the CRAs will agree on the assigned rating as they use the same information, such as accounting data and soft information, provided by the issuer. Iannotta [2006] demonstrates that this perception is false and finds that greater financial assets and larger capital ratios increase CRAs' differences in opinion.

Morgan [2002] believes that a disagreement between CRAs is a good proxy for the uncertainty associated with asymmetric information about the debt issuer. Flannery et al [2004] state that all firms suffer from information asymmetry to some extent, however in most industries this information asymmetry between inside and outside investors tends to be resolved via market-based mechanisms. Financial firms differ in this respect due to the difficulty for outside investors to value assets, hence the need for government regulation (Flannery et al [2004]). The banking industry is one of the most regulated industries in the world, mainly due to systemic risk and depositor protection (Iannotta [2006]). Morgan [2002, p.874]) states that 'Money goes in, and money goes out, but the risks taken in the process of intermediation are hard to observe from outside the bank' (p.874). He also suggests that the consequences of asset opacity within the banking sector, such as contagion and bank runs, are a reasonable justification for government regulation.

Prior research has failed to fully address banking sector split ratings and the datasets used in previous articles on this issue pre-date the global financial crisis. This paper makes a novel contribution in that it investigates the effects of the sub-prime crisis (2007-09) and the European crisis (2010-12), while being able to draw comparisons in the post-crisis period (2013-15). Due to the additional uncertainty arising during crisis periods, the creditworthiness

[1] Solicited ratings are requested by borrowers, they provide CRAs with private information and pay the CRA for the rating. Unsolicited ratings are assigned by CRAs to issuers based only on publicly available information without the request of the debt issuers (e.g. Byoun et al [2014]).

of a bank is more difficult to ascertain and therefore CRAs may disagree more often than during non-crisis periods. This paper makes an additional contribution to the literature on bank split ratings by using watchlist information in addition to rating levels.

This paper addresses the following research questions: Does bank opacity increase during crisis periods? Does conservativeness between Moody's and S&P change during crisis and non-crisis periods? The main results are summarised as follows: Moody's and S&P frequently disagree (74% of observations) in their bank rating opinions during the period 2007-2015. The results show that CRAs agree most frequently during the post-crisis period (36%) and have similar levels of agreements during the sub-prime crisis and European crisis periods (at 21% of observations). With regard to conservativeness, the results show that during the different time periods the percentage of times Moody's issues a higher rating begins to decrease and the percentage of times S&P issues a higher rating increases. In addition, the TWS has reduced substantially from 3.21 points in the sub-prime crisis to -0.18 points in the post-crisis period. This suggests that conservativeness between the two CRAs changes in response to levels of ambiguity.

The results confirm the prior anticipation, in the sense that times of crisis are characterised by higher levels of information asymmetry, and such ambiguity induces a greater prevalence of split bank ratings. Disagreements are more common for larger banks, those with a low credit rating, and those which reside in either a crisis country (PIIGS[2]) or North America. Regarding conservativeness, the overall results show that although S&P is the more conservative CRA, the extent to which Moody's issues a higher rating than S&P decreases across the time frame.

[2] PIIGS refers to Portugal, Ireland, Italy, Greece and Spain. These countries were those most seriously affected by the European sovereign debt crisis.

The remainder of the paper is organised as follows: Section 2 discusses the literature closely related to split ratings, Section 3 describes the data, Section 4 describes the methodology, Section 5 examines the results of the analysis and Section 6 concludes the paper.

Literature review

In the US, most publicly traded bond issuers receive rating assignments from the two major CRAs, and research shows that corporate ratings issued by Moody's and S&P can differ over 50% of the time (see Cantor et al [1997]), resulting in so-called split ratings. Prior research has considered reasons why a firm receives a split rating from the two CRAs and several different interpretations are proposed. Ederington [1986] suggests that split ratings are simply due to random errors, while Livingston et al [2008] attribute splits to expected future changes in ratings.

Morgan [2002] investigates rating disagreements between Moody's and S&P using a sample of 7,862 (848 Banking issuers, 150 insurance firms and 6,894 other sectors) new bonds issued between January 1983 and July 1993. Morgan [2002] argues that the idea of a split rating is simple: 'if bank risk is harder to observe, the raters in the business judging risk should disagree more often over bank bond issues' (p.874).

Morgan [2002] finds that the pattern of disagreement between Moody's and S&P suggests that banks and insurance firms are inherently more opaque than other sectors. He suggests that this uncertainty stems from 'certain assets, loans and trading assets in particular, the risks of which are hard to observe or easy to change' (Morgan [2002, p.874]). 'The gap between the mean ratings by Moody's and S&P was four times larger for bank issuers than for the typical nonbank issuer' (Morgan [2002, p.876]).

Following from Morgan [2002], Iannotta [2006] uses 2,473 (2051 banking issuers, 16 insurance firms and 406 other sectors) European bonds issued during 1993-2003 and examines whether or not banking sector issuers are more opaque than non-banking issuers. Iannotta

[2006] finds that, as a whole, there is strong evidence that banks produce more uncertainty than non-banks. Morgan [2002] find that insurance firms generated even more disagreement than banking sector issuers. This disagreement in results between Iannotta [2006] and Morgan [2002] could be due to the small number of insurance firms used within their respective samples, 0.65% (Iannotta [2006]) and 1.91% (Morgan [2002]).

Flannery et al [1998, 2004, 2013] disagree with Morgan [2002], but approach their research differently. All three papers explore whether financial firms are more opaque than non-financial firms but, unlike Morgan [2002], they do not use credit ratings in their analysis. Flannery et al [1998] review previous literature on the ability of market forces to identify and control risk-taking in banking firms. The research finds that there is no difference in the behaviour of share prices between banking and non-banking firms as both types of firm adjust promptly to new information. Flannery et al [2004] examine whether or not U.S. banking firms exhibit more or less asset opacity than non-banking firms using the market microstructure equity properties. They find very similar trading properties between banking and non-banking firms and that IBES[3] earnings forecasts indicate that banking assets are 'not usually opaque, they are simply boring' (p.419).

Flannery et al [2013] use a sample of publicly trading bank holding companies and examine the trading characteristics during normal and crisis periods between 1993 and 2009. They find limited (mixed) evidence that banks are unusually opaque during normal periods. 'Although the possibility that banking firms are ''opaque'' has played a central role in the 2007-09 financial crisis, existing empirical evidence on the opacity of banking firms is mixed' (Flannery [2013, p.56]).

Split ratings could also arise from the different methods used by CRAs. For example, Cantor and Packer [1995] state that S&P base a rating on the overall capacity of the issuer to

[3] Institutional Brokers' Estimate System

fulfil their financial obligation, whereas Moody's assessment is based on some judgement of recovery in the event of loss. With regard to S&P, they '...continually assess and reassess their rating methodologies' and 'adopt changes as needed to respond to the changing needs of investors, issuers and markets'.[4] Their ratings are '... a tool to evaluate credit risk, expressing our opinion about the likelihood that debt issued by companies and governments will be repaid in full and on time'.[5] This suggests that S&P continue to base rating assignments on the overall capacity of the issuer to fulfil their financial obligation. With regard to Moody's, their ratings are '...judgements about the future on the one hand, and since they are used by investors as a means of protection, on the other, the effort is made when assigning ratings to look at 'worst' possibilities in the 'visible' future, rather than solely at the past record and the status of the present'.[6] This proposes that Moody's assessment continues to be based on some judgement of recovery in the event of loss.

Based on the differing methods used by CRAs, Moody's is more likely to issue a more conservative (lower) rating than S&P (Cantor et al [1997]; Morgan [2002]; Livingston et al [2010]). Cantor et al [1997] find that when the ratings are split, S&P had a higher rating on 54.6% of occasions. Hence supporting the view that Moody's is viewed as being the more conservative CRA. Cantor et al [1997] show that 'the probability of Moody's rating higher than S&P has varied over time, beginning at slightly less than 40 per cent in 1983-1984, rising to around the 50 per cent level during the 1985-1988 period, but returning to the 40 per cent level in the 1990s' (p.7).

Livingston et al [2010] examine U.S. non-financial corporate bond issues between 1983-2008 rated by Moody's and S&P. They find that investors tend to differentiate between

[4] https://ratings.standardandpoors.com/about/who-we-are
[5] https://ratings.standardandpoors.com/about/who-we-are
[6] https://www.moodys.com/ratings-process/Ratings-Definitions/002002

the two CRAs and assign more weight to the more conservative CRA, Moody's, especially after 1998.

Morgan [2002] states that a conservative rater (a rater that worries more about over-rating) errs on the safe side by choosing stricter cut-offs and differences in cut-offs will, in general, cause lop-sided splits. Morgan [2002] suggests that in more opaque industries the difference in cut-offs will be wider and the splits will be more lop-sided as the conservative rater will err even further on the safe side due to the additional uncertainty. Furthermore, Morgan [2002] finds that Moody's was more likely to take the conservative side over splits than S&P.

Data and hypotheses

This paper investigates watch opinion splits between Moody's and S&P during the most volatile financial period of the 21st century. Previous research (Sy [2004]; Alsakka and ap Gwilym [2012]; [2013]) includes rating, outlook and watch announcements in its analysis when investigating rating opinions, however this research does not focus on banking sector issuers. As this paper focuses solely on banks, the most opaque industry (Morgan [2002]), it explores a different perspective at a finer level of detail by only focusing on more immediate, short term responses from CRAs, i.e. watch announcements.

The first research question examines whether bank opacity increases during crisis periods, leading to the following three hypotheses:

H1. Bank opacity increases during times of crisis because Moody's and S&P tend to disagree more on their rating assignments during the sub-prime crisis and European debt crisis compared to the post-crisis period.

H2. Moody's and S&P agree more on Australasian banks creditworthiness compared to North American and European banks because this region was less affected by the sub-prime and European debt crises.

H3. Moody's and S&P tend to disagree more on their rating assignments of North American banks during the sub-prime crisis period (2007-09) and disagree more on European banks during the European crisis, compared with the other two periods.

The second research question investigates whether the conservativeness between Moody's and S&P changes during crisis and non-crisis periods, leading to the following hypotheses:

H4. S&P is the more conservative CRA during times of crisis (sub-prime and European) because they change their ratings more quickly than Moody's[7].

H5. Moody's is the more conservative CRA during the post-crisis period.

The dataset consists of long-term issuer ratings and senior unsecured (foreign currency) ratings from Moody's and S&P during the period 1st January 2007 to 31st December 2015, for commercial banks in 17 developed countries: North America (USA and Canada), EU countries as at 1st January 1995, also known as the EU15 (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and UK) and Australasia (Australia and New Zealand). Developed countries are chosen to avoid rating restrictions due to the sovereign ceiling policy[8].

The sources of the ratings data are the Moody's website and the S&P Capital IQ database. Data on size (Total Assets) and Operating Profit are collected from Bankscope. The sample period of 2007-15 is characterised by two crises, namely the sub-prime crisis (2007-09) and the European sovereign debt crisis (2010-12). 2013-15 represents the post-crisis period.

[7] CRAs us an 'expected loss' approach which for Moody's includes assessments of 'probability of default' and 'loss given default' on an issuer, whereas S&P only assesses probability of default (Alsakka and ap Gwilym, 2010).

[8] The sovereign ceiling policy requires a firms' rating to remain at or below the sovereign rating of their country of domicile (Almeida et al [2016]).

To analyse split ratings, selected banks must be rated by both CRAs to establish a split or non-split rating relationship.[9] The final data set contains a total of 291,288 daily credit opinions across 133[10] banks in 17 different countries (see Appendix 1).

A mapped 60-point numerical scale of watchlist opinions is applied to the letter rating: AAA/Aaa = 60, AAA/Aaa negative watch = 59 ... CC/Ca negative watch = 2 to C/SD =1. The reason for choosing a 60-point rather than the more widely used 58-point scale (Sy [2004]; Alsakka and ap Gwilym [2012]) is due to the exclusion of outlook opinions from the dataset. Therefore, each rating has a positive (+1) and negative (-1) to incorporate watch events and the last 10 points on the scale are considered separately rather than grouping them together.

As a robustness test, the analysis is extended using a 20-notch scale, excluding the watchlist status. The mapped 20-notch scale is applied to the letter ratings of both CRAs for the ratings only. AAA/Aaa = 20, AA+/Aa1 = 19... CCC-/Caa3 = 2 to CC/Ca/SD/D = 1. The full mappings for both scales and both CRAs are presented in Appendix 2.

Methodology

Univariate analysis

It is crucial to differentiate between temporary and more permanent split ratings. A temporary split arises when there is a difference in the timings of similar rating actions across CRAs for the same issuer and it does not reflect any lasting fundamental differences in two CRAs' views on credit quality. Therefore, it is important to focus on more persistent rather than temporary splits, or to give weighting to observed splits according to their persistence. To achieve this, a Time Weighted Split (TWS) measure is generated. This refinement has not been

[9] Belgium and Greece are not included because there are no banks that are rated by both CRAs, or the banks are rated by both CRAs but do not have consistent debt type ratings This can arise because we select long-term issuer ratings and senior unsecured (foreign currency) ratings, e.g. Moody's deposit ratings are excluded.
[10] The relatively low number of banks are due to the data restrictions, a bank had to be publicly listed and rated by both CRAs (Moody's and S&P) at some point during 2007-2015. This requirement significantly reduces the number of banks available to be used in the dataset.

used in prior research (for banks nor other rating segments) and is therefore a further original aspect of this paper.

A split is defined as different numerical ratings from the two CRAs (on either the 60 point or 20 notch scale). This can occur if the issuer has different ratings from the CRAs and/or an issuer has the same rating from both yet one CRA has placed the issuer on a positive/negative watch whilst the other has not.

The TWS is calculated for each bank *i*:

$$\text{TWSi, } = \frac{\sum_{t=1}^{N}(split \text{ i x } days)}{N} \quad (1)$$

Where;

split = Moody's numerical rating – S&P numerical rating for bank *i* on a given day.

days = the number of days for which the split rating for bank i takes a given value.

N = total number of days per sample e.g. annual, crisis period or whole sample.

In general, larger and/or more persistent split ratings in a particular direction (e.g. Moody's rating persistently higher than S&P) within a given time period will produce a higher value of TWS for a given bank. A time-weighted absolute split is also utilised, i.e. using the absolute value of *split* in the above method. Using absolute values extends the analysis to examine solely differences of opinion between the CRAs, without considering which is more conservative.

The results are divided into three elements: overall, region, and time periods. Regions are split into three: North America, Australasia and Europe and there are three time periods: sub-prime crisis (2007-09), European-crisis (2010-12) and post-crisis (2013-15). In addition, each region is split into three-time frames to provide nine groupings.

Multivariate analysis

An Ordinary Least Squares (OLS) regression is used to observe whether there is a relationship between the variable of interest (TWS) and the independent variables (Bank Size, Sovereign Split and the Return on Assets) plus dummy variables (Sub-prime crisis period, European crisis period, Crisis country, Bank with a low credit rating and region).

The explanatory variables are selected by using two of the most commonly used accounting-based proxies, bank size (Net Assets) and profitability (Return on Assets (RoA)). Bank size is chosen because previous research suggests that larger banks are less opaque than smaller banks as more information is publicly available for larger banks (Morgan [2002]) and that bank uncertainty decreases with fixed assets (Iannotta [2006]). RoA is chosen because more profitable banks tend to be less concerned about the credit rating assigned. Banks with lower credit ratings may face higher financing costs which could lead to lower profitability (Hau et al [2013]).

Sovereign split was also selected because previous research (Williams et al [2013]; Drago and Gallo [2017]) suggests there is a strong link between a change in the sovereign rating and a bank rating within that country. Therefore, if the sovereign has a split rating, the bank rating may be more prone to be split. Dummy variables which represent the year of the rating action, the location of the bank and whether the rating is investment grade or speculative were also used.

Equation 2 aims to identify the potential determinants of split watch announcements. Equation 3 aims to identify in what circumstances a CRA is more conservative. For Eq. 2, larger splits between CRAs will provide a positive coefficient and for smaller splits the coefficient will be negative. For Eq. 3, a positive coefficient will represent S&P being the more conservative CRA and a negative coefficient will demonstrate Moody's being the more conservative CRA.

$$TWS_i^{WA} = \alpha + \beta_1 SizeB_{i,t} + \beta_2 SS_{i,t} + \beta_3 RoA_{i,t} + \delta_1 SPCY_t + \delta_2 EUCY_t + \delta_3 \mathrm{CC}_i + \delta_4 LCR_{i,t} + \delta_5 AP_i + \delta_6 NA_i + \varepsilon_{i,t} \quad (2)$$

$$TWS_i^{W} = \alpha + \beta_1 SizeB_{i,t} + \beta_2 SS_{i,t} + \beta_3 RoA_{i,t} + \delta_1 SPCY_t + \delta_2 EUCY_t + \delta_3 \mathrm{CC}_i + \delta_4 LCR_{i,t} + \delta_5 AP_i + \delta_6 NA_i + \varepsilon_{i,t} \quad (3)$$

TWS_i is a continuous variable and represents the Time Weighted Split per bank *i*. Both equations (2) and (3) use the 60-point scale, represented by (W). (A) represents the use of absolute values.

$SizeB_{i,t}$ represents the size of bank *i* in year *t*. The natural log of Total Assets per bank in US$ is used to establish Bank Size and this information is gathered using Bankscope. This variable is adjusted by the United States World Bank GDP deflator/inflator[11] with a base year of 2007.

$SS_{i,t}$ represents the split sovereign rating for the bank's country. It takes the value of the Moody's sovereign rating minus the S&P sovereign rating, using the 20-notch scale at the end of the year (and could be equal to zero).

$RoA_{i,t}$ represents the Return on Assets (RoA) for bank *i* in year *t*, calculated by collecting the operating profit figure in US$ from.[12] Operating profit is adjusted using the World Bank GDP deflator/inflator with a base year of 2007. Operating Profit is used as it ignores the capital structure of the bank and removes any cross-country differences in tax policies.

$SPCY_t$ represents the dummy variable for the sub-prime crisis and takes the value of 1 for 2007-09 and 0 otherwise.

[11] http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG.

[12] As profitability measures are highly variable, the data is winsorized to remove any outliers, at the 1st and 99th percentiles. Both winsorizing and truncating (trimming) were used for different estimations. The results using winsorizing are presented, because they are slightly more conservative.

$EUCY_t$ represents the dummy variable for the European debt crisis period, and takes the value of 1 for 2010-12 and 0 otherwise.

CC_i represents a bank residing in a Crisis Country. This takes a value of 1 if the bank is in Portugal (bailout), Ireland (bailout), Spain (spillover) or Italy (spillover), and 0 if not.

$LCR_{i,t}$ represents a bank with a low credit rating at year *t*. The variable takes the value of 1 if the bank had a rating of Baa1/BBB+ or lower at the end of the year, and 0 otherwise.

AP_i represents a dummy variable taking the value of 1 if bank i is located in Australasia (Australia and New Zealand) and 0 otherwise.

NA_i represents a dummy variable taking the value of 1 if bank *i* is located in the USA or Canada and 0 otherwise.

Europe is used as the reference region.

Some estimations use a clustered standard error with clusters at the bank level.[13]

Robustness check

An ordered probit model using the 20-notch scale is used as a robustness check to further test the stated hypotheses. Due to the discrete ordinal nature of credit ratings many researchers use an ordered probit model in their investigations (Morgan [2002]; Güttler and Wahrenburg [2007]; Alsakka and ap Gwilym [2010a], [2012a]). The model will estimate whether there is a

[13] in other cases, the White [1980] procedure is used to control for potential heteroscedasticity.

disagreement between CRAs or not (Eq. 4) and which CRA is more conservative (Eq. 5) based on the independent variable parameters.

$$TWS_i^{SPL} = \alpha + \beta_1 SizeB_{i,t} + \beta_2 SS_{i,t} + \beta_3 RoA_{i,t} + \delta_1 SPCY_t + \delta_2 EUCY_t + \delta_3 \mathrm{CC}_i + \delta_4 LCR_{i,t} + \delta_5 AP_i + \delta_6 NA_i + \varepsilon_{i,t} \quad (4)$$

$$TWS_i^{CON} = \alpha + \beta_1 SizeB_{i,t} + \beta_2 SS_{i,t} + \beta_3 RoA_{i,t} + \delta_1 SPCY_t + \delta_2 EUCY_t + \delta_3 \mathrm{CC}_i + \delta_4 LCR_{i,t} + \delta_5 AP_i + \delta_6 NA_i + \varepsilon_{i,t} \quad (5)$$

Disagreement is measured in Eq. (4) by the SPL (0/1) variable. Conservativeness is measured in Eq. (5) by the CON (-1/0/1)[14] variable. The independent variables are discussed above.

Results

Descriptive statistics

Exhibit 1 displays the descriptive statistics of the dataset.[15] The banks are selected mainly from developed countries, providing 96.4% of observations at investment grade. The bank with the highest Operating profit is Wells Fargo Bank reaching US$28 billion in 2015 and the least profitable bank in the sample is the Bank of Scotland PLC making a loss of US$23.5 billion in 2009; the mean profit of all banks in the sample is US$1.7 billion.[16]

The mean bank size in the sample is US$322 billion, the smallest bank in the sample is Deutsche Bank National Trust Company with total net assets of US$159 million in 2009 and the largest is Barclays Bank with total net assets of US$2.9 trillion in 2009. The average return on assets in the sample is 0.89%, with a maximum 16.19% and a minimum -11.43%. The remaining variables show the total number of observations for each.

[14] If Moody's issues a higher rating than S&P there will be a positive difference (1) and if S&P issues a higher rating, there will be a negative difference (-1) and no disagreement (0).
[15] The figures used here are inflated/deflated using the annual United States World Bank GDP.
[16] The figures used here are also inflated/deflated using the annual United States World Bank GDP.

Exhibit 2 displays the extent of the differences between Moody's and S&P using the 60-point and 20-notch scales, which identifies that the two CRAs agree around 25% and 30% of the time, respectively. The next largest category is Moody's issuing an opinion on creditworthiness 3 points higher than S&P, based on the 60-point scale, around 24% of the time. Due to the inclusion of watch level opinions in the 60-point scale, three points higher is the equivalent of 1 notch using the 20-notch scale. The 20-notch scale demonstrates characteristics similar to those of a transition matrix, where the highest probability is centred on the 0 point, i.e. non-split and the second largest probability is directly next to the centre and the further away the cell is from the centre the less likely it is to occur (see Bangia et al [2002]).

The first research question examines whether bank opacity increases during crisis periods, leading to the following three hypotheses:

H1. Bank opacity increases during times of crisis because Moody's and S&P tend to disagree more on their rating assignments during the sub-prime crisis and European debt crisis compared to the post-crisis period.

Exhibit 3 displays the results for the 60-point scale for the whole sample, showing that the overall level of disagreements between Moody's and S&P from 2007 to 2015 are 74.24% of cases.

To answer H1, Exhibit 3 shows that CRAs agree more during the post-crisis period (35.57%) and have similar levels of disagreements during the sub-prime crisis (20.79%) and European crisis (20.75%). Exhibit 4 uses the 20-notch scale and further supports the results of the 60-point scale, CRAs agree 39.73% of the time in the post-crisis period compared with 23.47% and 25.95% in the sup-prime and European crises. This suggests that in times of uncertainty CRAs tend to disagree more frequently, while they tend to agree more frequently during more tranquil times, particularly within an opaque industry (Morgan [2002]). Therefore, H1 can be accepted.

H2. Moody's and S&P agree more on Australasian banks creditworthiness compared to North American and European banks because this region was less affected by the sub-prime and European debt crises.

Exhibit 3 splits the data into regions, the results show that CRAs agree most on Australasian banks, 42.86% of occasions compared to the other regions. 21.43% and 25.42% of the time, for North American banks and European banks, respectively. This finding is supported when the regions are split into time-periods giving a rate of agreements between CRAs of 53.89%, for Australian banks during the post-crisis periods. The extent of disagreements is lower for Australasian banks compared to the other regions in all scenarios. The results are further supported by the multivariate analysis because the Australasian variable is significant with a negative coefficient, suggesting less splits within that region. The results in Exhibit 4 using the 20-notch scale further support the results found in Exhibit 3 in addition to the results of the ordered probit analysis in Exhibit 7. Therefore, H2 can be accepted.

H3. Moody's and S&P tend to disagree more on their rating assignments of North American banks during the sub-prime crisis period (2007-09) and disagree more on European banks during the European crisis, compared with the other two periods.

Exhibit 3, panel II shows disagreements between CRAs split into regions and time periods. During the sub-prime crisis CRAs disagree 80% of the time for North American banks, although the results show a larger level of disagreements for European banks (82%) during the same period. During the European crisis CRAs disagree 85% of the time for North American banks and 79% of the time for European banks. Even though the percentage of disagreements is larger for European banks in the sub-prime crisis, the extent of disagreement is higher for North American banks (4.54 points compared to 3.79 points for European banks). However, the extent of disagreements from European banks during the European crisis is less than North American banks (3.16 points compared to 3.29 points).

These results were unexpected because the main level of disagreement between CRAs for North American banks was expected to occur during the sub-prime crisis and for European banks during the European crisis, as these would be the most ambiguous times for both of the respective regions. This could have been due to the differing watch policies (Alsakka and ap Gwilym [2012]) used by the CRAs, but the results using only the ratings (20-notch) scale are similar so this theory cannot be supported. It is not fully apparent why these results were not as expected, however it could be due to the level of European investment into the North American housing market, with Northern Rock being the first European victim of such an economic shock (FT [2008]). The bank run on Northern Rock could have been the catalyst to a spillover/contagion effect which spread into the rest of Europe. Morgan [2002] suggests that one of the consequences of asset opaqueness within the banking sector is contagion and this could be compounded due to the lead lag relationship that exists between the three main CRAs. Alsakka and ap Gwilym [2010] found there is a strong interdependence amongst the three main CRAs. However, they also find that S&P is the most independent CRA and it is notable that S&P have made a large number of rating changes whereas Moody's have delayed making such changes during these crisis periods. Therefore, H3 cannot be accepted.

Reasons split ratings occur

Two earlier papers, Ederington [1986] and Morgan [2002], have differing view points on why split ratings occur. Ederington [1986] argues that split ratings are caused simply by random errors of the two CRAs, implying that split-rated bonds are likely to have credit risks bordering the rating cut-off points, known as the "the random error hypothesis of split ratings" (Livingston et al [2007], p.49). Morgan [2002] believes that as banks are the most opaque industry they are more likely to receive split ratings than firms from other industries, this is known as "the asset opaqueness hypothesis of split ratings" (Livingston et al [2007], p.49). Alsakka and ap Gwilym [2012] find that S&P have more emphasis on short term accuracy and

Moody's places its emphasis on long term stability. Therefore, this difference in rating policies could be the reason for split ratings.

Exhibit 5 displays the reasons behind the higher level of disagreements between CRAs. A positive coefficient suggests a reason for more splits and these results suggest that if a country's sovereign rating is split there is more likely to be a disagreement between CRAs for a bank rating in that country. This is due to the strong link between a change in the sovereign rating and a bank rating within that country (Williams et al [2013]; Drago and Gallo [2017]).

In addition, the results suggest that Moody's and S&P disagree mostly on banks' creditworthiness within one of the identified crisis countries (Portugal, Ireland, Spain or Italy). PIIGS countries were some of the worst affected OECD countries in the European sovereign crisis, which reflects Eurozone uncertainty within that period contributing to larger disagreements on bank ratings between Moody's and S&P. Furthermore, the multivariate results suggest that CRAs will disagree if a bank has a speculative grade rating or within North America, which was largely affected by the sub-prime crisis. The negative coefficient for the Return on Assets (ROA) variable was expected because more profitable banks are presumed to be less risky (Iannotta [2006]) and therefore fewer disagreements between CRAs should occur.

Exhibit 7 displays the results of the robustness test using the ordered probit regression (Eq.4). The results here support those found in Exhibit 5 as disagreements between CRAs tend to occur more where the sovereign rating of the country is split, within a crisis country, for speculative grade banks and within North America. The main difference here is the addition of splits occurring for larger banks (Iannotta [2006]).

The high number of disagreements between the two CRAs could be due to differing 'watch' policies and therefore they would not follow the actions of another CRA when applying watch signals. To examine further whether the differing watch policies between CRAs between

CRAs contribute towards the large number of disagreements, the analysis has been extended further to rating opinions without watch level events. Even though the 20-notch scale results show that slightly fewer disagreements between CRAs occur than when using the 60-point scale, but the overall impact is limited, suggesting that differing 'watch' policies are less influential and the uncertainty regarding the creditworthiness of banks is the main contributor to the split in credit opinions between CRAs.

The univariate analysis finds that during the time period examined, 2007-15, both CRAs tend to disagree on their rating opinions, although fewer disagreements occur during the post-crisis period compared with the sub-prime and European crises, which could suggest that both crises caused a large amount of uncertainty between CRAs and this led to more disagreements. Vu et al [2015] states that when CRAs disagree in their rating assignments it demonstrates some inconsistencies in information, which arises from ambiguity and induces wider splits. These results also broadly support previous research (such as Cantor et al [1997]; Morgan [2002]) and provide more evidence that ratings between Moody's and S&P are split over fifty per cent of the time (Cantor et al [1997]), particularly during crisis periods. With regards to bank assets, Skreta and Veldkamp [2009] suggest that when an issuer's underlying assets are transparent, CRAs provide similar ratings and Iannotta [2006] states that bank opacity decreases when fixed assets increase. Hau et al [2013] agree that underlying asset complexity is an important determinant in rating quality and accuracy.

Therefore, this result is anticipated as Moody's and S&P would be expected to disagree when bank opacity is lower, especially during times of uncertainty. Therefore, disagreements between CRAs are exacerbated within banks that reside in one of the most affected crisis countries,[17] a bank with a low credit rating[18] and those that are in North America.

[17] 'Crisis country' includes Portugal, Ireland, Spain and Italy.
[18] A low credit rating is regarded as Baa1/BBB+ or lower.

The second research question examines whether conservativeness between Moody's and S&P changes during crisis and non-crisis periods, leading to the following two hypotheses.

H4. S&P is the more conservative CRA during times of crisis (sub-prime and European) because they change their ratings more quickly than Moody's.

Exhibit 3 displays the univariate results of which CRA issues a higher/lower rating and in general, Moody's issues a higher rating 51.57% of occasions, compared to S&P issuing a higher rating 22.67% of the time and Moody's issues a higher rating by an average of 1.45 points. During the sub-prime crisis Moody's is higher 67.95% of the time compared to S&P being higher only 11.26% of the time. On average, Moody's issues a higher rating of 3.21 points. The European crisis suggests that Moody's continues to issue a higher rating but the extent is reduced to 53.35% compared with an increase to 25.90%, for Moody's and S&P, respectively. The extent to which Moody's issues a higher rating has also reduced substantially to an average of 0.09 points.

The multivariate results support S&P issuing a higher rating than Moody's as all the significant variables have positive coefficient suggesting that Moody's issues a higher rating for larger banks, banks within a crisis country, Australasian and North American banks. However, the only variables supported using the cluster robust standard error are Bank size and North America. Therefore, H4 can be accepted because S&P is the more conservative CRA during the sub-prime and European crises.

H5. Moody's is the more conservative CRA during the post-crisis period.

Within the post-crisis period Moody's issues a higher rating 34.23% of time, compared to S&Ps 30.20%, however the TWS shows that S&P are beginning to issue higher ratings with the TWS of -0.18 points. Split into regions and timeframes during the post-crisis period, Moody's is the more conservative CRA within Europe 77% of the time compared to S&Ps

60% by -1.43 points. Exhibit 4 shows the results using the 20-notch scale and the results follow the same pattern as those when using the 60-point scale. H5 can be accepted.

The results show that during the different time periods the percentage of times Moody's issues a higher rating begins to decrease and the percentage of times S&P issues a higher rating, increases. In addition, the TWS has reduced substantially from 3.21 points in the sub-prime crisis to -0.18 points in the post-crisis period. This suggests that conservativeness between the two CRAs changes as ambiguity levels change.

Overall, the results show that although S&P is the more conservative CRA, supported by Vu et al [2015], this is short lived, as the extent to which Moody's issues a higher rating decreases across time. Alsakka and ap Gwilym [2010] state that Moody's uses an 'expected loss' approach when issuing ratings, which includes assessments of both 'probability of default' and 'loss given default' whereas S&P only assesses probability of default. Altman and Rijken [2006] state that in 2002 Moody's attempted to respond to criticisms of rating timeliness by changing their rating assignments more frequently. However, investors responded by stating they 'value the current level of rating stability and do not want ratings to simply follow market prices' (Altman and Rijken [2006, p.54]), consequently Moody's decided to revert back to producing stable ratings. This could suggest that Moody's may be slower than S&P to apply a rating change.

The results provide some strong evidence that the number of splits between CRAs and the conservativeness of a CRA does change across all time periods examined as well as regions. Therefore, there appears to be no consistency in these areas across the business cycle.

Conclusion

The aim of this paper is to investigate whether opacity, and therefore disagreements between CRAs, increases during crisis periods and whether the conservativeness of CRAs changes during these periods. This paper makes a significant contribution to the literature by

investigating split ratings of banks based on watch status with the addition of credit ratings along with the inclusion of two crises and a post-crisis period. The paper attempts to answer questions relating to the opacity of bank ratings and the conservativeness of the two largest CRAs throughout differing time periods.

The main results are as follows: regarding disagreements, Moody's and S&P agree on bank creditworthiness in 25.8% of cases between 2007 and 2015; when the results are broken down into timeframes, agreements between CRAs increase to 35.6% during the post-crisis period but fall as low as 15.29% for North American banks during the European crises. Regarding conservativeness, S&P tends to be the more conservative CRA during the two crises but that changes post-crises as Moody's reverts to being the more conservative CRA.

In answering the first research question, the evidence is that CRAs tend to disagree on their rating opinions. Livingston et al [2007] suggests that 'some opaque firms may have a wide range of credit risk estimates at initial issuance, but the range of credit risk estimates happens to fall within rating boundaries…although such firms may have a non-split rating at initial issuance, small changes in the credit risk after the initial issuance may move the ranges of credit risk estimates up or down to cross a rating boundary, resulting in new split ratings' (p.60). As watch status has been included this has minimised the size of the rating boundary and therefore the impact of small changes in credit quality leading to a rating change is limited. Consequently, the split ratings identified are more likely to be due to opacity rather than slight changes in credit quality. The results support previous research (Cantor et al [1997]; Morgan [2002]) that rating assignments are split fifty per cent of the time and provide further evidence that ratings between Moody's and S&P are generally split within the banking sector.

The second research question examines conservativeness of both Moody's and S&P. The results show that although S&P is the more conservative CRA, however, this is short-lived as the frequency at which Moody's issues a higher rating decreases across time. During the

sub-prime crisis Moody's issues higher ratings than S&P, but by the post-crisis period the CRAs tend to issue similar ratings. Alsakka and ap Gwilym [2010] state that due to the differing methodologies used by CRAs, Moody's may be slower than S&P to apply a rating change. This is most certainly the case here. Previous research (Cantor et al [1997,1983,1993]; Morgan [2002]; Livingston et al [2010]) find that Moody's is the more conservative CRA and the time periods examined range from 1983 to 2008. Vu et al [2015] find the opposite regarding conservativeness with a dataset ranging from 2000-2012. Altman and Rijken [2006] state that Moody's had been previously criticised for the timeliness of their rating changes and after attempting to respond to such criticisms, investors responded by stating they 'value the current level of rating stability and do not want ratings to simply follow market prices' (Altman and Rijken [2006, p.54]), consequently Moody's decided to revert back to producing stable ratings. Therefore, it could be said that Moody's is the more conservative CRA but during times of uncertainty S&P makes changes to an issuer's creditworthiness more quickly than Moody's, which gives the impression that they are the more conservative CRA.

Bar-Isaac and Shapiro [2013] feel that the reputation of a CRA is imperative when issuing a rating, however they state that the value of reputation is dependent upon economic fundamentals that vary over business cycles. They find by using a dynamic model of ratings that a CRA is likely to issue a less accurate rating during booms than during recessions. Livingston et al [2010] investigate the relationship between S&P and Moody's corporate ratings and bond yield prices. They find that if there is a split bond rating and Moody's issues the higher rating the bond yield is priced 8 base points lower than bonds with a higher rating from S&P. Livingston and Zhou [2010] find that the bigger the rating split, the higher the return requested by investors, which is consistent with the view of Livingston et al [2007]. Previous research (Hand et al [1992]; Kaminsky and Schmukler [2002]; Bannier and Hirsch [2010]) find

that rating downgrades, namely watchlist, have a negative impact on stock market and this impact is stronger during crisis periods (Li et al [2008]).

Overall, a disagreement between CRAs is generally amplified during crisis periods. Furthermore, the ambiguous nature of creditworthiness could be deemed as a key factor in causing such disagreements, with the delay between applying rating changes remaining a key issue. Although the difference between the two CRAs reduces through the time periods, their varied methodologies continue to cause a notable divide. The findings of this research have implications on the pricing of risk (Livingston et al [2008]), stock market returns (Richards and Deddouche, 2003), CDS Markets (Micu et al [2006]) and foreign exchange markets (Alsakka and ap Gwilym [2012]) which is imperative to investors. From a company's perspective these results may have an impact on their financing opportunities (Terovitis [2016]) and market value (Richards and Deddouche [2003]). Therefore, the knowledge that S&P should be perceived as the more conservative CRA over Moody's during times of uncertainty should help market participants to maximise returns through business cycles. Regarding split ratings, this research confirms the perception that banking sector issuers maintain a higher level of opacity than their corporate equivalents.

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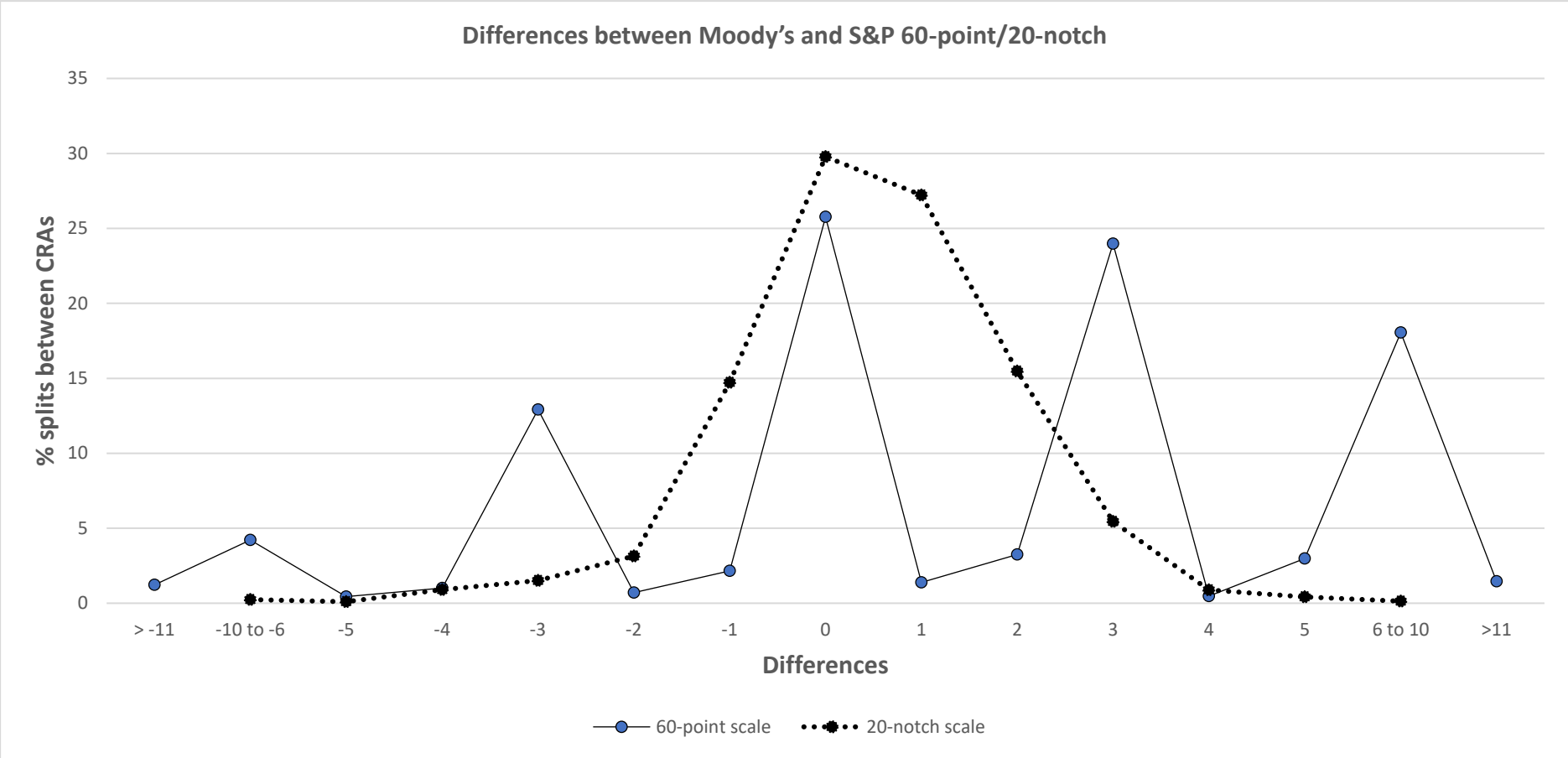
Exhibit 1. Descriptive statistics

Panel I	
No. of Banks	133
No. of Countries	17
No. of daily Observations	291,288
Investment Grade	96.4%
Speculative Grade	3.6%
Panel II	
No. of Observations	1119
Mean Bank Size ($m)	321,694
Minimum Bank Size ($m)	159
Maximum Bank Size ($m)	2,914,202
Standard Deviation ($m)	484,575
Mean Profit ($m)	1,699
Minimum Profit ($m)	-23,509
Maximum Profit ($m)	28,096
Standard Deviation ($m)	3,884
Mean ROA	0.89%
Minimum ROA	-11.43%
Maximum ROA	16.19%
Standard Deviation	1.56%
∑ Sovereign Split	-250
Crisis789	360
Euro Crisis	387
Crisis country	102
Low Credit Rating	51
Australasian banks	129
North America banks	451

This exhibit is split into two panels; Panel I displays the overall univariate summary statistics of banks and Panel II displays the regression statistics. Bank size, Profit and ROA are bank specific information used in the regression; ∑ Sovereign Split is the sum of all splits, Moody's minus S&P across the timeframe; the remainder, Crisis789, Euro Crisis, Crisis country, Low credit rating, Australian banks and North American banks are the total observations within each , used in the regression.

Exhibit 2. Differences between Moody's and S&P ratings based on the 60-point/20-notch scale



This graph displays the extent of the differences between Moody's and S&P using 60-point scale and 20-notch scale. The differences are calculated by taking the Moody's numeric rating minus the S&P numeric rating. Therefore, if Moody's issues a higher rating than S&P there will be a positive difference and if S&P issues a higher rating than Moody's there will be a negative difference. The difference is calculated by using the numerical scale in Appendix 2, if the difference is equal to zero then there is no split between CRAs. Using the 60-point scale (20- notch scale) a split of -1/+1 means that Moody's/S&P have a difference of 1 rating opinion and so on, up to a difference of >-11/+11 (>-6/>+6).

Exhibit 3. CRA daily splits based on 60-point scale.

Panel I						
Overall						
	Observations	Non-split	Moody's higher	S&P higher	TWS	TWS(A)
Overall (%)	291,288	25.76	51.57	22.67	1.45	3.35
Time Periods						
2007-09 (%)	93,001	20.79	67.95	11.26	3.21	3.95
2010-12 (%)	100,062	20.75	53.35	25.90	0.09	0.24
2013-15 (%)	98,225	35.57	34.23	30.20	-0.18	2.70
Regions						
Australasia (%)	32,897	42.86	42.08	15.06	1.00	1.92
N. America (%)	118,874	21.43	60.78	17.79	2.55	3.77
Europe (%)	139,517	25.42	45.96	28.62	0.61	3.33
Panel II						
Regions split into time periods						
2007-09						
Australasia (%)	10,355	34.37	44.59	21.04	1.02	2.34
N. America (%)	39,460	20.05	73.27	6.68	4.09	4.54
Europe (%)	43,186	18.20	68.69	13.10	2.93	3.79
2010-12						
Australasia (%)	11,520	39.92	39.32	20.76	0.82	2.06
N. America (%)	40,581	15.29	62.98	21.73	1.71	3.29
Europe (%)	47,961	20.77	48.57	30.66	0.57	3.16
2013-15						
Australasia (%)	11,023	53.89	42.62	3.49	1.18	1.38
N. America (%)	38,831	29.24	45.81	24.95	0.97	2.59
Europe (%)	48,371	36.47	23.02	40.51	-1.43	3.09

Exhibit 3 (Exhibit 4) displays the results of the daily splits using the 60-point scale (20-notch scale). Panel I has split the results into the three areas examined, overall, different time periods (Sub-prime crisis, European-Crisis and Post-crisis) and regions (Australasia, North America and Europe). Panel II presents the results by region in three time periods (Sub-prime crisis, European-Crisis and Post-crisis). TWS: Time Weighted Split. TWS (A): Time Weighted Split using Absolute values. 'Non Split' represents cases when both Moody's and S&P agree on a rating opinion. 'Higher' denotes the CRA which assigned the higher assessment of creditworthiness. 'TWS' represents the points on the 60-point scale (20-notch scale) and the results of Eq.1.

Exhibit 4. CRA daily splits based on 20-notch scale.

Panel I						
Overall						
	Observations	Non-split	Moody's higher	S&P higher	TWS^	TWS^(A)
Overall (%)	291,288	29.81	49.55	20.64	0.50	1.12
Time Periods						
2007-09 (%)	93,001	23.47	66.74	9.79	1.08	1.32
2010-12 (%)	100,062	25.95	51.53	22.70	0.03	0.08
2013-15 (%)	98,225	39.73	31.44	28.83	-0.07	0.90
Regions						
Australasia (%)	32,897	44.92	41.91	13.17	0.35	0.63
N. America (%)	118,874	25.68	58.86	15.46	0.87	1.26
Europe (%)	139,517	29.76	43.44	26.80	0.21	1.12
Panel II						
Regions split into time periods						
2007-09						
Australasia (%)	10,355	36.34	44.59	19.07	0.35	0.77
N. America (%)	39,460	23.11	71.15	5.75	1.36	1.50
Europe (%)	43,186	20.72	68.03	11.25	1.01	1.28
2010-12						
Australasia (%)	11,520	43.65	38.83	17.52	0.30	0.68
N. America (%)	40,581	20.59	61.00	18.41	0.61	1.10
Europe (%)	47,961	26.23	46.20	27.56	0.23	1.07
2013-15						
Australasia (%)	11.023	54.27	42.62	3.11	0.39	0.46
N. America (%)	38,831	33.61	44.14	22.26	0.35	0.87
Europe (%)	48,371	41.34	18.70	39.97	-0.51	1.03

Exhibit 5. Multivariate regression results for absolute values of split rating.

	Robust Std. Err.			Cluster Robust Std. Err.		
	60-point – Absolute (Eq.2)			60-point – Absolute (Eq.2)		
Time Weighted Split $(TWS)^{WA}$	Coef.	Robust Std. Error	p-value	Coef.	Robust Std. Error	p-value
Constant	**2.728*** **	0.384	0.000	**2.728*** **	1.011	0.008
Bank Size (BS)*i,t*	0.043	0.029	0.138	0.043	0.078	0.587
Sovereign Split (SS)*i,t*	**0.261*** **	0.072	0.000	**0.261** **	0.128	0.044
Return on Assets (RoA)*i,t*	**-16.417** **	5.577	0.003	**-16.417** **	7.925	0.040
Crisis789*t*	0.001	0.154	0.996	0.001	0.133	0.995
EuroCrisis*t*	-0.062	0.142	0.663	-0.062	0.082	0.454
Crisis country (CC)*i*	**1.170*** **	0.234	0.000	**1.170** **	0.543	0.033
LowCreditRating (LCR)*i,t*	**0.591***	0.357	0.099	0.591	0.860	0.493
Australasia (AP)*i*	**-0.935*** **	0.142	0.000	**-0.935** **	0.392	0.019
North America (NA)*i*	**0.933*** **	0.160	0.000	**0.933** **	0.442	0.037
R^2	0.1186		R^2		0.1186	
Number of Observations	1118		Number of Clusters		133^{+}	

+ Standard Error is clustered by Bank.

Exhibits 5-6 present the coefficient, standard error and p-value estimates of Eq. (2) - Eq. (3) using data samples of selected North American, European and Australasian countries during the period 2007 – 2015. The Exhibits show regression results for Cluster Robust Standard Errors. *TWS* represents the dependent variable, the Time Weighted Split of bank *i* for Absolute value 60-point scale (*WA*) and 60-point scale (*W*). The *TWS* is calculated once per bank and repeated 9 times, for each year, across the whole period the splits are examined (2007-15) within the regression analysis. Therefore, each bank has 9 observations in the overall *TWS*, unless a bank is not rated at any point during the sample period.

Bank Size $(BS)_{i,t}$ represents the bank size of bank *i* at time *t*, using Total Assets figure on the latest set of financial statement. Sovereign Split $(SS)_{i,t}$ represents the split between the sovereign rating assigned by Moody's and S&P for the country of bank *i* at time *t*. Moody's minus S&P has also been used here to examine the split and in equations 2 and 3 the absolute value of the sovereign split has been used. Return on Assets (RoA) is for bank *i* at time *t*. $Crisis789_t$ represents the dummy variable, Sub-prime crisis, and took a value of 1 if the event took place in 2007-09 or 0 if not. $EuroCrisis_t$ represents the dummy variable, European Crisis, and took a value of 1 if the event took place in 2010-12 or 0 if not. Crisis country $(CC)_i$ represents a bank residing in a Crisis Country. Crisis country took a value of 1 if the bank resided in Portugal (bailout), Ireland (bailout), Spain (spillover) or Italy (spillover), or 0 if not. Low Credit Rating $(LCR)_{i,t}$ represents a bank with a low credit rating at time *t*. A bank with a low credit rating, took a value of 1 if the bank had a speculative grade rating, Ba1/BB+ or less at the time of the event, or 0 if not. Australasia $(AP)_i$ and North America $(NA)_i$ represent dummy variables taking the value of 1 if bank *i* is located in Australasia (Australia and New Zealand) or North America (USA and Canada) and 0 otherwise. The data set has been winsorised to eliminate any outliers and Huber–White robust standard errors is applied.

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

Exhibit 6. Multivariate regression results for split rating.

	Robust Std. Err. 60-point (Eq.3)			Cluster Robust Std. Err. 60-point (Eq.3)		
Time Weighted Split (TWS)^{W}	Coef.	Robust Std. Error	p-value	Coef.	Robust Std. Error	p-value
Constant	**-3.267*****	0.659	0.000	**-3.267***	1.802	0.072
Bank Size (BS) *i,t*	**0.315*****	0.048	0.000	**0.315****	0.136	0.022
Sovereign Split (SS)*i,t*	0.051	0.946	0.588	0.051	0.156	0.744
Return on Assets (RoA)*i,t*	6.150	8.486	0.459	6.150	13.919	0.659
Crisis789*t*	0.052	0.222	0.816	0.052	0.170	0.760
EuroCrisis*t*	-0.012	0.207	0.953	-0.012	0.119	0.918
Crisis country (CC)*i*	**0.684****	0.335	0.041	0.684	0.771	0.377
LowCreditRating (LCR)*i,t*	-0.219	0.342	0.521	-0.219	0.643	0.734
Australasia (AP)*i*	**0.789*****	0.209	0.000	0.789	0.587	0.181
North America (NA) *i*	**2.260*****	0.237	0.000	**2.260*****	0.669	0.001
R^2	0.1133		R^2		0.1133	
Number of Obs.	1118		No. of Clusters		133^{+}	

+ Standard Error is clustered by Bank.

Full details are provided in the notes to Exhibit 5.

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

Exhibit 7. Ordered probit regression results for Eq.4 and Eq.5.

	Robust Std. Err. 20-notch – Absolute (Eq.4) TWS_i^{SPL}			Robust Std. Err. 20-notch – (Eq.5) TWS_i^{CON}		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
Bank Size (BS)*i,t*	**0.073*** **	0.026	0.005	**0.070*** **	0.022	0.001
Sovereign Split (SS)*i,t*	**0.215** **	0.093	0.021	-0.018	0.412	0.668
Return on Assets (RoA)*i,t*	2.661	3.343	0.426	**7.732** **	3.249	0.017
Crisis789*t*	-0.004	0.128	0.977	0.044	0.089	0.622
EuroCrisis*t*	-0.082	0.119	0.490	0.032	0.085	0.704
Crisis country (CC)*i*	**4.661*** **	0.163	0.000	**0.338*** **	0.122	0.006
LowCreditRating (LCR)*i,t*	**4.176*** **	0.108	0.000	0.004	0.162	0.978
Australasia (AP)*i*	**-0.529*** **	0.131	0.000	**0.346*** **	0.112	0.002
North America (NA)*i*	**0.403*** **	0.117	0.001	**0.476*** **	0.090	0.000
Number of Observations	1118			Number of Observations	1118	

Exhibit 7 present the coefficient, standard error and p-value estimates of Eq. (4) - Eq. (5) using data samples of selected North American, European and Australasian countries during the period 2007 – 2015. TWS_i^{SPL} represents the SPLIT dependent variable taking a value of 0 or 1 to determine whether there is a split or not split for bank *i* for Absolute values using the 20-point scale. TWS_i^{CON} represents the CONSERVATIVENESS dependent variable taking the value of -1, 0 or 1. If Moody's issues a higher rating than S&P there will be a positive difference (1) and if S&P issues a higher rating, there will be a negative difference (-1) and no disagreement (0).

Bank Size $(BS)_{i,t}$ represents the bank size of bank *i* at time *t*, using Total Assets figure on the latest set of financial statement. Sovereign Split $(SS)_{i,t}$ represents the split between the sovereign rating assigned by Moody's and S&P for the country of bank *i* at time *t*. Moody's minus S&P has also been used here to examine the split and in equations 2 and 3 the absolute value of the sovereign split has been used. Return on Assets (RoA) is for bank *i* at time *t*. $Crisis789_t$ represents the dummy variable, Sub-prime crisis, and took a value of 1 if the event took place in 2007-09 or 0 if not. $EuroCrisis_t$ represents the dummy variable, European Crisis, and took a value of 1 if the event took place in 2010-12 or 0 if not. Crisis country $(CC)_i$ represents a bank residing in a Crisis Country. Crisis country took a value of 1 if the bank resided in Portugal (bailout), Ireland (bailout), Spain (spillover) or Italy (spillover), or 0 if not. Low Credit Rating $(LCR)_{i,t}$ represents a bank with a low credit rating at time *t*. A bank with a low credit rating, took a value of 1 if the bank had a speculative grade rating, Ba1/BB+ or less at the time of the event, or 0 if not. Australasia $(AP)_i$ and North America $(NA)_i$ represent dummy variables taking the value of 1 if bank *i* is located in Australasia (Australia and New Zealand) or North America (USA and Canada) and 0 otherwise. The data set has been winsorised to eliminate any outliers and Huber–White robust standard errors is applied.

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% levels respectively.

Appendix 1. List of banks and countries in the data sample

Bank	Country	Bank	Country
ABN AMRO Bank N.V.	Netherlands	First-Citizens Bank & Trust Company	USA
American Express Centurion Bank	USA	First Merit Bank, N.A.	USA
ANZ Bank New Zealand Ltd.	New Zealand	HSBC Bank Australia Ltd	Australia
Arab Bank Australia Limited	Australia	HSBC Bank plc	UK
ASB Bank Ltd.	New Zealand	HSBC Bank USA, N.A.	USA
Australia & New Zealand Banking Grp. Ltd.	Australia	HSBC France	France
Banca Carige S.p.A.	Italy	Huntington National Bank	USA
Banca IMI SpA	Italy	Hypo Public Finance Bank	Ireland
Banca Nazionale Del Lavoro S.P.A.	Italy	ING Bank N.V.	Netherlands
Banca Popolare di Milano S.C.a r.l.	Italy	Intesa Sanpaolo Spa	Italy
Banco BPI S.A.	Portugal	JPMorgan Chase Bank, NA	USA
Banco Popular de Puerto Rico	USA	Jyske Bank A/S	Denmark
Banco Santander Puerto Rico	USA	Kiwibank Ltd.	New Zealand
BancorpSouth Bank	USA	Landesbank Baden-Wuerttemberg	Germany
Bank of America, N.A.	USA	Landesbank Hessen-Thueringen GZ	Germany
Bank of Ireland	Ireland	LeasePlan Corporation N.V.	Netherlands
Bank of Montreal	Canada	Lloyds TSB Bank Plc	UK
Bank of New York Mellon (The)	USA	Macquarie Bank Limited	Australia
Bank of New Zealand	New Zealand	Manufacturers and Traders Trust Company	USA
Bank of Queensland Limited	Australia	Morgan Stanley Bank International Limited	UK
Bank of Scotland plc	UK	Morgan Stanley Bank, N.A.	USA
Bank of the West	USA	National Australia Bank Limited	Australia
Banque Federative du Credit Mutuel	France	National Bank of Canada	Canada
Banque PSA Finance	France	National Westminster Bank PLC	UK
Barclays Bank PLC	UK	NIBC Bank N.V.	Netherlands
Bayerische Landesbank	Germany	Nordea Bank AB	Sweden
Bendigo and Adelaide Bank Ltd.	Australia	Nordea Bank Danmark A/S	Denmark

Bilbao Bizkaia Kutxa	Spain	Nordea Bank Finland Plc	Finland
BMO Harris Bank NA	USA	Nykredit Bank A/S	Denmark
BNP Paribas	France	Pohjola Bank plc	Finland
BOKF, NA	USA	Raiffeisen Bank International AG	Austria
BPCE	France	Raiffeisen Zentralbank Oesterreich AG	Austria
Branch Banking and Trust Company	USA	RCI Banque	France
Caisse Centrale Desjardins	Canada	Regions Bank	USA
Caisse Des Depots et Consignations	France	Royal Bank of Canada	Canada
Caixa Geral de Depositos S.A.	Portugal	Royal Bank of Scotland plc	UK
Caja de Ahorros y Pensiones de Barcelona	Spain	Santander UK PLC	UK
Canadian Imperial Bank of Commerce	Canada	Silicon Valley Bank	USA
Capital One Bank N.A.	USA	SNS Bank N.V.	Netherlands
Chase Bank USA, NA	USA	Societe Generale	France
Citibank International Plc	UK	Standard Chartered Bank	UK
Citibank, N.A.	USA	Suncorp-Metway Ltd.	Australia
Citizens Bank of Pennsylvania	USA	SunTrust Bank	USA
Comerica Bank	USA	Svenska Handelsbanken AB	Sweden
Commerzbank AG	Germany	Swedbank AB	Sweden
Commonwealth Bank of Australia	Australia	Swedbank Mortgage AB	Sweden
Compass Bank	USA	Synovus Bank	USA
Credit Agricole Corporate & Investment Bank	France	TCF National Bank	USA
Credit Agricole S.A.	France	TD Bank, N.A.	USA
Credit Industriel et Commercial	France	Toronto-Dominion Bank (The)	Canada
Credit Logement	France	Trustmark National Bank	USA
Credit Suisse International	UK	U.S. Bank National Association	USA
Danske Bank A/S	Denmark	U.S. Bank National Association ND	USA
DEPFA Bank plc	Ireland	UBS Limited	UK
Deutsche Bank National Trust Company	USA	Ulster Bank Limited	UK
Deutsche Bank Trust Company Americas	USA	UniCredit Bank AG	Germany
Deutsche Bank Trust Company Delaware	USA	UniCredit Bank Austria AG	Austria
Dexia Credit Local	France	UniCredit Luxembourg S.A.	Luxembourg

Discover Bank	USA	UniCredit SpA	Italy
DVB Bank S.E.	Germany	Union Bank, N.A.	USA
E*TRADE Bank	USA	Webster Bank N.A.	USA
Erste Group Bank AG	Austria	Wells Fargo Bank Northwest, N.A.	USA
FIA Card Services, NA	USA	Wells Fargo Bank, N.A.	USA
Fifth Third Bancorp	USA	Westpac Banking Corporation	Australia
First Hawaiian Bank	USA	Westpac Europe Limited	UK
First National Bank of Omaha	USA	Westpac New Zealand Limited	New Zealand
First Republic Bank	USA		

Appendix 2 – Mapped rating scales (20-notch and 60 point)

20-notch scale			**60-point scale**					
Moody's	S&P	No.	Moody's	S&P	No.	Moody's	S&P	No.
Aaa	AAA	20	Aaa	AAA	60	Positive	Positive	25
Aa1	AA+	19	Negative	Negative	59	Ba3	BB-	24
Aa2	AA	18	Positive	Positive	58	Negative	Negative	23
Aa3	AA-	17	Aa1	AA+	57	Positive	Positive	22
A1	A+	16	Negative	Negative	56	B1	B+	21
A2	A	15	Positive	Positive	55	Negative	Negative	20
A3	A-	14	Aa2	AA	54	Positive	Positive	19
Baa1	BBB+	13	Negative	Negative	53	B2	B	18
Baa2	BBB	12	Positive	Positive	52	Negative	Negative	17
Baa3	BBB-	11	Aa3	AA-	51	Positive	Positive	16
Ba1	BB+	10	Negative	Negative	50	B3	B-	15
Ba2	BB	9	Positive	Positive	49	Negative	Negative	14
Ba3	BB-	8	A1	A+	48	Positive	Positive	13
B1	B+	7	Negative	Negative	47	Caa1	CCC+	12
B2	B	6	Positive	Positive	46	Negative	Negative	11
B3	B-	5	A2	A	45	Positive	Positive	10
Caa1	CCC+	4	Negative	Negative	44	Caa2	CCC	9
Caa2	CCC	3	Positive	Positive	43	Negative	Negative	8
Caa3	CCC-	2	A3	A-	42	Positive	Positive	7
Ca	CC	1	Negative	Negative	41	Caa3	CCC-	6
C	R	1	Positive	Positive	40	Negative	Negative	5
	SD	1	Baa1	BBB+	39	Positive	Positive	4
	D	1	Negative	Negative	38	Ca	CC	3
			Positive	Positive	37	Negative	Negative	2
			Baa2	BBB	36	C	R	1
			Negative	Negative	35		SD	1
			Positive	Positive	34		D	1
			Baa3	BBB-	33			
			Negative	Negative	32			

Positive	Positive	31
Ba1	BB+	30
Negative	Negative	29
Positive	Positive	28
Ba2	BB	27
Negative	Negative	26