Home Biased Corporate Credit Ratings?

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Abstract

This paper investigates the existence of 'home bias' in corporate ratings of Moody's and Standard & Poor's. More specifically, we examine whether we can find evidence of rating inflation for corporate issuers that are domiciled in the home country of the credit rating agency. We document an 'inverse home bias', i.e. the ratings of non-home issuers are inflated relative to the ratings of home issuers. In particular, home issuers with the same credit risk as non-home issuers are rated, on average, 2 notches worse by Moody's and Standard & Poor's. We attribute this finding of rating inflation of non-US issuers to the dominance of financial benefit over reputational cost as they expanded into non-US markets.

JEL classification: G01, G15, G21, G24

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1. Introduction

Despite the predominant role of credit rating agencies (CRAs) in financial markets, where they impose an information dissemination and verification function, the actual role of CRAs and their expertise and indepence have regularly come under attack. More recently, CRAs face growing criticism and regulatory pressure for their inability to adequately predict firm defaults. In particular, the conflict of interest inherent to the issuer-pay business model is an often cited reason for the inflation in ratings observed during the 2008 financial crisis (Alp, 2013; Bonsall, 2014; Xia, 2014). This is further aggravated by the lack of transparency with respect to rating methods and procedures, which makes it very difficult for investors to assess the intrinsic rating quality (Skreta and Veldkamp, 2009; Griffin and Tang, 2012; He et al., 2012). In addition to the growing concerns about the conflict of interest and the opaque rating processes, there is the apprehension that Standard & Poor's (S&P) and Moody's Investor Services (Moody's) are too heavily centered on the US, further raising doubts about the accuracy of their ratings. So far the debate on 'home bias' has mainly focused on sovereign ratings. For example, European officials have publicly accused Moody's and S&P of favoring the United States, which until August 2011 maintained a triple-A rating despite carrying an unsustainable deficit and increasingly high levels of public debt. In 2015, S&P, Moody's and Fitch have a collective EU market share of around 96.1%[1], while in the US the market share is around 95.8%[2]. S&P and Moody's are both

[1] This market share calculation is based on the 2014 credit rating activities at group level in the EU (EC, 2015). The market share is 40.2%, 36.5% and 19.4% for S&P, Moody's and Fitch respectively.

[2] This market share calculation is based on the 2014 credit rating activities at group level in the US (SEC, 2015). The market share is 48.6%, 34.8% and 12.4% for S&P, Moody's and Fitch respectively.

based in the US. Fitch is a subsidiary of the French group FIMALAC with dual headquarters in New York and London. Over the past decades, the regional coverage of these Big Three CRAs has changed significantly. While in 1990, over 95% of listed companies rated by Moody's and S&P and 85% of those rated by Fitch were domiciled in the US, in December 2014 respectively 48%, 44% and 40% of rated firms by S&P, Moody's and Fitch were US-domiciled (Cfr. Table A.1). This geographic shift further motivates the main focus of this paper on the existence of home bias in corporate ratings. More specifically, the main question we address in this paper is whether we can find evidence of rating inflation for corporate issuers that are domiciled in the home country of the CRA[3]. In particular, to examine the existence of 'home bias' for Moody's and S&P, we assess the true information value of credit ratings and investigate whether we can find evidence of rating inflation for home issuers. More specifically, by using credible Probability of Defaults (PDs) to control for the true credit risk, we are able to compare the 1-year average log PD per rating grade between home and non-home issuers. In this study we rely on the 1-year PD estimates provided by the Credit Research Initiative (CRI) under the Risk Management Institute (RMI) at the National University of Singapore (NUS). The forward intensity model to estimate the PDs is developed by Duan et al. (2012). They show that using a forward intensity model in estimating the PDs is outperforming the model developed by Duffie et al. (2007) i.e. the DSW model. In addition, they provide a performance indication of their model and show to be very accurate with both an in-and out-of-sample accuracy exceeding 80% (Duan et al., 2012).

[3] As the headquarters of Fitch are based in both the US and Europe, we exclude Fitch from our research.

Our results show that ratings for non-US issuers are inflated relative to the ratings for US issuers. More specifically, when looking at the average difference in credit ratings between home and non-home issuers, we observe that the ratings of US (home) issuers assigned by Moody's and S&P are around 2 notches lower than the ratings of non-US (non-home) issuers with the same credit risk. We attribute the rating inflation for non-US issuers to the dominance of financial benefit over reputational cost in non-US markets. More specifically, the geographic shift in the rating coverage that Moody's and S&P have experienced over the past years suggests that future expected income in non-US markets is relatively high compared to the US market. In fact, over the past decades the increase in rating income from non-US markets has increased significantly[4]. Consequently, in the US market where the incremental financial income from issuing inflated ratings is relatively low, reputational capital will outweigh financial capital.

This paper adds to the policy and academic debate on home bias in many different ways. The recent apprehension that CRAs are too heavily centered on the US and the lack of empirical research on home bias for corporate issuers motivate the focus of our paper. The shift in geographical coverage that the Big Three CRAs have experienced over the past decades from 'only' rating issuers domiciled in the US to a broad geographical spread has not been seriously addressed. The analysis by Guttler and Wahrenburg (2007) is probably the closest to our research in that this is the most recent paper to empirically investigate home bias for corporate ratings. However, whereas their sample is restricted to issuers that are close to default, is limited to the period 1997-2004 and only includes 20%

[4] This needs to be further confirmed for S&P.

non-US issuers, we include all public rated issuers, our sample period covers 1990 until 2014 and includes 45% and 40% of non-US issuers for S&P and Moody's respectively. In addition, we are the first to explicitly compare the information value of credit ratings between home and non-home issuers using a credible PD model to control for the true credit risk. Our results indicate a clear difference between ratings of home and non-home issuers and suggest that rating inflation due to 'home bias' depends on the trade-off between reputational and financial capital.

The remainder of the paper is structured as follows. The related literature and research hypothesis are discussed in the next section. Section 3 describes the data and applied methodology. The main results are presented in section 4 and our findings are summarized in the final section.

2. Related literature and research hypothesis

2.1. Home bias literature

The academic research on the existence of 'home bias' in credit ratings is rather scarce and is mainly focused on sovereign ratings with the evidence so far being mixed (Beirne and Fratzscher, 2013; Soudis and van Hoorn, 2013; Fuchs and Gehring, 2017). By empirically modeling the link between sovereign credit ratings and economic fundamentals over the period 2000-2011, Beirne and Fratzscher (2013) show that changes in S&P's eurozone sovereign ratings are justified by the countries' own economic fundamentals. Furthermore they provide evidence that during the sovereign debt crisis the link between the market price of sovereign risk and ratings became much steeper. Assuming that ratings correctly reflect a country's fundamentals, a steeper sovereign price-rating link for eurozone countries than for non-eurozone countries suggests that markets 'overprice' the sovereign risk of eurozone countries. However, assuming that markets price fundamental risk accurately, this steeper relationship would imply that sovereign ratings for eurozone countries relative to non-eurozone countries were too favorable during the crisis. The latter stands in sharp contrast to the contention that CRAs have exacerbated the European sovereign debt crisis. While Fuchs and Gehring (2017) agree that most of the variation in sovereign ratings can be explained by economic and political fundamentals of the rated countries, they claim to have discovered evidence of 'home bias' in sovereign ratings assigned by 9 CRAs headquartered in 6 different countries. More specifically they find that the average CRA rates its home country one notch higher than justified by how it assesses other sovereigns. In a reaction to Fuchs and Gehring (2017), S&P issued a response criticizing the authors' methodology and disputing their findings. More specifically, they formally state that the CRA displays no 'home bias' and applies the same set of criteria to the 128 sovereigns it rates. Interestingly, Soudis and van Hoorn (2013) also documents the existence of 'home bias' in sovereign ratings. More specifically, for a sample of 76 countries rated by Moody's, S&P and Dagong, they find that for the period 2010 to 2012, Western high income countries received a rating on average one notch higher from both US agencies compared to the rating by Dagong, while other regions of the world received ratings from both US CRAs of up to three notches lower than the ratings by Dagong. As the authors observe that the two US based CRAs are consistent with one another, they cannot attribute their findings to random measurement errors. The authors conclude that ratings by Moody's and S&P are biased and do not represent a 'global' objective assessment of relative default probability. More specifically, they find that political proximity to the CRA's home country is an important driver of rating inflation.

Only a few academic papers exist on 'home bias' in corporate ratings and moreover the empirical evidence for these type of ratings is mixed (Nickell et al., 2000; Shin and Moore, 2003; Guttler and Wahrenburg, 2007; Cornaggia et al., 2014). Nickell et al. (2000) find evidence that for the period 1970-1997, Japanese obligors in higher rating grades were more likely to be downgraded by Moody's than their US counterparts, while lower-rated Japanese obligors were less likely to be upgraded. The authors argue that these findings can be explained by the fact that US CRAs behave more conservatively in markets that they are less familiar with and thus provide evidence that those agencies are biased towards their home market, the US. Shin and Moore (2003) document that ratings assigned by Moody's and S&P to a sample of 92 Japanese bond issuers, are systematically lower (i.e. worse) than those assigned by Japanese CRAs (i.e. R&I and JCR). However, despite clear differences in ratings between the American and Japanese CRAs, the rank correlations are relatively high (averaging about 0.80) and the assessment of relative creditworthiness is similar across the different CRAs. Furthermore, the authors do not find evidence that lower ratings assigned by Moody's and S&P are a consequence of dismissing the possible advantage of the unique features of Japanese corporate governance. Guttler and Wahrenburg (2007) further show that for a sample of publicly traded issuers that defaulted during the period 1997-2004, Moody's and S&P assigned more conservative ratings to US issuers than to non-US issuers and do not find any evidence of CRA's home preference. The authors attribute this finding to a better forecasting ability of CRAs in their home market, better financial statement quality in the US and to differences in regional bankruptcy legislation. Cornaggia et al. (2014) on the other hand, show that analysts who grew up in the same state as the issuer, ascribe significantly higher ratings (i.e. more faborable ratings) for a sample of municipal bonds issued by Moody's or S&P, compared to ratings from analysts who grew up outside the state. Consequently 'home bias' within the US can be observed. In particular, they show that the effect is driven by analysts states of origin, but not by where analysts reside at the time they produce ratings. Therefore, they are able to conclude that their results reflect favoritism by home analysts rather than superior information.

2.2. Research hypothesis

Credit Rating Agencies (CRAs) provide information about the credit risk of bond issues and issuers and the way the information is ultimately used in financial markets may affect the information production process. The Securities and Exchange Commission (SEC) has designated certain CRAs as Nationally Recognized Statistical Rating Organizations (NRSROs) and ratings provided by these agencies can be used for various regulatory purposes. In fact, investors will often only consider the ratings of NRSROs when making investment decisions. In reality, the SEC's action has actually facilitated the creation of an oligopoly in the CRA industry. There seems to be a consensus amongst policymakers and regulators that increasing competition would enhance credit rating quality (e.g the Credit Rating Agency Reform Act of 2006). Recent evidence suggests that this depends on the type of competition that enters the market. For example, Becker and Milbourn (2011) empirically show that during the period 1995-2006 increased competition from Fitch (i.e. issuer-paid CRA) coincides with a lower overall rating quality of Moody's and S&P issuer and bond ratings. On the other hand, Xia (2014) shows that after Egan-Jones Ratings Company (EJR) (i.e. an investor-paid CRA) came onto the market, the ratings quality of S&P's corporate issuer ratings improved. Rating quality is further impeded by 'rating shopping' behavior of issuers who shop around for the best rating. Bolton et al. (2012), for example, build a theoretical model that shows that the rating industry organized as a duopoly would generally be less efficient than a monopoly. Under a duopoly, issuers have more opportunities to shop for a good rating and thus only purchase the best rating, providing further incentives to CRAs to inflate their ratings.

In addition to the competitive environment and rating shopping, the conflict of interest inherent in the sell-side CRAs' business model also complicates the supply of meaningful ratings. Griffin and Tang (2012) show that one of the Big Three CRAs frequently made positive adjustments to its credit rating model estimation of CDOs. More specifically they document that the actual size of the AAA tranche exhibits a correlation of only 0.49 with the size from the CRA credit risk model and conclude that these positive adjustments cannot be explained by likely determinants such as credit enhancement. Moreover, Jiang et al. (2012) find that the adoption of the issuer-pay model results in inflated bond ratings. They document that S&P, after adopting the issuer-pay model, starts assigning better ratings in particular to bonds that are more prone to conflicts of interest (e.g. bonds that are likely to pay higher fees). Bonsall (2014) reinterprets the findings of Jiang et al. (2012) and shows that after adopting the issuer-pay model, CRAs actually become relatively more accurate and timely predictors of default. He observes that, as a consequence of the increased information flow between CRAs and bond issuers, bond ratings become more informative. The more 'optimistic' ratings observed by Jiang et al. (2012) are actually associated with stronger future financial performance and do not provide evidence of rating inflation. In any case, legislators' concerns are significant enough for the Dodd-Frank Act, which was installed in 2010, to require the SEC to study alternative CRA business models.

For a long time, credit rating agencies have argued against increased regulation and supervision, claiming that concerns for their reputation discipline their actions. To test this argument, Covitz and Harrison (2003) empirically investigate, for a sample of 1,200 bond issuers during the period January 1997 to August 2002 - of which 90% of the bonds were issued by firms domiciled in the US - whether conflicts of interest or rather reputational concerns affect the rating actions by Moody's and S&P. Their findings do indeed suggest that Moody's and S&P are primarily motivated by reputation-related incentives as they cannot find any evidence that rating changes are driven by the conflicts of interest proxies (e.g. size of issuer) they include in their model. Theoretical models of reputation also confirm the relationship between the quality of information production and the desirability of a positive reputation. For example, in their "cheap talk" framework, Goel and Thakor (2011) show that rating agency effort is increasing in the returns to reputation. However the value of reputation depends on economic fundamentals and varies across the business cycle. More specifically, as shown by Bar-Isaac and Shapiro (2013), rating quality is countercyclical and CRAs are more likely to issue less accurate ratings during a boom, i.e. when fee-income is high, competition in the labor market for analysts is tough, and default probabilities are lower (see also Bolton et al. (2012)).

CRAs thus face a trade-off between reputational and financial capital. To maximize their reputational capital, CRAs will aim to issue high-quality ratings that accurately reflect the true credit risk of an issuer. On the other hand, in order to maximize their financial capital, CRAs will issue a rating that is favorable to the issuer who ultimately pays the CRA. The incentive to inflate ratings is further augmented by issuers shopping for ratings. In equilibrium, an optimization between reputational and financial capital will take place.

In this paper we investigate whether the geographic shift to non-home countries that CRAs have made over the past decades has affected rating inflation. More specifically, we investigate whether we can find evidence of home bias, i.e. rating inflation for corporate issuers that are domiciled in the home country of the CRA.

On the one hand, taking into account that over the past decades the proportion of fee income from non-US issuers has increased substantially (Cfr. Table A.2), it could be argued that the financial capital outweighs the reputational capital for non-US issuers and thus rating inflation is expected for non-US issuers. More specifically, rating inflation can be used as a device to enter new markets and outbid competing CRAs. On the other hand, we expect inflated ratings in the home country of the CRA as the rating process might be subject to political pressure, the 'lobbying' activities of private actors and the self-interests of the agency staff (Fuchs and Gehring, 2017). In line with this argument, the SEC announced a new set of rules for tighter controls on the rating process and increased measures to prevent analysts from producing inflated ratings to increase sales (SEC, 2014). In addition to political pressure and the self-interests of the agency staff, it is possible that CRAs behave more conservatively towards the markets they are less familiar with, resulting in relatively 'inflated' ratings for the home issuers (Nickell et al., 2000; Shin and Moore, 2003; Cornaggia et al., 2014).

3. Data and methodology

3.1. Data and sample description

Our data set consists of corporate long-term issuer ratings for Moody's and S&P which we link to the probabilities of default (PDs) obtained from the Credit Research Initiative (CRI) under the Risk Management Institute (RMI) at the National University of Singapore (NUS). In December 2014, the CRI has provided daily updates of term structures (i.e. PD in 1, 3, 6, 12, 24, 36 and 60 months) of PDs for over 32,000 exchange-listed firms in 106 economies located in the Asia-Pacific Region, Europe, the US, the Middle East, Latin America and Africa. Furthermore, historical time series of PDs for delisted firms are available resulting in a sample of PDs for over 60,000 listed firms since December 1990. The term structure of PDs is estimated using a forward intensity model developed by Duan et al. (2012). The forward intensity functions used to generate the RMI PDs are exponential linear functions of some state variables (i.e. 2 macroeconomic factors and 10 firm-specific attributes) where the coefficients depend on the forward starting time. A description of the state variables used can be found in Table A.3. The CRI model's parameters are re-calibrated monthly and the inputs to the functions are updated on a daily basis[5].

[5] In this study we use the monthly PD values calculated using the calibration parameters of December 2014. For more details on the model implementation, please refer to the NUS-RMI Credit Research Initiative Technical Report. Version: 2014, Update 1 (http://d.rmicri.org/static/pdf/2014update1.pdf).

Our sample covers the period December 1990 to December 2014 and includes the monthly observations of long-term issuer ratings of listed companies from Moody's Investor services and Standard & Poor's which are retrieved via Bloomberg. Following the earlier literature, a numerical value is assigned to each rating on a 17-grade rating scale as follows: AAA/Aaa = 1, AA+/Aa1 = 2, ..., CCC/Caa1 and lower = 17. Table A.1 shows that in December 1990, most of the corporate issuers rated by Moody's and S&P were US domiciled. More specifically, for S&P and Moody's, 98% and 96% of the corporate issuers rated were domiciled in the US. From 1991 onwards we gradually observe a geographic shift with, in December 2014, for S&P and Moody's respectively 48% and 44% of the rated corporate issuers domiciled in the US. In total, the sample of S&P and Moody's includes 5,112 and 3,092 firms located in 72 and 63 countries respectively. In the total sample, around 55% and 60 % of the corporate issuers for S&P and Moody's respectively are domiciled in the US (Cfr. Table A.4).

3.2. Methodology

To examine the existence of 'home bias' for Moody's and S&P, we identify the average variation in credit ratings between the US and other regions for a given default rate. Earlier studies, including Cheng and Neamtiu (2009) and Becker and Milbourn (2011) examine the correlation between credit ratings and defaults as a measure of ratings' responsiveness to credit risk. While corporate default events are limited for the non-US regions, the power of this regression would be limited. Thus, following Xia (2014) and Baghai et al. (2014) we rely on predicted defaults rather than on realized defaults. In particular, we rely on the firm-specific 1-year

RMI-CRI PDs[6]. These RMI-CRI PDs are estimated using a forward intensity model developed by Duan et al. (2012) that produces a term structure of PDs from 1 month up until 5 years.

Following Alp (2013) we estimate an ordered probit model where we model ratings as a function of the firm's log PDs (as an indicator of the company's credit risk profile) and a home country dummy that equals one if the issuer is domiciled in the home country of the CRA. The regression model can be written as follows:

$$Rating_{i,t} = \begin{cases} 17 & \text{if } Z_{i,t} \in [\mu_{16}, +\infty[\\ 16 & \text{if } Z_{i,t} \in [\mu_{15}, \mu_{16}] \\ \vdots & \\ 2 & \text{if } Z_{i,t} \in [\mu_1, \mu_2] \\ 1 & \text{if } Z_{i,t} \in]-\infty, \mu_1] \end{cases} \tag{1}$$

$$Z_{i,t} = \beta_0 + \beta_1 PD_{i,t} + \beta_2 HomeD_i + \alpha_T + \varepsilon_{i,t} \tag{2}$$

With $Rating_{i,t}$ denotes the long-term issuer rating of firm i at the end of month t, β_0 is the intercept, $PD_{i,t}$ is the natural logarithm of the probability of default and $HomeD_i$ is a dummy variable which equals 1 when the issuer of the rating is domiciled in the US, and α_T are year dummies. $Z_{i,t}$ is the latent variable linking firm characteristics to the rating categories $Rating_{i,t}$ according to partition points μ_i. As the PD consists of both firmspecific and macrospecific variables other

[6]Because the PDs are very small numbers that range over many orders of magnitude, we transform them into log PDs to make the data more concentrated.

control variables are not included. To assess the economic importance of this home dummy variable, following Alp (2013), we divide the home country dummy coefficient by the average distance between the rating categories μ_i. Doing so gives us the average number of rating notches that home issuers are rated better or worse relative to the non-home issuers, ceteris paribus[7].

Subsequently, in the second part of our analysis, we estimate the average log PD per rating grade and test if there is a difference in credit risk between home and non-home issuers that receive the same rating. To statistically test this difference, we make use of a two-sided t-test for difference in means. Relying on the central limit theorem, this parametric test can be used because our number of observations per rating grade is sufficiently large to make the assumption that the arithmetic mean is approximately normally distributed. After comparing the average log PD per rating grade between home and non-home issuers, we create our own credit risk categories. Doing so allows us to assess what the difference in average log PD between home and non-home issuers implies about a firm's credit quality. More specifically, we divide our ranked monthly log PDs per CRA into seventeen equal parts[8]. The estimated parts are used to categorize the average log PD per rating grade in one of the seventeen buckets. For example, if the average log PD is smaller than the third part value but larger than the second part value, it will be classified in the third category. In that way, we are able to transform the average log PD per rating grade into one of the seventeen parts.

[7]To get this average number of differences in rating notches, we assume the distance between the rating notches to be equal.

[8]This is as much categories as the ratings.

4. Empirical results

Figures B.1 reports the summary statistics of the long-term corporate issuer ratings and the 1-year log PDs for Moody's and S&P for the different regions. In the perfect case of no home bias we should be able to observe a positive relationship between the average log PD and the average rating for the different regions. This implies the worse the rating, the higher the probability of default. Overall, we observe the lowest average default rates for the US and Canada, while for the other regions a higher average default rate is observed. Also, we observe a higher (i.e. worse) average rating together with this lower 1-year average log PD for issuers from the US and Canada than for non-US issuers located in the Asia-Pacific Region, Europe and the Middle East. For Moody's we also observe this 'inverse home bias' relationship for Africa. Therefore, this first data screen suggests that the ratings of US issuers are not inflated relative to non-US issuers for the specific regions for Moody's and S&P.

As these summary statistics are naturally informal in that the ratings are ordinal in nature, we proceed with estimating an ordered probit model where we can assess the average number of rating notches that home issuers are rated better or worse relative to the non-home issuers for a given log PD. Table A.6 confirms previous findings and shows that in addition to the log PD, the home country dummy is in general statistically significant. The positive sign of the log PD implies that an issuer with a higher probability of default, ceteris paribus, will receive a higher (i.e. worse) rating. The positive sign of the home country dummy implies that an issuer rated in the home country of the CRA, ceteris paribus, will on average receive a worse rating, which is in line with previous results. To assess the economic importance of these results, we estimate the difference in credit ratings between home and non-home issuers by dividing the dummy coefficient with the average distance between the rating categories[9]. The results indicate that home issuers rated by S&P and Moody's, on average receive a rating which is around 2 notches worse than that for non-US issuers with the same log PD. For S&P the 'inverse home bias' is most pronounced for Europe while for Moody's it is most pronounced for the Middle East region with a difference of more than 4 notches.

After identifying the average variation in credit ratings between home and non-home issuers for a given log PD we subsequently compare the probability of default per rating grade between home and non-home issuers. In particular, Table A.7 presents the *t*-test for differences in the 1-year average log PD per rating grade between US and non-US issuers for the different regions. If ratings are a good rank measure of credit risk, we should observe that the better-rated firms[10] have a lower log PD. Interestingly we observe that Moody's rated US and non-US issuers in the AAA-rating grade have a higher average log PD relative to the issuers in the AA+ rating grade. This suggests that ratings by Moody's are inflated towards the AAA-rating grade. In line with Kisgen and Strahan (2010), Ellul et al. (2011) and Opp et al. (2013), we attribute this finding of rating inflation for the AAA category to the regulatory advantage that is typically quite significant for this rating grade. However, contrary to previous studies (Cfr. Kisgen and

[9]The following example clarifies our calculation. For S&P, the average rating notch distance is $(\mu_{16}$ - $\mu_1)/15 = 0.6504$. The dummy coefficient for home is 1.1998. Hence the US-domiciled issuers are on average rated 1.8447 notches worse than non-home issuers.

[10]Recall that in our case, firms with a better rating have been assigned a lower numerical value.

Strahan (2010) and Ellul et al. (2011)) we do not observe this rating inflation due to regulatory advantage at the investment grade/junk threshold.

Looking at the difference in average log PD per rating grade between home and non-home issuers, for most rating grades we observe a statistically lower average log PD for US issuers than for non-US issuers[11]. Studying the different regions, in most cases the 'inverse home bias' relationship can be observed. While previously on average, no difference between credit ratings for US issuers and issuers from Canada was observed, we find an alternation between 'home bias' and the 'inverse home bias' for different rating grades[12].

To provide some further insight in what the difference in average log PD between home and non-home issuers tells us about a firm's credit quality we introduce our own estimated credit risk categories. Using the estimated part values for each CRA (Cfr. Table A.8), we classify the average log PD per rating grade into one of the seventeen buckets[13]. The categories are designed in the same way as the numerical value of the ratings (i.e. the higher the categorical value, the higher the probability of default). Graphs B.2 and B.3 display, the classification for each average log PD per rating grade for S&P and Moody's. To have a per-

[11] It should be noted that as of the B+/B3 rating grade we no longer observe this and for the lower rating grades we can actually observe a higher average log PD for US issuers compared to non-US issuers with the same rating. While the difference in PD is rather trivial, it does suggest that there is some rating inflation for US issuers compared to non-US issuers and thus some degree of home bias at the lowest end of the rating distribution.

[12] For S&P, we find 'home bias' at the AAA, AA+, A- rating grades, from BBB+ to BB and from B+ until CCC rating grades. All the other rating grades show the 'inverse home bias'. For Moody's, we observe 'home bias' at the A2 until Baa2 rating grade and at the Ba1, B1 and B3 rating grades. All the other rating grades represent the 'inverse home bias'.

[13] E.g. the S&P 12-month average log PD for US issuers in the AA+ rating category equals -9.47. This value is smaller than the third part value (i.e. -9.22) but larger than the second part value (-10.04). We thus classify the average log PD for US issuers rated AA+ in the third category.

fect relationship between credit ratings and our own log PD categories we should observe a positive 45° line. Only for the US issuers from S&P (Cfr. Graph B.2) we observe this, although not perfectly, positive relationship between the credit ratings and our own credit risk categories. For the other regions, especially Europe, Asia-Pacific and the Middle East we do not observe this positive relationship and we find inflated ratings, especially at the lower end of the distribution. For Canada and Africa we also observe a positive relationship between credit ratings and our average credit rating categories. While the categories lie below or above the US rating categories, on average no home bias can be observed. For Moody's US issuers we almost observe the 45° line with an exception at the AAA-rating grade, where the ratings are inflated (Cfr. Graph B.3). For Europe, Asia-Pacific and the Middle East region we observe inflated ratings at the lower end of the distribution. We also observe inflated ratings relative to the ratings given by US firms.

All the above results indicate inflated ratings for non-home issuers, especially in Europe, Asia-Pacific and the Middle East, suggesting an 'inverse home bias'. Knowing that for our sample period the proportion of fee income from non-US issuers has increased substantially, this 'inverse home bias' is likely to be driven by the dominance of financial capital over reputational capital for non-US issuers.

5. Conclusion

This paper explores the existence of 'home bias' in corporate credit ratings of Moody's and S&P. More specifically, by comparing the information value of credit ratings between home and non-home issuers using the probability of default, we investigate whether we can find evidence of rating inflation for corporate issuers that are domiciled in the home country of the CRA. Our results indicate that for both CRAs, the ratings for non-US issuers are inflated relative to the ratings of US issuers, especially in Europe, Asia-Pacific and the Middle East. We attribute this finding of rating inflation for non-US issuers to the dominance of financial capital over reputational capital in the non-US markets. More specifically, taking into account that over the past decades the proportion of fee income from non-US issuers has increased substantially, it could be argued that the financial capital outweighs the reputational capital for non-US issuers and rating inflation is used by CRAs as a way to gain market share in non-US markets.

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Appendix A. Tables

Table A.1: The regional coverage of listed corporate LT issuer ratings in percentage

Year	S&P sample US	Moody's sample US	Fitch sample US
1990	98.09%	95.65%	84.75%
1991	94.04%	91.70%	73.33%
1992	91.19%	89.13%	70.33%
1993	87.15%	86.50%	68.47%
1994	85.19%	87.87%	70.77%
1995	77.43%	66.85%	69.48%
1996	74.06%	64.77%	67.54%
1997	71.99%	64.74%	63.98%
1998	73.08%	63.46%	63.61%
1999	71.19%	73.19%	62.37%
2000	66.89%	69.59%	59.39%
2001	63.39%	65.29%	58.65%
2002	61.03%	62.96%	55.57%
2003	55.18%	62.03%	52.95%
2004	52.91%	60.44%	52.42%
2005	52.21%	58.92%	48.20%
2006	50.84%	47.59%	44.23%
2007	51.06%	46.14%	42.10%
2008	48.96%	45.03%	39.97%
2009	48.11%	45.78%	38.91%
2010	50.05%	46.69%	41.48%
2011	49.80%	45.91%	40.97%
2012	49.55%	45.81%	41.09%
2013	48.93%	44.69%	40.66%
2014	47.97%	44.40%	40.39%

This table shows the regional coverage of the samples of Moody's, S&P and Fitch per year. The percentage of the US sample is shown.

[14] Please refer to the NUS-RMI Credit Research Initiative Technical Report for more details on the computation of the DTD. Version 2014, Update 1(http://d.rmicri.org/static/pdf/2014update1.pdf).

Table A.2: Fee income per region

	Moody's			S&P	
Year	fee income US	fee income non-US	Year	fee income US	fee income non-US
1997	82.71%	17.29%	1997		
1998	80.37%	19.63%	1998		
1999	75.04%	24.96%	1999		
2000	71.21%	28.79%	2000		
2001	71.20%	28.80%	2001		
2002	68.23%	31.77%	2002		
2003	65.23%	34.62%	2003		
2004	64.84%	35.16%	2004		
2005	64.21%	35.79%	2005		
2006	64.14%	35.86%	2006		
2007	61.54%	38.46%	2007		
2008	53.54%	46.46%	2008		
2009	54.46%	45.54%	2009	51.98%	48.02%
2010	58.04%	41.96%	2010	54.22%	45.78%
2011	56.03%	43.97%	2011	51.50%	48.50%
2012	58.98%	41.02%	2012	54.18%	45.82%
2013	58.73%	41.27%	2013	53.39%	46.61%
2014	59.18%	40.82%	2013	53.16%	46.84%
2015	63.16%	36.84%	2013	57.25%	42.75%

This table represents the fee income for Moody's investor's Services and S&P ratings. We make a distinction between the regional and non-regional fee income. For S&P the details in the annual reports only go back until the year 2009.

Table A.3: Covariates used to estimate the forward intensity model

Variable	Description
IR	Stock index return
STiR	Three month short term interest rate representative for the economy
$\text{DTD}_{\text{level}}$	Level of distance to default
$\text{DTD}_{\text{trend}}$	Trend of distance to default
$\text{CASH/TA}_{\text{level}}$	Level of cash and short term investments divided by total assets
$\text{CASH/TA}_{\text{trend}}$	Trend of cash and short term investments divided by total assets
$\text{NI/TA}_{\text{level}}$	Level of net income divided by total assets
$\text{NI/TA}_{\text{trend}}$	Trend of net income divided by total assets
$\text{SIZE}_{\text{level}}$	Level of the log of firm's market capitalization divided by the economy's median market capitalization
$\text{SIZE}_{\text{trend}}$	Trend of the log of firm's market capitalization divided by the economy's median market capitalization
M/B	Market to book ratio
Sigma	a 1 year idiosyncratic volatility measure

This table represents the covariates that are used to estimate the PD using the forward intensity model. The subscript 'level' denotes the average in the previous year, 'trend' denotes the difference between current value and its previous 12-month average. The stock index return is the trailing one-year simple return on a major stock index of the economy (e.g. S&P 500 index for the US). The firm's distance to default is a volatility adjusted leverage measure based on Merton (1974). As financial firms are normally excluded when estimating the DTD, the standard DTD computation must be extended to give meaningful estimates for financial firms as well[14]. The market to book ratio is defined as the current value of market capitalization and total liabilities divided by total assets. Sigma is computed by regressing the daily returns of the firm's market capitalization against the daily returns of the economy's stock index, for the previous 250 days. Sigma is defined as the standard deviation of the residuals from the regression.

Table A.4: Observations per country per CRA

Asia-Pacific Region	S&P		Moody's	
Country	Firms	Obs.	Firms	Obs.
Australia	109	11,524	37	4,341
Bangladesh	3	75	1	25
China	17	553	0	0
Hong Kong	123	8,814	76	3,717
India	34	2,732	19	1,896
Indonesia	44	3,181	6	321
Japan	439	40,503	263	33,686
Kazakhstan	7	381	6	206
Malaysia	18	2,186	3	386
New Zealand	11	935	2	109
Pakistan	2	118	1	90
Philippines	18	1,655	9	790
Singapore	32	2,694	17	1,086
South Korea	41	4,386	21	2,419
Sri Lanka	4	171	1	33
Taiwan	40	3,495	2	150
Thailand	27	3,261	17	811
Vietnam	5	177	0	0

Latin-America	S&P		Moody's	
Country	Firms	Obs.	Firms	Obs.
Argentina	16	1,682	9	787
Brazil	75	5,947	64	3,557
Chile	29	3,442	15	1,394
Colombia	9	51	7	253
Jamaica	1	65	0	0
Mexico	32	3,025	22	1,886
Peru	8	505	4	103

Middle East	S&P		Moody's	
Country	Firms	Obs.	Firms	Obs.
Bahrain	4	152	1	83
Israel	7	1,009	1	124
Jordan	5	224	0	0
Kuwait	12	1,234	3	237
Oman	2	68	0	0
Saudi Arabia	15	1,555	1	96
Turkey	16	1,257	14	454
UAE	19	939	11	683

North America	S&P		Moody's	
Country	Firms	Obs.	Firms	Obs.
Canada	254	23,089	138	12,431
United States	2,806	303,852	1,849	196,487

Africa	S&P		Moody's	
Country	Firms	Obs.	Firms	Obs.
Egypt	3	153	0	0
Morocco	3	361	1	14
Nigeria	10	498	0	0
South Africa	11	1,143	2	48
Tunisia	8	653	0	0

Europe	S&P		Moody's	
Country	Firms	Obs.	Firms	Obs.
Austria	15	1650	12	1212
Belgium	9	1116	6	629
Bulgaria	2	82	1	98
Croatia	1	94	1	28
Cyprus	2	83	2	141
Czech Republic	5	488	1	100
Denmark	8	759	7	855
Estonia	2	44	1	63
Finland	15	1,641	11	1,404
France	108	13,267	68	7,495
Germany	104	10,184	53	6,096
Greece	17	1,791	10	960
Hungary	4	373	1	115
Iceland	1	31	4	265
Ireland	11	1,128	4	574
Italy	72	6,864	39	3,762
Latvia	1	24	0	0
Malta	0	0	1	59
Lithuania	3	141	1	27
Luxembourg	5	339	4	83
Netherlands	33	3,578	26	2,530
Norway	15	1,436	21	2,017
Poland	18	1,434	2	90
Portugal	13	1,334	9	1,029
Romania	2	103	1	22
Russian Federation	35	1,237	11	453
Slovakia	1	38	0	0
Slovenia	5	222	1	40
Spain	39	4,080	22	2,166
Sweden	35	4,480	18	2,336
Switzerland	37	4,025	7	799
Ukraine	2	57	4	220
United Kingdom	173	17,499	120	12,640

Total	S&P		Moody's	
	Firms	Obs.	Firms	Obs.
Full sample	5,112	517,826	3,092	317,011

This table reports the number of firms per country for S&P and Moody's included in the study. The corresponding firm-month observations are reported as well.

Table A.5: Firm observations per year per CRA for home and non-home issuers

	S&P															
	US		Canada		Europe		Asia-Pacific		Africa		Middle East		Latin America		Total	
	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.
1990	427	427	0	0	4	4	0	0	0	0	0	0	0	0	431	431
1991	460	5,307	6	63	13	89	2	8	0	0	0	0	0	0	481	5,467
1992	521	5,870	11	95	20	184	9	71	0	0	0	0	0	0	561	6,220
1993	598	6,640	21	191	30	290	16	158	0	0	0	0	0	0	665	7,279
1994	682	7,661	26	268	47	434	54	345	0	0	0	0	0	0	809	8,708
1995	773	8,608	35	322	65	680	90	921	0	0	0	0	0	0	963	10,531
1996	933	10,084	47	467	100	1,007	130	1,243	0	0	0	0	17	136	1,227	12,937
1997	1,149	12,350	57	622	163	1,493	227	2,210	4	27	5	46	26	257	1,631	17,005
1998	1,360	14,776	71	687	197	2,034	284	2,997	5	50	7	66	37	392	1,961	21,002
1999	1,449	15,618	79	812	255	2,576	355	3,655	5	60	8	82	41	471	2,192	23,274
2000	1,431	15,468	88	864	348	3,448	405	4,522	5	52	8	96	51	560	2,336	25,010
2001	1,367	15,097	118	1,198	382	4,063	430	4,739	11	69	8	96	55	613	2,371	25,875
2002	1,306	14,631	115	1,279	404	4,352	441	5,009	11	132	13	143	51	577	2,341	26,123
2003	1,292	14,553	112	1,277	409	4,526	528	5,123	11	132	18	176	52	580	2,422	26,367
2004	1,316	14,834	116	1,322	413	4,642	515	5,836	13	132	22	237	56	620	2,451	27,623
2005	1,334	14,852	119	1,349	422	4,778	532	5,997	12	131	27	304	60	627	2,506	28,038
2006	1,332	14,780	118	1,326	443	4,979	539	6,075	12	134	33	371	66	753	2,543	28,418
2007	1,286	14,438	118	1,311	440	5,091	441	4,928	17	179	34	403	80	874	2,416	27,224
2008	1,232	14,000	107	1,231	441	5,013	450	5,099	19	219	48	521	90	1,015	2,387	27,098
2009	1,180	13,466	106	1,203	430	4,867	438	4,446	22	238	51	566	93	1,035	2,320	25,821
2010	1,210	13,637	111	1,257	426	4,932	387	4,284	21	243	54	611	102	1,148	2,311	26,112
2011	1,233	13,975	122	1,371	435	5,017	404	4,580	22	251	55	593	116	1,262	2,387	27,049
2012	1,232	14,083	132	1,467	438	5,044	412	4,639	22	251	59	639	121	1,359	2,416	27,482
2013	1,250	14,291	133	1,555	437	5,043	434	4,945	23	248	64	741	126	1,450	2,467	28,273
2014	1,267	14,406	138	1,552	451	5,036	438	5,011	23	260	68	747	126	1,447	2,511	28,459
	Moody's															
	US		Canada		Europe		Asia-Pacific		Africa		Middle East		Latin America		Total	
	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.	Firms	Obs.
1990	320	320	0	0	9	9	0	0	0	0	0	0	0	0	329	329
1991	350	3,962	9	91	21	181	2	8	0	0	0	0	0	0	382	4,242
1992	384	4,300	13	131	29	299	45	306	0	0	0	0	0	0	471	5,036
1993	446	4,867	20	208	37	412	103	923	0	0	0	0	0	0	606	6,410
1994	514	5,690	23	260	46	514	177	1,725	0	0	0	0	0	0	760	8,189
1995	580	6,436	31	291	53	609	196	2,214	0	0	0	0	0	0	860	9,550
1996	665	7,280	35	385	75	772	206	2,335	0	0	0	0	10	75	991	10,847
1997	788	8,399	45	496	89	913	218	2,468	0	0	0	0	13	135	1,153	12,411
1998	889	9,445	52	510	108	1,097	226	2,583	0	0	0	0	18	186	1,293	13,821
1999	875	9,531	57	575	129	1,310	231	2,634	0	0	0	0	19	213	1,311	14,263
2000	823	9,119	58	602	166	1,669	231	2,698	0	0	1	6	21	232	1,300	14,326
2001	819	8,881	55	593	197	2,066	232	2,630	0	0	2	22	23	253	1,328	14,445
2002	776	8,759	52	562	215	2,336	230	2,613	0	0	3	34	24	270	1,300	14,574
2003	792	8,866	52	591	239	2,603	224	2,522	1	4	3	36	27	267	1,338	14,889
2004	794	8,970	60	675	248	2,747	215	2,432	1	12	3	36	31	326	1,352	15,198
2005	810	9,082	62	720	252	2,856	214	2,358	1	3	3	25	33	359	1,375	15,403
2006	809	8,917	59	630	256	2,879	205	2,287	0	0	3	27	37	369	1,369	15,109
2007	781	8,876	52	568	259	2,954	224	2,390	0	0	3	36	38	405	1,357	15,229
2008	753	8,662	46	544	259	2,927	217	2,346	0	0	11	127	40	435	1,326	15,041
2009	746	8,494	49	543	261	2,967	187	1,956	0	0	11	132	42	445	1,296	14,537
2010	792	8,848	49	549	268	3,084	179	1,943	0	0	15	150	50	525	1,353	15,099
2011	818	9,314	57	631	277	3,205	197	2,192	0	0	18	183	66	706	1,433	16,231
2012	840	9,552	68	714	282	3,288	195	2,102	1	7	22	235	79	821	1,487	16,719
2013	862	9,890	66	761	287	3,301	195	2,199	2	14	28	307	88	972	1,528	17,444
2014	868	10,027	69	801	289	3,310	192	2,202	2	22	27	321	87	986	1,534	17,669

This table reports the number of companies with the corresponding firm-month observations included in the sample per year per CRA per region.

Table A.6: Ordered logit models

	Standard & Poor's						
	US vs Canada	US vs Europe	US vs AP	US vs AFR	US vs Middle East	US vs LA	US vs all
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
LogPD	0.4468***	0.4244***	0.4347***	0.4601***	0.4575***	0.4569***	0.3860***
	(0.0141)	(0.0134)	(0.0121)	(0.0142)	(0.0141)	(0.0139)	(0.0113)
HomeD	0.1729	1.8869***	1.2217***	0.3196	1.5361***	0.0678	1.1998***
	(0.1358)	(0.0851)	(0.0767)	(0.2145)	(0.1887)	(0.1279)	(0.058)
Economic value	0.2585	2.801	1.8185	0.4711	2.2627	0.1009	1.8447
Obs.	326,941	383,474	390,693	306,660	310,290	319,028	517,826
Firms	3,060	3,599	3,780	2,841	2,886	2,976	5,112
	Moody's						
	US vs Canada	US vs Europe	US vs AP	US vs AFR	US vs Middle East	US vs LA	US vs all
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
LogPD	0.4258***	0.3821***	0.4162***	0.4357***	0.4359***	0.4284***	0.3470***
	(0.0190)	(0.0173)	(0.0167)	(0.0191)	(0.0190)	(0.0187)	(0.0149)
HomeD	-0.0419	2.0028***	1.1158***	2.332	2.4213***	-0.0161	1.1801***
	(0.1803)	(0.1126)	(0.1004)	(1.5449)	(0.31202)	(0.1541)	(0.0750)
Economic value	-0.0717	3.3583	1.8655	3.9721	4.1149	-0.0274	1.9983
Obs.	208918	244,795	246,553	196,549	198,164	204,467	317,011
Firms	1,987	2,318	2,330	1,852	1,880	1,970	3,092

This table reports the estimated coefficients of the ordered probit models with the ratings as dependent variable and the 1-year log PD and home dummy as explanatory variables. Standard errors are between brackets.
AP = Asia-Pacific; AFR = Africa and LA = Latin-America.
The economic values are calculated as the dummy coefficient divided by the average notch length per model.
*** Significance at 1%, ** Significance at 5%, * Significance at 10%.

Table A.7: 1-year average log PD per rating grade with the corresponding t-test

S&P	US	Canada	t-test	Europe	t-test	AP	t-test	AFR	t-test	Middle East	t-test	LA	t-test	Non-US	t-test
AAA	-10.30	-11.10	3.75	-6.89	-33.14	-7.63	-21.81	/	/	/	/	/	/	-7.60	-31.63
AA+	-9.47	-11.08	3.12	-7.28	-19.59	-6.81	-20.15	/	/	/	/	/	/	-7.18	-24.50
AA	-9.44	-9.22	-1.15	-6.89	-44.72	-8.16	-19.02	/	/	/	/	/	/	-7.50	-37.82
AA-	-8.85	-6.31	-21.63	-6.47	-54.01	-8.22	-11.65	/	/	-7.53	-5.45	-7.66	-1.55	-7.14	-44.60
A+	-8.79	-7.16	-17.34	-6.97	-47.53	-7.89	-18.59	/	/	-7.46	-9.35	-6.25	-7.28	-7.33	-45.87
A	-8.54	-8.13	-5.27	-6.64	-63.80	-7.22	-39.22	-7.82	-2.83	-6.93	-15.49	-6.51	-14.05	-6.98	-67.21
A-	-8.29	-9.06	12.90	-6.93	-49.70	-7.77	-17.51	-7.53	-3.33	-6.83	-16.53	-8.18	-1.12	-7.50	-36.05
BBB+	-8.27	-8.99	13.12	-7.04	-46.66	-7.47	-28.41	-7.61	-1.89	-6.96	-14.87	-8.23	-0.64	-7.48	-39.50
BBB	-8.01	-8.66	14.17	-6.97	-40.45	-6.98	-43.18	-6.06	-18.50	-6.59	-19.99	-7.14	-14.51	-7.15	-48.65
BBB-	-7.53	-7.66	2.99	-6.88	-20.12	-6.49	-40.35	-6.45	-7.63	-6.23	-11.66	-6.99	-12.14	-6.81	-38.45
BB+	-7.19	-7.44	4.44	-6.81	-9.30	-6.37	-23.34	-6.11	-8.59	-6.90	-2.25	-6.46	-11.90	-6.68	-21.39
BB	-6.87	-7.22	6.47	-6.38	-13.63	-5.78	-40.68	-6.19	-8.11	-6.24	-7.61	-6.06	-18.01	-6.14	-37.73
BB-	-6.47	-6.34	-2.73	-6.25	-5.91	-5.82	-17.82	-5.98	-4.18	-6.15	-3.33	-5.82	-12.97	-6.06	-19.19
B+	-5.92	-6.34	8.19	-6.27	8.29	-5.70	-6.52	-5.85	-0.62	-6.20	2.19	-5.73	-2.90	-5.98	2.73
B	-5.45	-5.77	5.66	-5.90	8.85	-5.10	-10.92	-5.18	-2.50	-5.49	0.22	-6.01	8.82	-5.47	0.86
B-	-5.01	-5.09	1.01	-5.64	9.95	-5.01	-0.03	-5.80	2.37	-5.77	4.30	-5.60	8.07	-5.38	9.92
CCC+...	-3.72	-4.37	7.58	-4.88	15.63	-4.28	9.35	-5.31	2.60	-4.74	/	-5.42	24.13	-4.71	24.20
Moody's	US	Canada	t-test	Europe	t-test	AP	t-test	AFR	t-test	Middle East	t-test	LA	t-test	Non-US	t-test
Aaa	-9.23	-5.96	-8.17	-5.42	-17.65	-6.54	-8.91	/	/	/	/	/	/	-5.83	-20.85
Aa1	-9.67	-7.50	-11.47	-5.93	-44.02	-7.44	-20.23	/	/	/	/	/	/	-6.58	-37.67
Aa2	-8.86	-6.89	-12.55	-6.29	-31.83	-7.61	-12.42	/	/	-4.86	-6.64	-5.00	-2.51	-6.74	-30.66
Aa3	-9.09	-6.49	-15.04	-5.93	-54.96	-6.87	-29.19	/	/	-6.39	-7.81	-6.87	-7.03	-6.30	-57.99
A1	-8.64	-5.67	-18.79	-6.57	-49.75	-7.24	-26.57	/	/	-6.23	-12.93	-6.87	-3.65	-6.78	-53.65
A2	-8.61	-8.86	1.65	-6.60	-54.09	-7.05	-35.35	/	/	-6.64	-8.16	-8.02	-2.19	-6.86	-59.32
A3	-8.27	-9.56	14.12	-6.98	-37.14	-7.07	-33.67	-3.29	-10.21	-6.22	-10.09	-7.42	-3.15	-7.16	-41.65
Baa1	-8.20	-9.10	11.18	-7.07	-31.54	-6.81	-36.09	-7.52	-0.81	-6.59	-12.56	-7.12	-12.53	-7.13	-41.22
Baa2	-8.19	-8.19	0.06	-7.09	-32.19	-6.21	-62.46	/	/	-5.99	-13.93	-7.47	-9.50	-6.92	-56.89
Baa3	-7.71	-7.66	-0.88	-6.69	-24.75	-6.13	-54.14	-7.49	-0.31	-7.32	-1.91	-7.00	-9.57	-6.54	-51.29
Ba1	-7.17	-7.47	3.94	-6.49	-12.45	-5.94	-29.27	-7.11	-0.11	-5.94	-8.44	-6.50	-8.36	-6.34	-26.45
Ba2	-7.01	-6.75	-3.35	-6.52	-7.95	-6.11	-22.33	/	/	-5.83	-3.00	-6.14	-12.59	-6.27	-23.66
Ba3	-6.62	-6.36	-3.35	-6.13	-8.22	-5.57	-24.99	/	/	/	/	-6.36	-3.87	-5.94	-22.21
B1	-6.32	-7.05	9.09	-6.08	-4.04	-5.65	-14.15	/	/	-4.49	-1.89	-6.48	2.26	-6.13	-5.75
B2	-5.94	-5.48	-5.79	-5.38	-7.47	-5.13	-13.62	/	/	/	/	-5.55	-5.25	-5.35	-15.83
B3	-5.63	-6.15	6.28	-5.81	2.29	-5.46	-1.54	/	/	/	/	-6.04	3.03	-5.88	5.17
Caa3...	-4.78	-4.73	-0.53	-4.91	1.59	-4.72	-0.65	/	/	/	/	-5.27	4.82	-4.88	2.23

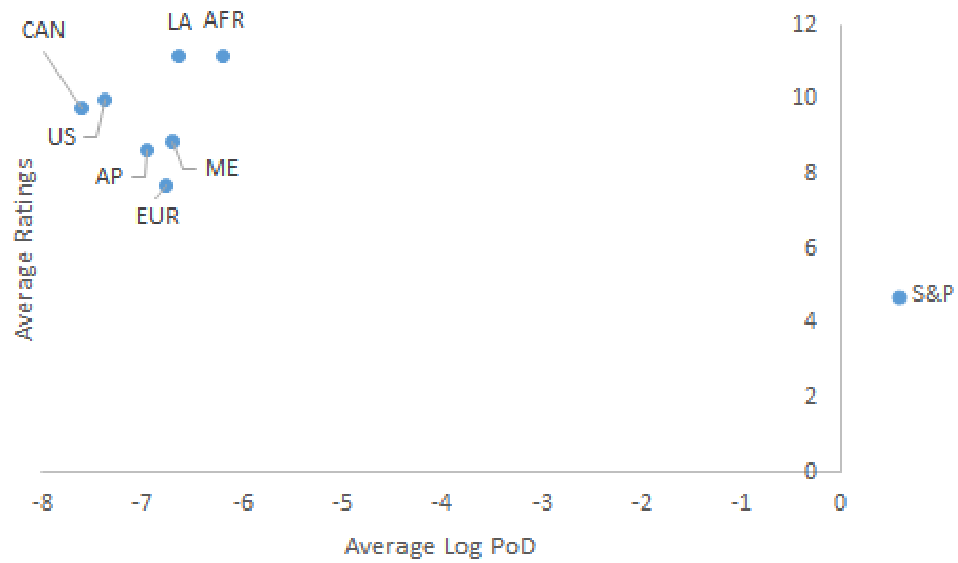
This table reports the average log PD per rating grade for the different regions. The t-statistic for the difference in average log PD between the US and the specified region is reported.
AP = Asia-Pacific, AFR= Africa, LA = Latin-America.

Table A.8: Upper bounds to estimate the 17 categories of credit risk

parts	Upper bounds	
	S&P	Moody's
1	-11.34	-11.43
2	-10.04	-10.12
3	-9.22	-9.30
4	-8.63	-8.70
5	-8.15	-8.21
6	-7.73	-7.78
7	-7.35	-7.40
8	-7.01	-7.05
9	-6.70	-6.72
10	-6.40	-6.41
11	-6.10	-6.10
12	-5.80	-5.78
13	-5.47	-5.45
14	-5.11	-5.09
15	-4.66	-4.64
16	-3.99	-3.96

This table reports the upper bounds we use to create our 17 categories of credit risk for S&P and Moody's.

Appendix B. Figures



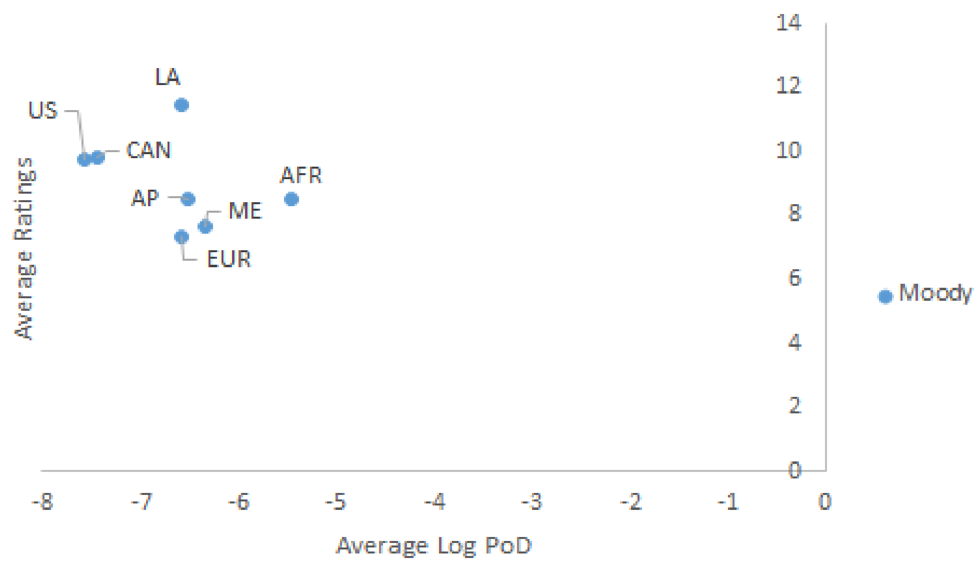
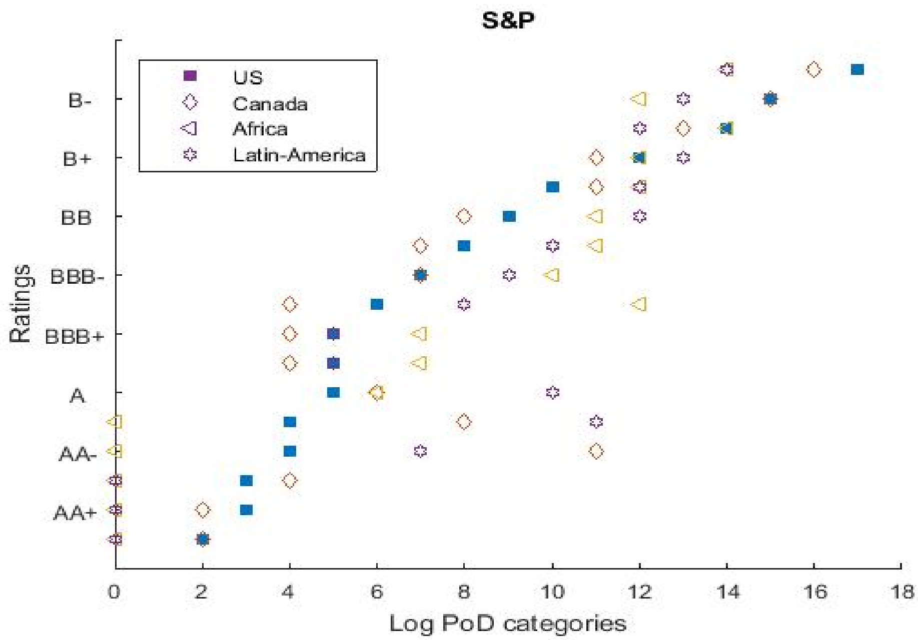


Figure B.1: Summary statistics
These figures represent the average rating with the corresponding average log PD for the different regions for Moody's and S&P.
LA = Latin-America; CAN = Canada; AP = Asia-Pacific Region; ME = Middle East; AFR = Africa and EUR = Europe.



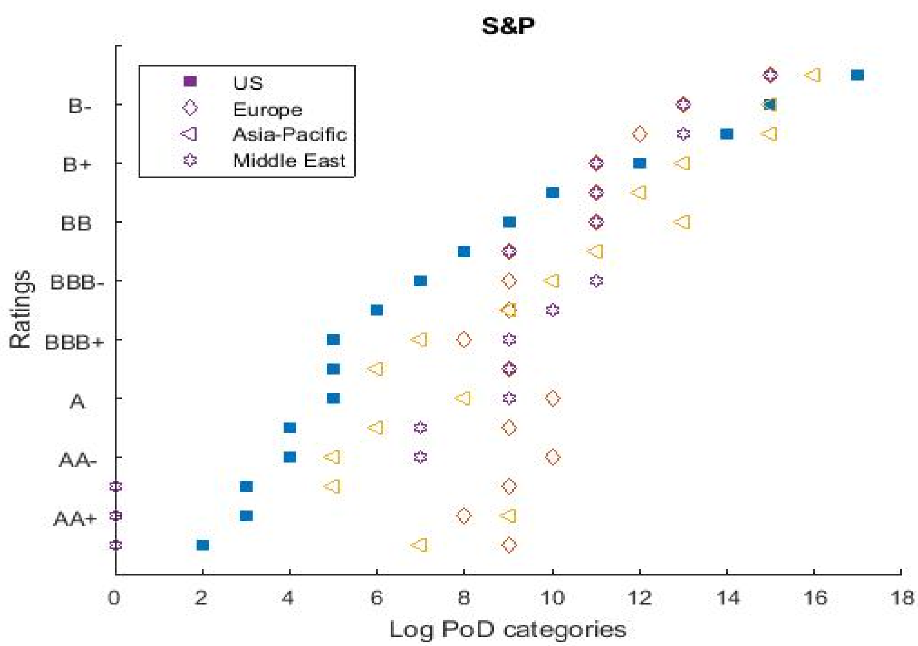


Figure B.2: S&P's corresponding implied risk category for each rating grade
These figures represent the corresponding implied risk category for each rating grade for the different regions by S&P.

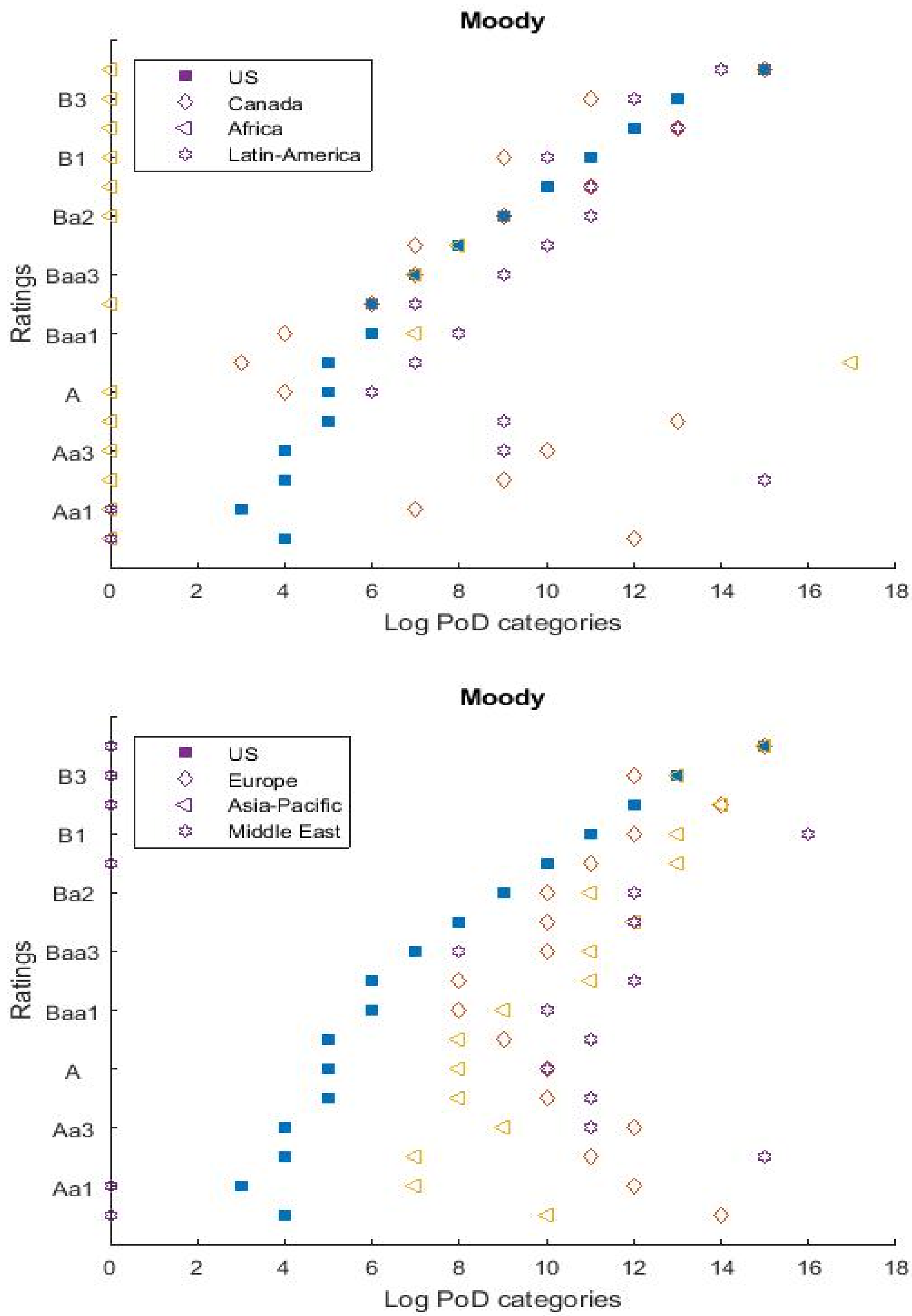


Figure B.3: Moody's corresponding implied risk category for each rating grade
These figures represent the corresponding implied risk category for each rating grade for the different regions by Moody's.