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Structural Shifts in Bank Credit Ratings

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Abstract

We investigate the time variation in credit rating standards awarded to financial institutions of commercial bank credit ratings awarded by the three principal CRAs from 1990 to 2015 in a world-wide context by testing for well-defined structural shifts. We focus on the part of the ratings that cannot be accounted using publicly available information. We test whether major financial events are conditioning, ex-post such changes Distinctively in this paper's timespan our analysis covers four periods: (i) before and (ii) after the 2001-2 corporate collapses, followed by (iii) before the global financial crisis and (iv) after the global financial crisis. We find substantial differences in the assignment of bank credit ratings among the three major agencies, Moody's, Fitch, and S&P. Agencies differ both in terms of re-adjustment of ratings but also on the speed of response to the evens. All three agencies tightened ratings during the 2008 crisis and kept reducing them in its aftermath.

Keywords: Ordered Logit, Credit Rating Agencies, Bank Ratings, Structural Breaks

JEL classification: C35, G21, G23

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1. Introduction

The ability of the three principal CRAs (i.e., Standard and Poor's, Moody's, and Fitch) to assess appropriately the risk of financial institutions came under increased scrutiny after the financial crisis of 2007/08. Many banks that failed during the crisis had enjoyed investment grade ratings immediately before they defaulted, and the situation was similar for the ratings of bank products. Many large institutions around the world bordered on collapse, and national governments were forced to implement massive bailout programs to prevent serious financial damage and ameliorate the subsequent economic downturns. The overall impression created was that the entire rating system was flawed. In line with this, the United States Financial Crisis Inquiry Commission (F.C.I.C.) reported in January 2011 that 'the three credit rating agencies were key enablers of the financial meltdown'.

Many banks that failed during the crisis had enjoyed investment grade ratings immediately before they defaulted, and the situation was similar for the ratings of bank products. Many large institutions around the world bordered on collapse, and national governments were forced to implement massive bailout programs to prevent serious financial damage and ameliorate the subsequent economic downturns. The overall impression created was that the entire rating system was flawed.

In the aftermath of the crisis credit rating agencies have been scrutinized for their reliability of their ratings. Ex-post they were found out to be overly optimistic and didn't accurately reflect the underlying risk in certain financial products. As a result, regulatory reforms have been introduced to enhance transparency and accountability in the credit rating industry.

In line with this, the United States Financial Crisis Inquiry Commission (F.C.I.C.) reported in January 2011 that 'the three credit rating agencies were key enablers of the financial meltdown'. In the European Union the response to the major deficiencies that were observed in the rating industry, the existing EU CRA framework was significantly tightened in the period 2009-2013.

The CRA regulation established a common regulatory approach in order to enhance the integrity, transparency, responsibility, good governance, independence of credit rating activities and competition in the rating industry. These rules gave the European Securities and

Market Authority (ESMA) sole, central supervision of CRAs, which can only operate if authorised by ESMA. The impact of such regulatory changes is analysed by Jones et. al (2022).

By and large the methodology employed by all CRAs is based on both quantitative analyses based of data and qualitative assessment (unobserved) to form anticipations for a variety of aspects affecting credit risk. These include e.g., financial, business, operational, legal, regulatory, ESG, climate, industry-specific, sovereign, as well as case-specific subjective factors.

Unlike the data analysis, the qualitative methodological part aims at incorporating expert views and market views in the process to forecast the likelihood of default, in complementing the purely data driven part of the analysis.

The analysis instigates an expert score produced by a team of rating analysts, which is subsequently subjected to notching adjustments reflecting the analyst views on the firm's resilience and ability to meet its obligations. The outcome of the qualitative analysis is the expert given credit scores that eventually combine with the data analysis to form the published rating.

All CRAs claim that methodology should not be received as a deterministic formula, but rather as a general multifactorial framework for the forward-looking assessment of institutional credit risk in a changing economic and financial environment, which can also be combined with additional information to address specialized issues.

The examination the ratings awarded by the CRA triggered, in the aftermath of the global financial crisis, research interest in their behaviour over time and two prominent studies by Alp (2013) and Baghai et al. (2014) provided empirical analysis. Both studies examined corporate ratings and reported, that could not detect an upwards bias in the ratings before the subsequent financial difficulties. These studies tested for the discrete changes over time on their chosen proxy for the part of the ratings that cannot be accounted by the data and concluded that rating standards were subsequently tightened.

At the same time the theoretical literature began to analyse the agency and incentive problems relating to the awards of bank credit ratings (Mathis et al., 2009; Bolton et al., 2012; Opp et al., 2013) to provide insight to the reliability of the ratings based on market structure and CRA behaviour up to the crisis.

To date literature on credit rating standards has focused, almost exclusively, on corporate credit ratings (Lucas and Lonski, 1992; Blume et al., 1998; Cheng and Neamtiu, 2009; Becker and Milbourn, 2011; in addition to the two studies mentioned above), the literature on modelling and predicting banking ratings is sparse.

Although it is apparent that the quality of bank credit ratings was important for the development of the global financial crisis of 2007-8, it was also relevant to the upheaval in the financial sector in the years that followed. Empirical analysis of the quality of bank rating standards before, during, and after the global financial crisis of 2007-8 can give valuable answers regarding the behaviour of the CRAs during this turbulent period.

The paper makes several contributions to the literature regarding the behaviour of Credit Rating Agencies. First, it is focused exclusively on commercial financial intermediaries' banks. Unlike non-financial corporations the balance sheets of financial firms are comparatively more complex. Although not universal, for a large number of banks their overall credit worthiness includes the valuation and liquidity of subprime RMBSs and RMBS-backed CDOs and multifaceted interdependencies affecting their mutual survival. The nature of such relationships characterising this industry has been acknowledged by the literature. Acknowledging such interdependencies new measures of systemic risk specifically for banks, at both the sectoral and individual levels have been developed, such as the Delta Conditional Value-at-Risk (ΔCoVaR), introduced by Adrian and Brunner Meier (2006), and the Marginal Expected Shortfall (MES), by Acharya et al. (2017). Both such metrics are constructed using data, for each bank, incorporating information about other institutions in the sector. In the light of their sectoral structure evaluating the credit worthiness of financial institutions brings additional problems, in comparisons to typical corporations, for Credit Rating Agencies.

We carry out the analysis, by broad geographical areas and we test for the similarity of behaviour of all three agencies across three world-wide regions. To our knowledge no such study has presented econometric evidence covering the sectors world-wide and incorporating the ratings of all three major agencies.

Second, in the adopted specification we test for the impact of 'credit rating' competition in inflating or otherwise affecting ratings, by allowing for the impact of the ratings of other CRAs, than the awarding agency on the grading granted. Again, the test is conducted across agencies and regions.

Our third contribution is the adoption of a specification that allows to test whether the parts of the ratings, over and above that accounted by the published data, is event invariant. The tests do not simply establish whether the contribution of such expertise changed for period to period but whether such possible changes can be 'periodized' with respect to the major financial events listed above, or such events did not alter behaviour systematically.

Furthermore, by linking the specific periods, albeit exogenously selected, to the structural breaks in the specification conditional on financial information ascertain whether the agencies exhibited pro-active rather than adaptive behaviour. In addition, along the same theme, we test whether, if such periodisation is supported by the econometric evidence, the adjustments were gradual or immediate. Again, we compare the behaviour of all three CRAs across the regions.

Overall, the paper makes several novel empirical contributions, regarding the determination of bank credit ratings. We carry out the analysis, by broad geographical areas and we test for the similarity of behaviour of all three agencies across three world-wide regions. To our knowledge no such study has presented econometric evidence covering the sectors world-wide and incorporating the ratings of all three major agencies. This approach allows us to capture variances in rating standards adjustments that are influenced by regional economic conditions, regulatory environments, and market dynamics, offering insights that are not readily apparent in studies with a narrower focus. Second, in the adopted specification we test for the impact of 'credit rating' competition in inflating or otherwise affecting ratings, by allowing for the impact of the ratings of other CRAs, than the awarding agency on the grading granted. Again, the test is conducted across agencies and regions. Our third contribution is the adoption of a specification that allows to test whether the parts of the ratings, over and above that accounted by the published data, is event invariant. Furthermore, our study delves into the procyclicality of credit rating changes and their correlation not merely with macroeconomic conditions but specifically with macroeconomic shocks. This analysis offers a novel contribution by illustrating how CRAs' rating adjustments respond to unexpected economic disturbances, rather than just cyclical economic trends. This perspective provides a nuanced understanding of CRAs' behaviour in the face of economic volatility, which is particularly relevant in the context of global financial stability. By focusing on these dimensions, our study aims to shed light on the intricacies of CRA behaviour in a way that complements and expands upon existing research. We believe that these unique insights substantiate the contribution of our work to the literature on credit ratings.

This topic is covered by limited econometric evidence. The impact on ratings due to bank compliance to regulation and liquidity has been examined using a small number of European banks by Demirgüç-Kunt et al. (2008), and Poon et al. (2009) respectively. Neither of these studies analyse the ratings across agencies, the first is focused on Moody's and the second ion Fitch. In a similar vein Pasiouras et al. (2006) incorporate market structure analyse credit ratings across a small but diverse international sample of country-level data and bank level data from 71 countries and 857 banks.

In addition to the use of traditional econometric specifications, Gaganis et al. (2021) and Pasiouras et al. (2007) adopt fuzzy set methodology and multicriteria decision making aids to account for the observed ratings using only publicly available data. The first study focuses on Moody's ratings for 55 European banks, and the second on Fitch's ratings for Asian banks. In comparison with the previous studies this paper encompasses a substantially larger international sample size, a long time period and most importantly by analysing the bank credit ratings across all three main CRAs allows for meaningful comparisons regarding the time evolution of their awarded ratings both across region and across major financial events.

The paper is organised as follows: Section 2 reviews the literature on the determination of credit ratings for banks and non-financial firms. Section 3 provides a short summary of the rating methodologies employed by each of the CRAs. Section 4 presents our empirical strategy. This section contains the econometric model for bank credit ratings, the data used and the results. These are subdivided by bank location and rating agency along with tests for structural stability. Finally, our conclusions are presented in Section 5.

2. Literature Review

After the onset of the global financial crisis of 2007-8, the role of rating agencies came under scrutiny by both regulators and academia. A new stream of theoretical literature emerged, in which two papers were key. The first, by Mathis, McAndrews, and Rochet (2009), looked at how a CRA's concern for its reputation affects its ratings quality. The authors present a dynamic model of reputation, in which a monopolist CRA may switch between lying and truth-telling to build up or exploit its reputation. They focus on whether an equilibrium can exist in which the CRA tells the truth in every period, and they demonstrate that truth-telling incentives are weaker when the CRA has more business from rating complex products. The second paper by Bolton, Freixas, and Shapiro (2012) also uses a dynamic model to explore how strategic CRAs establish equilibrium in a setting where CRAs are competitive. In this model, CRAs face more conflicts of interest when reputation costs are lower, and investors are more trustworthy. As a result, the authors report two interesting results: first, competition among CRAs reduces reporting efficiency because of rating shopping; second, published ratings are inflated in the good times of economic expansion.

There are two main strands of empirical literature. The first focuses on the characteristics of credit ratings (e.g., Alp, 2013) and the second examines the information content of bank rankings (e.g., Hau, Langfield, and Marques-Ibanez, 2012).

Alp (2013) is a study on the S&P long-term issuer ratings of US non-financial firms' bond issues. It tests the time-series variation of rating standards. Her main findings are twofold: first, from 2002 to 2007, a structural shift occurs towards stringency, and second, from 1985 to 2002, a 'divergent pattern' exists between investment-grade standards (which tighten) and speculative-grade rating standards (which loosen). Alp's (2013) work is closely related to an earlier paper by Blume, Lim, and Mackinlay (1998), which studied the investment-grade rating standards of bonds issued by US corporations between 1978 and 1995 using the S&P bond-level ratings. This paper found that the evident deterioration in the credit quality of these assets seemed to be driven, at least in part, by the stricter standards employed by the rating agencies.

These two studies, in their exploration of how rating standards change over time, are indicative of the first strand of studies mentioned above that examine how publicly available information is used to predict credit ratings, something that was demonstrated in the past by various authors (Horrigan, 1966; Pogue and Soldofsky, 1969; West, 1970; Pinches and Mingo, 1973, 1975; Altman and Katz, 1976).

Amato and Furfine (2004), using a sample of US firm ratings by S&P, examine the effect of the business cycle on credit ratings and find that CRAs do not assign ratings that are excessively pro-cyclical, whereas Auh (2013) finds that rating standards are in fact clearly pro-cyclical, i.e., ratings during an economic downturn are stricter than those assigned during an expansion.

Dimitrov, Palia and Tang (2015) examine the impact of the Dodd-Frank Act 2010 on corporate bond ratings by all three principal CRAs in the US. The authors find that because of the Act, CRAs assign lower ratings, which leads to more false warnings. Subsequently issued downgrades are thus less informative. The study of Baghai, Servaes, and Tamayo (2014) is a study that, like Alp's (2013), belongs to the growing sub-strand of literature that focuses on the time-series variation in rating standards. They use a sample of US firms' ratings by S&P, from 1985 to 2009, and find that CRAs have become more stringent or conservative during this period, with average ratings dropping by three notches. The authors note that this finding is inconsistent with the observed decrease in default rates during this period.

Contrary to the majority of studies that converge to the stringency or conservatism of rating standards, Jorion, Shi, and Zhang (2009) argue that the apparent tightening of rating standards can be primarily attributed to an improvement in accounting quality over time. The authors come to this conclusion for investment-grade issuers from a sample of U.S. firms from 1985 to 2002 for S&P long-term issuer credit rating.

One of the earliest studies on bank ratings is that of Cantor and Packer (1995). This finds evidence that uncertainties about banks' creditworthiness led agencies to disagree more about the ratings of banks than about the ratings of firms in other industries. A similar result is reported by Morgan (2002) in his use of logit regressions to identifying the determinants of differences in the ratings assigned by Moody's and S&P. His work is motivated by the inherently opaque nature of banks to outside agents, including the CRAs that assess the risks taken by banks.

Hau, Langfield, and Marques-Ibanez (2012) undertook a comprehensive analysis of bank credit ratings. The authors examine the information content of European and US bank credit ratings drawn from approximately 39,000 quarterly bank ratings over the period 1990–2011 from the three principal CRAs. The authors use a new method for evaluating rating quality by ranking banks according to their credit rating and their expected default frequency two years later. They find that rating quality is countercyclical, i.e., the information content of credit ratings is higher during banking crises, and that bank ratings in the upper investment grade range do not correspond to their expected default probabilities, i.e., they are less risky. In addition, they find that large banks enjoy systematically better credit ratings relative to their expected default risk, and banks that provide large securitization business to a CRA are expected to receive a more favourable rating from that CRA.

Other studies in this strand are Peresetsky and Karminsky (2008), who find that Moody's ratings take into account external factors such as political risk, and Bellotti et al. (2010), who focus on the prediction techniques of bank ratings using both ordered logit modelling and Support Vector Machine (SVM) techniques. Caporale, Matousek, and Stewart (2011) use probit and logit models to examine Fitch ratings for banks in different countries in the European Union and find that bank country is a crucial factor in ratings. The same authors, in a later study, return to their use of country indices in an international sample of 90 countries, in which they emphasise both the significance of fundamental quantitative financial analyses and the country effect. They find that during periods of financial instability, both CRAs and quantitative models are likely to produce highly inaccurate predictions of ratings (Caporale, Matousek, and Stewart, 2012). These authors' findings are close to the results obtained by Peresetsky and Karminsky (2008) in demonstrating the influence on bank ratings of external factors, such as the legal framework, government support, model of ownership, etc. Similarly, Iannotta, Nocera, and Sironi (2013) examine the influence of government ownership of European Union banks on all three principal CRAs' ratings. Using an ordered logit model, the authors find evidence that banks that are publicly owned receive higher ratings than banks that are privately owned.

Packer and Tarashev (2011) observe the behaviour of all three principal CRAs' bank ratings and provide evidence that after the outbreak of the subprime crisis, bank ratings fell and the differences between different agencies' bank ratings decreased. The authors also highlight the importance of the external support banks received from national authorities. Van Laere et al. (2012) find that S&P's rating standards for banks are stricter than Moody's, while Moody's are more sensitive to the economic climate. They also find that although the CRAs' rating standards changed in response to the financial crisis, they did not become aligned, and the level of discretion in the rating process increases with bank opacity. In another study, Shen, Huang, and Hasan (2012) examine why bank credit ratings are different for banks with constant financial ratios but in different countries. The authors model the issuer ratings of S&P to determine the reasons behind the variation in ratings and they conclude that asymmetric information differences among banking systems are the key factor. Similarly, Huang and Shen (2015) examine the effect of sovereign credit ratings on bank credit ratings and conclude that the sovereign rating is an important determinant that affects the bank ratings, albeit in a different fashion for S&P and Fitch.

Finally, Pastor and Fernandez de Guevara (2014) look at the three principal CRAs during 2000-2009. The study's main finding is that ratings are pro-cyclical, as the worsening of bank credit ratings that followed the global financial crisis of 2007-8 is partly attributed to the hardening of rating standards. The analysis of Salvador, Fernández de Guevara and Pastor (2018) uses a sample of banks from Europe, US, and Japan during the period of 2004 to 2013 and finds that CRAs harden their rating policies as a result of the global financial crisis, but by different degree for each CRA. Fitch was found to be the most stringent, then S&P, and finally Moody's. Meriläinen and Junttila, (2020) examine the role of asset liquidity in Western European banks' credit rating downgrades and upgrades over the 2005–2017 period. The analysis suggests that changes in bank credit ratings have been more favourable for banks that have a liquid asset portfolio.

In another study, King, Ongena, and Tarasev (2017) examine and conclude that the Fitch's decision to release standalone ratings for rated banks did not affect bank all-in ratings. The change to Fitch's rating methodology resulted in more positive than negative ratings, which was surprising given the standalone rating refinements.

3. Bank Rating Methodologies by the three big CRAs

Shortly following the worldwide financial crisis of 2007-2008, the three major credit rating agencies initiated a re-evaluation of their methodologies for rating banks. This re-evaluation led to significant downgrades in the ratings of banks, particularly those in Europe and the United States, as noted in the study by Parker and Tarashev (2011). Notably, all three credit rating agencies implemented substantial changes in their assessment methodologies in 2011, a pivotal moment when lessons from the crisis were absorbed, and institutions responded accordingly (as indicated by Fitch Ratings, 2011a, Moody's, 2009 and Standard & Poor's, 2011a). The assessment methodologies applied to banks have two elements in common: the intrinsic or stand-alone element and the external support element.

3.1. Fitch Ratings bank rating methodology

The Fitch Ratings methodology for banks includes specific factors of bank credit risk that relate to either the intrinsic creditworthiness of the bank or its potential for receiving external support (Fitch Ratings, 2018).

The overall or all-in rating is called the Issuer Default Rating (IDR) and it is derived from the Viability Rating (i.e., the bank's intrinsic creditworthiness) and the External Support Rating. Long-term IDRs are assigned to all banks, whereas short-term IDRs are assigned to the few banks that issue exclusively short-term (no longer than 13 months) instruments.

The Support Rating (SR) were introduced in 2007 to reflect the future likelihood of the bank receiving extraordinary support by a third party, which might be the state (sovereign support) or an institutional owner (Fitch Ratings, 2011c, 2018)., and supporters are assigned their own long-term IDR, as assessed by Fitch on a five-point scale, i.e., from 1 to 5, with 1 representing the highest probability of support, The support ratings definitions have remained materially unchanged since their first introduction (Fitch Ratings, 2011c, 2018). Intrinsic creditworthiness is currently assessed by a stand-alone rating called the Viability Rating (VR). In early 2011, Fitch first signalled its intention to refine the scale of standalone ratings (Fitch Ratings, 2011a, 2011b) that had existed ever since Fitch began rating banks. Transparency was improved by withdrawing the Individual Rating in early 2012 and mapping the new VR on a 19-point scale that corresponds exactly to that of its all-in ratings ('issuer default ratings'), King, Ongena and Tarasev (2017) note that the all-in ratings were unaffected.

The key factors in Fitch's most recent bank rating criteria (Fitch Ratings 2018) are: a) Operating Environment, b) Company Profile, c) Management and Strategy, d) Risk Appetite, and e) Financial Profile. . In the latest bank rating criteria report (Fitch Ratings, 2018), Fitch identifies four factors for the financial profile assessment: a) asset quality, b) earnings and profitability, c) capitalisation and leverage, d) funding and liquidity. For each factor, Fitch uses a mixture of core and complementary metrics. Core metrics have the greatest relative explanatory power in determining factor scores for banks globally.

3.2. Moody's Investors Service bank rating methodology

Moody's Investors Service current rating methodology for banks (Moody's, 2018) is overall similar to that of Fitch, being comprised of intrinsic/standalone and external support elements. The Baseline Credit Assessment (BCA) is the assessment of the standalone financial strength of a bank. It measures the probability of default in the absence of any kind of external support. The assessment of external support is based upon the Joint Default Analysis (JDA) framework that comprises the following three elements: a) Affiliate Support, b) Loss Given Failure (LGF), and c) Government Support. The last element reflects the inter-relationship between the public's body support provider and the bank.

This analysis results in the long-term local and foreign currency ratings for different instruments that range from bank deposits to preferred stock.

Long-term or short-term Issuer Ratings (Foreign or Domestic) is Moody's all-in ratings assigned to banks based to the above methodology. According to Moody's (2018), the Issuer Rating is an opinion of the bank's ability to honour its senior unsecured debt and debt-like obligations, while Long-term or short-term Counterparty Risk Rating (Foreign or Domestic) is an opinion of the bank's ability to honour the uncollateralised portion of its non-debt counterparty financial liabilities (CRR liabilities).

A major change in Moody's methodology for banks took place just before the start of the financial crisis. In 2007, to incorporate the external support available to banks in its all-in ratings, Moody's introduced a new bank rating methodology (Moody's, 2007a, 2007b, 2007c): the Joint Default Analysis (JDA). The JDA framework initially assessed four types of support: operating parent, cooperative group, regional government, and national government, to arrive at all-in or issuer ratings. For each type of support, the capacity and willingness to provide support were considered, as was the probability of the external support entity being itself in default when the bank needed support (i.e., the joint default probability). As a response to the financial crisis Moody's undertook significant changes to its global bank rating methodology (Moody's, 2014). Among these was the withdrawal of the rating for a bank's standalone intrinsic strength, i.e., the Bank Financial Strength Rating (BFSR) that had been refined in 2009 (Moody's, 2009) as part of the recalibration of bank ratings. The new standalone rating put greater emphasis on forward-looking assessments of bank capital ratios, based on analyses of expected losses for risk assets in stress scenarios.

The BCA is Moody's current methodology for banks, and it has three sub-components: a) Macro Profile, b) Financial Profile, and c) Qualitative Adjustments (Moody's, 2018). Each sub-component has 2 to 4 factors and some of these are further decomposed into sub-factors. Thus, Financial Profile has two main factors: Solvency and Liquidity.

The two factors and the five fundamental credit sub-factors of the Financial Profile are identified with weights and then each sub-factor is assigned a score is assigned using historical financial information (this is despite Moody's assertion that no single historical ratio or set of such ratios can capture the complexity of a bank's financial profile).

3.3. Standard & Poor's bank rating methodology

Comparative to Moody's and Fitch, Standard & Poor's (S&P) methodology for banks (Standard & Poor's, 2011c) is comprised of two elements: intrinsic risk and external support. The first element is called the Stand-alone Credit Profile (SACP) and the second is Extraordinary or Group Support. Once the SACP is determined for a rated bank, the likelihood of extraordinary support is established, and an Indicative Issuer Credit Rating (ICR) is assigned. TS&P is the agency that has implemented the most significant changes to its bank rating methodology as a result of the global financial crisis. After a series of revisions in the aftermath of the crisis (e.g., Standard & Poor's, 2010a, Standard & Poor's, 2010b and Standard & Poor's, 2011a), the agency published a new rating methodology for bank that, save for a number of minor updates, has remained virtually unchanged until today (Standard & Poor's, 2011c).

SACP is not a rating as such but is rather a component of the issue rating or issuer credit rating (ICR). By this process, S&P may assign a SACP as a component of a rating to provide information on an issuer's creditworthiness in the absence of extraordinary support or burden; it is thus similar to Fitch's standalone metric and is graded in a lower-case scale ('aaa', 'aa+', etc.), which parallels the ICR's rating scale.

The assessment of SACP is based on six factors. The first two factors represent macro analysis (or macro factors) of the creditworthiness of a bank's environment, while the last four represent microanalysis (or bank-specific factors).

The first two factors are economic and industry risk, and they draw from the Banking Industry Country Risk Assessment (BICRA) methodology (Standard & Poor's, 2011b). Those two factors depict the strengths and weaknesses of the entity's operating environment and they set the basis for the SACP. The remaining four factors represent the bank's specific strengths and weaknesses: namely, its business position, capital and earnings, risk position, and funding and liquidity.

3.4. Geographical factor in bank credit ratings

In the related empirical literature, the geographical or country factors are found to be important for bank credit ratings. For example, Parker and Tarashev (2011) observe remarkable differences across geographical regions when examining the downgrading of banks in the context of the global financial crisis. The authors find that all three principal CRAs have substantially lowered the ratings of US and European banks relative to the rest of the world's regions, i.e., Asia and Pacific.

All three principal CRAs incorporate an external support factor that reflects the sovereign's ability and propensity to support a bank. In this context, the starting point for assessing the external support factor is the country's rating of sovereign bonds (e.g., Fitch, 2018). In another study, Salvador, Fernández de Guevara, and Pastor (2018) find that although the three principal CRAs, overall, hardened their bank rating policies as a result of the global financial crisis, the implementation of these was diverse depending on the country or geographical area. This is attributed to the fact that the factors (e.g., bank size, loan loss provisions, loans/total assets ratio, sovereign rating) used as explanatory variables for the adjustment of ratings do not have the same relative importance in all country groups. However, this can only be consistent if the external support factor in the rating methodologies changed for some countries or a geographical area as a result of the global financial crisis.

In each market in which Fitch rates banks, it assigns a country an operating environment score. This is one of the five factors of the Viability Rating (Fitch, 2018). The operating environment score is derived from two metrics: GDP per capita and the World Bank's Ease of Doing Business ranking[1]. The implied operating environment score is adjusted for a number of sub-factors: Sovereign Rating, Size and Structure of Economy, Economic Performance, Reported and Future GDP/Capita, Macroeconomic Stability, Level and Growth of Credit, Financial Market Development, Regulatory and Legal Framework, Regional Focus, and International Operations. The last two are bank specific and they may adjust the assigned country score accordingly. A possible explanation for the dispersion of the geographical factor could be that the three principal CRAs use different calibrations of their rating methodology to assign ratings to the different geographical areas. This is because all three agencies divide their research departments into a number of overseas offices/areas, each of which is responsible for the research in its own region. This devolved operating

[1] Fitch calculates a percentile rank for each country, which is the percentage of all countries (including those with sovereigns not rated by Fitch) that have a lower score on the Ease of Doing Business Index.

structure could be the reason behind the different calibrations or biases in the application of their methodologies.

Table 1 presents the broad geographical breakdown for the research of each principal CRA.

[Table 1]

4. Empirical Analysis

4.1. Empirical Strategy

This is the first study that identifies time-series variation in bank credit rating standards. Compared other corporate entities banks are rather complex institutions due to the uniqueness of the deposit contract and their extended interdependence and the importance of their solvency for the smooth functioning of the credit system, the lifeblood of a market economy. The impact of the asset complexity on ratings has been examined by Skreta and Veldcamp (2009) where they conclude that “Increasing complexity...could create systematic biases in disclosed ratings, despite the fact that each rating agency produces an unbiased estimate of the asset’s true quality”.

We employ the methodology following Alp (2013), which in turn is based on Blume, Lim, and Mackinlay (1998) who estimate an ordered probit model to study S&P’s standards of rating as a function of firm characteristics and year indicator variables. It is the year indicator variables in both studies that are used to capture the time-series variation in credit rating standards which cannot be attributed to other variables in the ratings equations.

Our analysis covers the late 1980s up to 2015. Bank credit ratings are modelled as a function of financial explanatory variables and year indicator variables. Year indicator variables are also used by both Alp (2013) and Blume, Lim, and Mackinlay (1998) to capture stringency or loosening of rating standards relative to the first year in their equivalent samples (i.e., 1985 and 1978). In short, the first year of the sample in each study is the reference year. This is a narrow definition of stringency, since the question is formulated as if a firm holding the same risk characteristics receives a higher or lower rating using the model used in the initial time period.

In our sample, using quarterly data, the years up until 1999 are represented as one, and thus year indicator variables capture stringency or loosening of rating standards from

2000 until 2015. So, if rating agencies continue to use their pre-1999 models to assign ratings, we study whether a commercial bank, having the same characteristics, receives a higher or lower rating after 1999. Higher ratings imply a comparative loosening of rating standards, while lower rating imply stringency.

The ordered logit model used in our analysis can be broken down into two parts. The first part corresponds to the 17 rating categories, according to the rating transformation presented below. The dependent variable, R_{it} denotes the credit rating of bank *i* at quarter *t* according to the latent variable Z_{it} and the partition points μ_i distinguish each rating category as follows:

$$R_{it} = \begin{cases} 17 & \text{if } Z_{it} \in [\mu_{16}, \infty) \\ 16 & \text{if } Z_{it} \in [\mu_{15}, \mu_{16}) \\ 15 & \text{if } Z_{it} \in [\mu_{14}, \mu_{15}) \\ \vdots & \\ 3 & \text{if } Z_{it} \in [\mu_2, \mu_3) \\ 2 & \text{if } Z_{it} \in [\mu_1, \mu_2) \\ 1 & \text{if } Z_{it} \in (-\infty, \mu_1) \end{cases} \quad (1)$$

The second part relates the latent variable to the explanatory variables:

$$Z_{it} = a_t + \beta' X_{it} + \varepsilon_{it} \quad (2)$$

Where Z_{it} is the latent variable of bank *i* at quarter *t*, a_t is the intercept for quarter *t*, β is the vector of slope coefficients, and X_{it} is the vector of the explanatory variables of bank *i* at quarter *t*. In vector X_{it} the included financial explanatory variables are the values observed at quarter *t-1*. In this way, credit ratings are regressed on the previous quarter's financial data, or on the data available up to the fourth quarter of the previous year. We adopt this formulation because we assume the CRAs first receive the publicly available information for a bank and then decide on the bank's credit rating. This approach is similar to Baghai, Servaes, and Tamayo (2014) who, using annual data, consider the first rating available three months after the fiscal year-end and match this rating with the fiscal year-end financial statement data. This three-month lag is to ensure that the financial data are available to the rating agencies at the time the rating is issued. In similar fashion, Alp (2013), who estimates a model with yearly variables, uses the calendar year-end values of the ratings and matches them with financial data available before the year-end.

4.2. Data

Our data consists of a worldwide panel of 1,208 commercial banks with their equivalent credit ratings by Fitch, Moody's, and S&P. The financial database used to collect bank credit ratings and financial data is Bankscope by Bureau Van Dijk.

4.2.1. Bank Selection in Bankscope

The selection criteria used in Bankscope to construct our sample of banks with credit ratings from the three CRAs are: bank's specialisation, size, and whether the bank is considered to be the ultimate owner in the ownership structure. For the specialisation criterion we consider values of Commercial Banks, Savings Banks, Cooperative Banks, and Bank Holding & Holding Companies (BH&HCs)[2]. The reason for this selection is to maintain homogeneity in our sample by concentrating on commercial banks that play a fundamental role in the economy, i.e., their function is vital for economic development and growth. For the size criterion we consider banks that had book value of assets greater or equal to $5bill. in 2006 (i.e., the year before the global financial crisis began) or in the last year a bank's data are available. The reason for the size criterion is to have a sample that will account for most of the global banking system (i.e., at least 90% of the total book value of assets of the global banking system[3]). Lastly, the use of the ultimate owner criterion is to

[2] Many banks from the initial sample were excluded 'by hand' because even though they were BH&HCs in Bankscope, they were not commercial banks (e.g., Citigroup Inc and Goldman Sachs Group, Inc in the US are both characterised as BH&HCs in Bankscope, but the former is a commercial bank and is retained in the sample while the latter is an investment bank and excluded from it).

[3] The sample in Ellul and Yerramilli (2010) comprises the 100 largest Bank Holding Companies (BHCs) in the US, with respect to the book value of their total assets at the end of 2007. Although there were over 5,000 BHCs in the US by the end of 2007, the sample of the 100 largest BHCs in Ellul and Yerramilli (2010) accounted for approximately 92% of the total book value of assets in the US banking system. So, given our size criterion our

avoid double counting the ratings of banks that are junior within a single ownership structure (e.g., Banco Santander SA is included as the ultimate holder in the Santander Group, but all its subsidiaries such as Santander UK Plc are excluded).

4.2.2. Bank Credit Ratings

The measures of credit ratings used in our dataset are the long-term issuer ratings of each CRA, being the primary issuer ratings that represent opinions of creditworthiness throughout the business cycle rather than short-term fluctuations (Moody's, 2018; Kiff, Kisser and Schumacher, 2012). Specifically, the credit ratings we use are the long-term issuer default rating (IDR) for Fitch, the long-term Issuer rating (foreign) for Moody's, and the foreign currency long-term Issuer Credit Rating (ICR) for S&P. Credit ratings are recorded at the end of each quarter, thus constituting a time series of quarterly data.

The full data set is an unbalanced panel of approximately 90,000 quarterly bank ratings from 1987[4] to 2015. Bank ratings are distributed among the three CRAs as follows: 30,173 quarterly bank ratings by Fitch, 31,161 by Moody's, and 28,445 by S%P. Table 2 shows the distribution of our full world sample per World Region and CRA.

[Table 2]

4.3. Rating Transformation

By and large, we usually find that credit ratings in the related literature are transformed to an ordinal numerical scale consisting of no more than 10 categories. Blume, Lim, and Mackinlay (1998) use an ordinal scale of 4 categories to map the 4 investment grade rating categories (AAA, AA, A, and BBB) of S&P's bond-level ratings of US corporations. Amato and Furfine (2004) use an ordinal scale of 8 categories to map the 8 upper rating categories (AAA, AA, …, CC) of S&P's corporate ratings of US firms. Finally, Salvador, Fernández de Guevara and Pastor (2014) use an ordinal numerical scale of 6 categories to map all rating categories of Spanish bank credit ratings by the three principal CRAs, and in a companion paper of 2018, the same authors use an ordinal numerical scale of

US sample is comprised of the 260 largest commercial banks in the US, which should account for more than 90% of the total book value in US banking system.

[4] Our initial sample contained 76 additional quarterly bank credit ratings from 1980 to 1986, but they were dropped because no financial variables existed in Bankscope for that period.

11 categories to map ratings from all three principal CRAs; furthermore, they group the lowest notches that contain only a small number of observations into a single category.

In our study, all credit ratings are transformed from their letter form into a numerical value that corresponds to an ordinal scale ranging from 1 to 17, as shown in Table 3. A value of 1 corresponds to the lowest rated banks (CCC+/Caa or worse) and 17 corresponds to the highest rated banks (AAA/Aaa). This is the same transformation used by Alp (2013), Shen, Huang, and Hasan (2012), and Van Laere, Vantieghem, and Baesens (2012)[5],

The reason for using an ordinal scale of 17 numbers instead of the typically more restricted scale is that our sample is large compared to the available data in previous studies. The choice of 17 categories is comparable to the studies mentioned above that are of comparable sample sizes (e.g., more than 20,000 observations).

[Table 3]

Table 4 presents the basic summary statistics for the bank credit ratings by each CRA for the world sample, and for each world region separately.

[Table 4]

Overall, Fitch, on average, assigns lower ratings than either Moody's or S&P, and the Fitch ratings appear to be less volatile. Moody's assigns the highest ratings to US & Canada banks, and S&P assigns the highest ratings to European and RoW banks. The final observation from the presented evidence is that European and US & Canada banks receive from all three CRAs significantly higher ratings compared to RoW banks.

In Table 5 the mean ratings information is sub-divided into three sub-periods. The pre-crisis period is split into two sub-periods because we believe it is interesting to see how CRAs may have assigned, on average, higher ratings just before the crisis began; this is more observable in the analysis presented in the next sub-section.

[Table 5]

The results in the table above are close to what was expected. All CRAs' ratings exhibit a modest tendency towards higher grades in the period 2006-8 just before the onset of the crisis, compared to the 2000-5 period. Not surprisingly, all CRAs assign lower ratings in the period after the global financial crisis 2009-15.

[5] In Alp (2013) and Shen, Huang and Hasan (2012) number 17 corresponds to the highest credit rating, while in Laere, Vantieghem and Baesens (2012) the opposite is true, i.e., number 1 corresponds to the highest credit rating.

4.4. Control Data

Rating agencies face many difficulties in the assessment of banks' creditworthiness due to the unique features of the banking industry. Moreover, there is evidence that agencies disagree more about bank ratings than about corporate ratings because banks are inherently opaquer (Morgan, 2002). Therefore, it is crucial that we select the most appropriate explanatory variables.

4.4.1. Financial Explanatory Variables

When assessing a bank's rating, we first must assess a bank's intrinsic or standalone creditworthiness. To this end, we choose from the literature six key financial characteristic variables that are also related to the CRAs' financial profile factors presented above. These financial characteristic variables are bank size, profitability, leverage, asset structure, funding structure, and trading share.

Bank size is measured by the natural log of total assets, which is found in almost all relevant literature (Erkens et al, 2012, Laeven and Levine, 2009, Ellul and Yerramilli, 2010, Hau et al., 2012, Van Laere et al., 2012). Size is a very important factor because it relates to the external support element that features in all three principal CRA methodologies. It is also used in related literature (Caporale et al., 2011; Shen et al., 2012), the assumption being that size is positively related to likelihood of external support from the authorities in the event of the bank encountering problems. A secondary feature of size is that as bank size increases, so does its opaqueness, rendering it more difficult to rate. Profitability is measured by Return on Average Assets (ROAA)[6] which is also a commonly used variable (Erkens et al, 2012; Ellul and Yerramilli, 2010, Hau et al., 2012). Leverage is measured by Total Assets divided by Equity[7], also found in Hau et al. (2012) and Van Laere et al. (2012), where the inverse ratio is used (i.e., common equity to total assets). Asset structure is measured by (i) Net Loans divided by Total Assets and (ii) Net profits on trading and derivatives divided by Total Assets, a measure used by Hau et al. (2012) that aims to capture the (traditionally more stable) activity of granting loans versus the (less predictable) financial market activity. Lastly,

[6] Alternatively, Net Income to equity or Profits/Assets are also used in similar literature.
[7] Alternative measures for leverage found in similar literature are Total liabilities divided by total assets (Erkens et al, 2012) and Ratio of Tier1 capital to assets (Ellul and Yerramilli, 2010).

funding structure is measured by Short-term Funding divided by Total Assets, as in Hau et al. (2012).

All financial variables are collected from Bankscope on a quarterly basis. If no data are available for a specific quarter, we assume as valid value the value from the previously available quarter, but only up to the fourth quarter of the previous year. This is because if no quarterly data are available, then we either have fourth-quarter data or semi-annual data (i.e., only for the second and fourth quarter). In line with the three principal CRAs (Fitch, 2018; Moody's 2018; Standard & Poor's, 2011c), we prefer consolidated level data, unless no data exists at the consolidated level when we choose the data at unconsolidated level. Such cases are for the years prior to 2000 or for banks that are solo entities (with no subsidiaries). In order to rule out outliers and mitigate their impact on their results, Alp (2013), Baghai et al. (2014), and Salvador, Fernández de Guevara and Pastor (2018) winsorize all continuous financial explanatory variables (albeit in different ways[8]). We report results without winsorizing the data as the regression results using both methods barely differ.

4.4.2. Year Effects

The estimation of Year effects is key for the purpose of this study. We use year dummy variables to capture year effects; this is a common practice in the estimation of the time-series variation in rating standards. Blume et al. (1998), Jorion, Shi, and Zhang (2008), Alp (2013), and Baghai et al. (2014) all use year dummies to capture the tightening (stringency) and loosening of rating standards relative to the omitted year, which is in most cases the first year of the study's sample. We use a broader definition of stringency in which all years until 1999 are represented as one, and thus year indicator variables capture stringency or loosening of rating standards from 2000 until 2015.

4.4.3. Other Explanatory Variables

The financial control variables described above relate to the intrinsic risk of a bank. The other major element of bank credit ratings is the degree of external support upon which a bank is expected to be able to rely. As noted earlier, each CRA defines this differently, but

[8] Alp (2013) winsorizes all continuous variables at 1% and 99%, Baghai, Servaes, and Tamayo (2014) winsorize all explanatory variables at 99th percentile and some at the 1st percentile, while Salvador, Fernández de Guevara and Pastor (2018) winsorize the explanatory variables at 1% and 99%.

they all take into account the ability and likelihood of the bank being supported by its government in times of need. Thus, we consider that this variable can be best represented by the sovereign credit ratings of a bank's country. For all banks, we include as a regressor their country's sovereign credit rating from the relevant CRA at the equivalent time period (e.g., where the focal bank has a Fitch credit rating at period *t*, we obtain the bank's country credit rating assigned by Fitch at period *t*). The country ratings are similarly transformed from their letter form into a numerical value that corresponds to the 1-17 ordinal scale. The source of sovereign credit ratings is again Bankscope.

The use of sovereign credit ratings as an explanatory variable is not often found in related literature. However, the sovereign crisis in the Eurozone Countries revealed how the stability of a country's banks is strongly related to the creditworthiness of the country, and vice versa (BIS, 2011). Studies such as Huang and Shen (2015) provide evidence of the significant and asymmetric impact of sovereign credit ratings on bank credit ratings. In studies where an international sample of bank ratings is analysed, what usually happens is that country fixed effects act as a proxy of the economic environment on bank credit ratings (e.g., Hau et al., 2012; Iannotta et al., 2013, etc). Similarly, in Caporale et al. (2011) and in Caporale et al. (2012), where the sample consisted of 90 countries, a country index was developed to capture cross-country differences because the large sample size meant it was not feasible to estimate their model using country fixed effects.

We take the view that fixed country effects cannot fully account for the impact of cross-country differences on time-series variation in bank credit ratings. We note that it is not the economic environment per se that the three principal CRAs view as the external support element. For example, Fitch includes systemic risk measures in sovereign ratings, which are thus indirectly incorporated in the stand-alone rating of banks. In this case including country fixed effects as a proxy of the economic environment without taking into account the sovereign credit rating appears to be out of line with the three principal CRAs' methodologies. In two studies that use sovereign credit ratings as an explanatory variable, GDP growth rate is also used as a measure of the economic environment (Salvador, Fernández de Guevara and Pastor, 2018; Van Laere et al., 2012).

Our last explanatory variable is a Multiple Rating dummy that aims to capture the effect of the level of competition, if any, among the three CRAs. According to industrial organisation literature, the role of competition is positive for product quality. So, we would expect that rating competition could provide the rating agencies with incentives to improve their rating processes and methodologies in order to acquire a good reputation for accurate ratings. However, Becker and Milbourn (2010) claim that the entry of Fitch to the CRA market in the late 1990s led to a deterioration in ratings' quality. Such a phenomenon is attributed to another channel of ratings competition: more intense competition among rating agencies can induce rating shopping, which can reduce rating quality (Bolton et al., 2012). In another context, Bongaerts et al. (2012) examine three existing theories about multiple ratings: information production, ratings shopping, and regulatory certification, to make inferences about the economic role credit rating agencies play in the corporate bond market.

According to information production theory, investors are averse to uncertainty, which is reduced by shopping for extra ratings. Under the rating shopping theory, issuers shop for an additional rating in the hope of improving their existing rating. Finally, according to the regulatory certification theory, market and regulatory forces create the need to separate out issues, so speculative-grade ratings (the weaker ones) need an additional rating. Our Multiple Rating dummy follows Hau et al. (2012) in taking the value of 1 when, for the given period, another rating agency has issued a rating for a particular bank, and 0 otherwise.

4.5. Unbalanced Panel Data

Our final sample consists of approximately 1,200 of the world's largest banks, so it does not constitute a randomly selected sample. Conventionally in the contest of a linear model the use of random effects would be inappropriate, and a fixed effects model should be estimated. However, in our case, since our chosen specification is not linear, an ordered logit model estimation by fixed effects would result in unreliable inference as the model would encounter incidental parameters problem (Greene and Hensher, 2009) rendering both parameter estimation and inference problematic. As in Alp (2013) and subsequently in Baghai et al. (2014) we base our inference on standard errors clustered at the bank level for robustness to heteroscedasticity and autocorrelation. The use of the Huber–White robust estimator clustered at the bank level provides reliable variance estimates that adjust for within-cluster correlation.

4.6. Empirical Results

In this section we proceed with the empirical results. We estimate the model first for the full world sample of banks, and then for the separate world regions. We obtain estimates of the time-varying rating changes converted into notches, upon which we conduct structural break tests for the full world sample and the separate world regions.

4.6.1. Results with full world sample

In this sub-section we estimate the ordered logit model of equations (1) to (2) for the full world sample of banks. Tables 6, 7, and 8 show the coefficient estimates for the full world sample using the ratings of Fitch, Moody's, and S&P. The coefficients of Log of Assets and R.O.A.A. are all significant and have the same sign across all three CRAs, which is both expected and in line with the literature. The results for the estimated parameters associated with the other financial characteristics are somewhat ambiguous for the full world sample. The coefficient of Total Assets/Equity has a negative sign (as expected) and it is statistically significant for both Fitch and S&P, but it is insignificant for Moody's. The Net Loans/Total Assets coefficient and the Deposits & Short-term Funding/Total Assets coefficient both have a negative sign for Fitch, as expected, the other operating income/Average Assets coefficient has a negative sign, as expected, for both Moody's and S&P. Aside from the above financial characteristics, our model incorporates the remaining explanatory variables described in the previous section. The Country Rating coefficient has a positive sign and is significant for all three CRAs; it is thus indicative of the importance of sovereign ratings, the accepted measure of external support, to determining a bank's credit rating. From the results of the Multiple rating dummy coefficient, it seems that Fitch gives higher credit ratings when at least one of the other two CRAs have also rated a particular bank in the same quarter, an inference that does not hold for the other two CRAs. Lastly, the Year indicator coefficients, which are the epicentre of this study, also give noteworthy results. We observe that all year indicator coefficients for all three CRAs have negative signs, and 13 out of the 16 are statistically significant. Negative signs can be interpreted as rating standards from 2000 to 2015 having become more stringent relative to the period up to 1999.

[Tables 6, 7, 8]

All the coefficient estimates of the ordered logit model in our analysis are informative with respect to their signs, but they are uninformative as how much they impact on the units of measurement of credit ratings. They therefore do not quantify the 'behaviour' of CRAs. In order to infer these changes, we present in the last two columns of each table information that translates the coefficient values to ratings notches. For each of the non-dummy variables, column three presents the product of its estimated coefficient and the variable's standard deviation[9] divided by the average distance between the rating categories, i.e., the average notch length. The product of the coefficient and the standard deviation measures the change in the conditional expectation in the latent variable, given one standard deviation increase in the explanatory variable. The denominator, i.e., the average distance between the rating categories is calculated by finding the average distance between cut-off points[10] (i.e., the average rating notch length is calculated as $(\mu_{16}-\mu_1)/15$, where μ_{16} is the last cut-off point, μ_1 is the first, and 15 denotes the number of the in-between categories). Column four presents a similar transformation of dummy variables to units of rating notches. This is done by calculating dummy coefficients as multiples of the average distance between the rating categories or as explained previously, the average distance between cut-off points. The values of column three in all tables present some interesting results, as they show some diversity in the value of this type of information across agencies. The financial characteristics that contribute most to all three CRAs determination of bank credit ratings for the full world samples are log of assets and ROAA. However, CRAs differ in their consideration of additional financial information, with Fitch considering only Net Loans/Total Assets, Moody's considering only Total Assets/Equity, and S&P considering only Other Op. Income/Avg. Assets,

In terms of impact, an increase/decrease of one standard deviation in log of assets coefficient on average increases/decreases a bank's rating from Fitch by 0.73 notch, from Moody's by 0.79 notch, and S&P by only 0.48 notch. Furthermore, the multiple ratings dummies, as mentioned above, has a significant value only for Fitch, suggesting that in the presence of another CRAs credit rating, a bank's Fitch rating increases by 0.37 notch. Country Rating appears to be another key contributor in determining bank credit ratings for all three CRAs. An increase/decrease of one standard deviation in the country's rating will on average increase/decrease a bank's rating from Fitch by 1.87 notches, from Moody's by 2.24 notches, and from S&P by 2.09 notches. Given the focus of this study, we are mainly interested in the magnitude to which the year indicator variables affect credit ratings. To assess the existence of a trend, we concentrate on the transformation of year indicator coefficients to units of rating notches, as explained above. The results are presented in

[9] Standard deviations of variables in each table differ, as they are calculated for each CRA subsample, i.e., standard deviation of Log of Assets for the Fitch full sample is different from the standard deviation of Log of Assets for the Moody's full sample.
[10] In an ordered logit model, the distances between cut points are not equal.

column (4) in all tables. Figure 1 plots column 4 in Tables 6, 7, and 8 that respectively correspond to the full world sample regression of Fitch, Moody's, and S&P.

[Figure 1]

All three plots in Figure 1 show a pattern towards stringency from 2000 to 2015, but with discrepancies that vary across the three CRAs. Fitch displays a downward trend or tightening of credit standards from 2000 to 2003, standards stabilise from 2003 to 2007, and there is a steep decrease in 2007, after which the pattern is generally stable. Moody's displays a slightly downward trend from 2000 to 2005/6, an abrupt loosening of standards from 2006 to 2007, and then a sharply stable downward trend indicating stringency. This ceases in 2014. Lastly, S&P displays a downward trend or tightening of standards from 2000 to 2003. Between 2003 and 2007 it displays an upward trend or loosening of standards. From 2007 to 2013 there is a downward trend and from 2013 to 2015 a stable pattern. What clearly emerges from this pattern is that none of the CRAs foresaw the oncoming financial crisis. Moody's and S&P were positively optimistic in 2006, while Fitch kept ratings constant from 2003. The ratings in the early 2000's, in the light of the corporate bankruptcies, were tighter/more conservative than they had been in 2000 but even within this new stricter environment, the CRAs failed to anticipate the crisis that was to engulf the financial system. To shed more light on these results, we now estimate bank ratings per broad geographical area to establish whether ratings behaviour was homogenous across the word's banking system.

4.6.2. Results per world region

In this sub-section we estimate the same ordered logit model but this time for different world regions. The findings in related literature (Parker and Tarashev, 2011; Salvador, Fernández de Guevara and Pastor, 2018) indicate that the hardening of bank rating policies by the three principal CRAs as a result of the global financial crisis differed by geographical area. A possible explanation for the observed differences in rating standards could be due to either a different calibration of the bank rating methodologies or simply to bias in how they are applied, given that CRAs structure their research departments into a number of offices/areas around the world, each of which is responsible for the research in its region of concern/monitoring. We separate our full world sample into three broad geographical areas: Europe, US & Canada, and the Rest of the World (RoW). The estimation results for the three world regions are presented in Tables 9, 10, and 11.

From all subsamples, regression results are very similar to the full world sample regressions. Specifically, coefficients of Log of Assets, R.O.A.A., and Country Rating are, in most cases, significant and positive as expected. As for the remaining financial characteristics, the Country Rating coefficient has a positive sign (reflecting the full sample) and is highly significant, with the exception of the US&Canada/Fitch subsample, where is significant at 10%. The statistical significance of the estimated parameters for the other financial variables varies across both agencies and regions. The pseudo R^2s in 8 out of the 9 USA&Canada/Fitch cases achieve almost twice the explanatory power of the equivalent Moody's and S&P models.

[Tables 9, 10, 11]

As noted previously, Fitch seems to award higher credit ratings when at least one of the other two CRAs have also rated a particular bank in the same quarter. As before, we assess the impact of the coefficient values on the ratings by computing the notch mapping. This is reported in columns 3 and 4 of the tables. The Log of Assets is the financial characteristic that contributes most to all ratings save for the Europe/S&P subsample (where its contribution is second most important). For the Europe/S&P subsample, Dep. & Funding/Total Assets is the financial characteristic that contributes most. There is no obvious pattern in the world region or CRA ordering of the remaining financial characteristics. In terms of the impact of the financial variables on ratings, an increase/decrease of one standard deviation in log of assets on average increases/decreases a bank's rating in the Europe/Fitch subsample by 0.76 notch, in the Europe/Moody's subsample by 0.64 notch, and in the Europe/S&P subsample by 0.30 notch. For the US and Canada, the adjustments are higher; Fitch is likely to change ratings by 1.50 notches, Moody's by 1.47 notches, and S&P by 1.06 notches. Finally, turning to RoW banks. Fitch is likely to change ratings by 0.64 notch, Moody's by 0.68 notch, and S&P by 0.55 notch.

The Country Rating appears to be a key contributor in determining bank credit ratings for all three CRAs save for the US&Canada subsamples. This is an expected outcome because the USA's country rating was one of highest in the world throughout the entire sample period. There is much similarity across all three CRAs in their responses to changes in country ratings, if we look first at the Europe subsample, we see an adjustment of 2.30 notches by Fitch, 2.43 by Moody's, and 2.45 by S&P. Broadly similar results hold for the RoW sub-sample where the corresponding adjustments are 2.17, 2.61, and 2.68 notches, respectively. Lastly, we look at time-series variation in bank credit ratings for the regional subsamples in the same way as with the full world sample. We transform the year indicator coefficients to units of rating notches and present Figures 2, 3, and 4 for Europe, USA & Canada, and RoW, respectively.

[Figure 2]

For the European subsample in Figure 2, we observe differentiated patterns of the three plots that correspond to the 2000-to-2015-time trends for Fitch, Moody's, and S&P. Fitch displays a slightly downward pattern for the whole period. From 2000 to 2003 we observe a downward trend of approximately 0.5 notch, then from 2003 to 2007 we observe a rather stable, if modest, upward pattern with only minor deviations. The events of 2007 seem to 'surprise' all CRAs and, with the crisis spreading, there is from 2007 to 2009 a rather abrupt tightening of standards (0.5 notch). After the initial turmoil subsides, the pattern from 2009 to 2015 stabilises (with minor discrepancies) for Fitch whereas both Moody's and S&P adopt a rather pessimistic view of the European banks' credit worthiness, as their ratings exhibit a strong downward trend.

[Figure 3]

For the US & Canada subsample in Figure 3, we detect patterns that are not dissimilar to the European patterns previously observed. Fitch's ratings display a downward pattern for the whole period. From 2000 to 2007 there is gentle downward trend that cumulatively reduces the average rating by 1.0 notch. With the onset of the crisis from 2007 up until 2011, ratings exhibit a sharp downward slope which translates into a sudden and very noticeable tightening of credit standards that creates a cumulative four-year decline of 1.5 notches (note that over the previous 8 years the overall decline was approximately 1 notch). From 2011 till the end of our sample no further trends are detected, with ratings stabilising at their 2011 levels. The pattern for Moody's displays a downward trend of approximately 1.0 notch from 2000 to 2004. This is triggered by the major corporate failures in the early 2000's. By 2004, there is a degree of optimism about bank 'health', and there is a period of stability until standards loosen abruptly (by almost 1.0 notch) in 2006 to 2007. As with Fitch, there is an unsurprisingly steep downward slope from 2007 to 2012 that translates into a sudden tightening of credit standards resulting in a reduction of 3 notches within 3 years. This lower ratings level becomes the stable pattern over 2012 to 2015. Lastly, S&P displays a downward trend of approximately 1.0 notch from 2000 to 2003. From 2003 to 2006 it displays an upward slope or loosening of standards of approximate 0.5 notch. From 2006 it displays stable standards, and the sharp downward slope translating to a sudden tightening of credit standards kicks in from 2008 to 2010. From 2010 to 2015 we observe a rather stable pattern.

For the RoW subsample in Figure 4, we distinguish similar patterns for only two of the three plots, i.e., for Fitch and S&P, with Moody's displaying a fairly stable pattern throughout the whole period, with minor deviations of no more than 0.5 notch in total. The Fitch ratings pattern mimics the agency's pattern profile for the USA and Europe, it displays a downward pattern from 2000 to 2005, a slightly upward pattern from 2005 to 2008, and from 2008 to 2014 a slightly downward pattern. S&P displays a downward trend of more than 1.0 notch from 2000 to 2004, from 2004 to 2007 it displays an upward slope or loosening of standards of approximately 0.5 notch, and from 2007 to 2015 it displays a rather stable pattern.

[Figure 4]

Overall, the credit ratings assigned by the three CRAs gave investors no early warning signal that the banks' creditworthiness might be precarious on a global scale. Their behaviour seems reactive rather than anticipatory. There is evidence that the lessons from the well-publicised corporate failures coloured their ratings allocation strategies at the turn of the century, however once the situation stabilised, they seemed to adopt a more optimistic outlook that was not entirely warranted by the information provided by financial data. The events of 2007 took them by surprise, resulting in abrupt downgrades most particularly for Europe and the USA and Canada. Government interventions to stabilise the financial situation did not result in an improved outlook for the CRAs; it merely shored up the frailties of the post-2007 banking sector. We subsequently test, whether the CRAs altered their behaviour regarding the importance of their own expert judgement, as capture by the parameters associated with the annual dummy variables, in the light of the major global financial and economic events over the period.

4.6.3. Structural Break Tests

The year indicator estimates across the three broad geographical areas, despite differences in magnitude, have a degree of similarity. We observe a uniform shape to the ratings standards that starts with a move towards more stringent standards from 2002 to 2005, a loosening of these until 2008, and finally an abrupt tightening from 2009. The visual evidence presented above implies the existence of at least three structural breaks in the year indicators. We therefore proceed with structural break tests to examine a possible change in the level and slope of the year indicators.

4.6.3.1. Structural Break Tests for the full world sample

In order to verify the overall pattern of the three structural breaks that we initially identified, we proceed with structural break tests for both the level and slope of the year indicators. The ordered logit model of equations (1) to (2) is modified so that year indicators are removed from the vector of the explanatory variables X_{it}, and three dummy variables D_1, D_2, and D_3, are added, to test for the three structural breaks. This defines four time periods. In this way equation (2) becomes:

$$Z_{it} = b_1 D_1 + b_2 D_2 + b_3 D_3 + \beta' X_{it} + \varepsilon_{it} \qquad (3)$$

Dummy variable D_1 takes the value 1 for the years 2002 to 2005, dummy variable D_2 takes the value 1 for the years 2006 to 2008, and dummy variable D_3 takes the value 1 for the years 2009 to 2015. The coefficients b_1, b_2, and b_3 associated with the three dummy variables measure the intercepts of the different time periods.

In Table 12 the values of the three coefficients of equation (3) are reported for the same models as in previously, i.e., for the world sample of bank ratings by each of the three principal CRAs. By each coefficient we report the coefficient estimate in units of rating step length, while the last column reports the *p*-value for the Wald χ^2 test for the hypothesis that all coefficients are equal to zero.

[Table 12]

For all CRAs, the results of the Wald test reject the null hypothesis of zero coefficients, confirming that the intercepts for each specific time period are different.

In the same fashion, in order to test the slopes of the year indicators for the four time periods distinguished by the three structural breaks, we re-write equation (2) as:

$$Z_{it} = b_{02} t D_0 + b_{11} D_1 + b_{12} t D_1 + b_{21} D_2 + b_{22} t D_2 + b_{31} D_3 + b_{32} t D_3 + \beta' X_{it} + \varepsilon_{it} \qquad (4)$$

We add dummy D_0 which takes value 1 for the years until 2001, and a quarterly trend variable t, with coefficient estimates b_{02}, b_{12}, b_{22}, and b_{32} that measures the rate of change in rating standards by the slope of the year indicator for each of the four time periods**.**

In Table 12b, in the same fashion as 12a reports that the null of equal coefficients across the period periods for all three models of the principal CRAs is rejected.

Intercept coefficients of Moody's and S&P are significantly lower than the previous period's coefficients, but they are also lower than the following period's coefficients. Their slope coefficients during 2006-8 are positive, confirming a clear loosening of rating standards. This is not the case for Fitch, where the intercept coefficient during 2006-8 is higher than the previous periods and the slope coefficient remains negative. The last period 2009-15, where rating standards seem to tighten, again shows differences among the three CRAs, there seems to be a different degree of tightening of the rating standards, with Moody's being more rigorous. The intercept coefficients for the period 2009-15 for all three CRAs increase substantially, but the increase relative to the intercept coefficient of the previous period is greater for Moody's and S&P. The slope coefficients for Moody's and S&P turn negative from positive in the previous period of 2006-8, while for Fitch the slope coefficient sign remains negative and decreases. Fitch's ratings show a constant hardening (conservatism) of bank rating standards throughout the whole period, and this was intensified in the last period of 2009-15. In contrast, Moody's and S&P loosened their bank rating standards just before the global financial crisis and then sharply hardened them again, with Moody's being more severe (by approximately 0.80 notch in 2009-15 compared to the period 2006-8, whereas S&P' is significantly lower at 0.50 notch).

4.6.3.2. Structural Break Tests per world region

Likewise, we proceed with structural break tests for each of the three subsamples. For Fitch, both the intercept and slope coefficients indicate no loosening of rating standards during the 2006-8 period. The intercept and slope coefficients for Moody's and S&P indicate a relaxing and then a hardening of rating standards. Of the two, Moody's is more severe. Moody's hardening of rating standards in 2009-15 is 1.24 notches against the 2006-8 figures, whereas S&P's is 0.53 notch.

For the US & Canada subsample (Table 13), Fitch's intercept and slope coefficients do not indicate an attempt to upgrade ratings between 2006-8, but there is a subsequent hardening of rating standards for the whole of the remaining period 2009/15.

[Table 13]

As in the European sub-sample (Table 14), the results for Moody's and S&P's intercept and slope coefficients indicate the loosening of rating standards in 2006-8 (S&P's rather less so), which then fairly severely harden in 2009-15 More specifically Moody's hardens 2 notches against 2006-8, whereas S&P's change is 1.39 notches.

[Table 14]

Lastly, for the RoW subsample (Table 15), we observe for Fitch, similar to above, neither the intercept nor the slope coefficients indicate a loosening of rating standards in 2006-8, What distinguishes this model from those of the other world regions is the abrupt hardening of rating standards in 2002-5 by almost one notch. For Moody's the results are ambiguous since on the one hand we have an inversion of the sign of the slope coefficients for the periods 2002-5 and 2006-8 (from negative to positive), but on the other hand the Wald χ^2 test for the hypothesis that all intercept coefficients are equal to zero is not rejected.

[Table 15]

4.7 Robustness Tests

In this section we proceed with a variety of alternative specifications of the above models to establish the robustness of our results. Blume et al. (1998) indicate two main criticisms that may challenge the validity of their results: first, the assumption that the slope coefficients of their model are constant over time, and second, the likelihood that important explanatory variables have been omitted. The first criticism is also noted by Alp (2013) as an underlying assumption for the year indicator approach, i.e., if slope coefficients change over time, then year indicators are misleading as a measure of change in rating standards. The second criticism is also addressed by Alp (2013) and, indeed, in most of the related literature (Baghai et al., 2014; Salvador, Fernández de Guevara and Pastor, 2018). In the following two sub-sections we proceed with robustness tests for alternative or additional variables and then we examine the robustness of our year indicator approach. For the sake of brevity, given the extent of all the tests below, findings are not presented[11].

[11] Results available from authors on request

4.7.1. Robustness to Year Indicator Approach

As noted above, the underlying assumption behind the year indicator approach is that slope coefficients are constant over time. If slope coefficients are not constant but change over time, then the calculated year indicators are misleading, and thus the conclusions for our structural shifts for the rating standards are unreliable.

In order to test for constant slope coefficients, we include the square and cube terms of all financial explanatory variables in order to allow for nonlinearities. The increase in all models' explanatory power compared to the base models is minor, and the figures of the year indicator estimates barely alter. For the increase in the explanatory power, it is indicative to say that the *adjusted* R^2 of the Fitch base model of the world sample increases only by 0.014 when the square and cube terms of all financial explanatory variables are added.

4.7.2. Robustness to Additional Explanatory Variables

Omitting important explanatory variables could challenge the validity of our results, since an omitted variable(s) could be behind the explanatory power of the year effects, i.e., year effects may be capturing the time trend of an omitted variable or variables. Hence, we re-test with a number of alternative or additional explanatory financial variables and specifications. However, it should be noted that with some of the alternative explanatory variables used in the robustness tests below, there is a limited number of observations; this is due to the fact that for most banks there is limited financial data before 2005 or 2000. Accordingly, we proceed with alternative specifications using appropriate different explanatory financial variables for the key financial characteristics as defined previously. First, for profitability, as an alternative to ROAA we use a) Return on Average Equity (ROAE), b) Net Interest Margin, and c) Net Interest Revenue divided by Average Assets. Second, for leverage, as an alternative to Total Assets divided by Equity we use: a) Tier 1 Ratio[12], b) Total Capital Ratio[13], and c) Equity divided by Net Loans. Third, for asset structure and funding structure, as an alternative to Net Loans divided by Total Assets, Net profits on trading and derivatives divided by Total Assets, and Short-term Funding divided by Total Assets, we use: a) Total Loans divided by Customer Deposits, b) Interbank Assets

[12] Tier 1 capital divided by total risk weighted assets.
[13] Total capital divided by total risk weighted assets.

divided by Interbank Liabilities, and c) Customer Deposits divided by Total Funding excluding Derivatives.

All the above alternative variables give similar results in that the figures of the year indicator estimates change only very slightly. Furthermore, we proceed with the use of additional explanatory financial variables. We include the Growth of Total Assets and Growth of Gross Loans, but both have no significance for any of the three CRAs. Next, we use a number of different variables that cover asset quality or risk factor, which was introduced in the revised standalone methodologies of both Fitch and Moody's after 2011. The variables we use are, a) Loan Loss Reserves divided by Impaired Loans, b) Impaired Loans (NPLs) divided by Gross Loans, c) Impaired Loans divided by Equity, and d) Loan Loss Reserves divided by Gross Loans. Even though some of the above are significant in the re-specified regressions, again the figures of the year indicator estimates change only very slightly. Finally, we turn to bank size, which as explained previously is an important factor for bank ratings because it is related to the likelihood of gaining external support from authorities. This is however a factor that is difficult to approximate directly.

Salvador, Fernández de Guevara, and Pastor (2018) use a government support indicator for approximating the importance of bank size for ratings. This indicator is directly provided by Fitch for the period of the authors' analysis, and for Moody's the indicator is constructed as the difference between the issuer rating and the Baseline Credit Assessment (BCA). For S&P, the authors cannot construct this indicator, so a robustness check is not performed in this instance. As our sample starts many years before the revised standalone indicators of Fitch and Moody's were introduced, it is not possible to replicate their methodology Thus, our robustness check for bank size proceeds by calculating bank size divided by the GDP of the country in which the bank is based or mainly operates; this generates an approximation of the bank's importance to its country's economy. Once again, the estimated coefficients associated with the year indicators barely change.

5. Conclusions

This paper analysed the time-series variation in bank credit rating standards by the three principal CRAs from 2000 to 2015. We investigate whether the criticism that credit rating standards for banks during the period of analysis were relxed and subsequently tightened is empirically supported. Overall we distinguish three structural breaks in the bank credit rating standards that divide the time-span of our analysis into the following periods: a) the period after the 2001-2 high profile corporate collapses, resulting in tighter credit rating standards compared to the previous period; b) the period before the onset of the global financial crisis, when bank credit rating standards loosened; and c) the period after the global financial crisis, when bank credit rating standards tightened. We compare these with the initial period immediately preceding the 2001-2 high profile corporate collapses.

Each of the three principal CRAs displays a different evolution of ratings in each of the three sub-periods. Fitch has implemented a constant tightening of bank rating standards throughout, and this ‘trend’ was intensified after the global financial crisis. The Fitch pattern is more noticeable in the European and US & Canada subsamples. Specifically, Fitch credit ratings for European banks tightened by 0.33 notch after the global financial crisis, by 1.33 notches for US and Canadian banks, and by a very modest 0.08 notch for RoW banks.

In comparison, Moody’s started with a modest tightening of bank rating standards after the post Dot-Com crash. This was followed by a slackening in the period preceding the global financial crisis period, revealing an increased optimism that was hastily reversed after the emergence of the crisis. Moody’s loosening of bank rating standards in the pre-global financial crisis period is more evident for European banks than for the US and Canadian banks. Credit ratings by Moody’s for European banks loosened by 0.43 notch, by only 0.05 notch for US and Canadian banks, and by 0.09 notch for RoW banks. The toughening of Moody’s rating standards in the post-global financial crisis period is stronger for European and US and Canadian banks but is not evident for the RoW banks. Moody’s tightened the ratings for European banks by 1.24 notches, for US and Canadian banks by 2.00 notches, and by 0.09 notch for RoW banks (cf. Fitch).

S&P’s ratings’ evolution was akin to Moody’s in showing a tightening of bank rating standards in the post Dot-com crash period. This was followed by a systematic ratings upgrade in the last years of the Great Moderation. The crisis reversed this trend, triggering a series of overall downgrades that continued for a number of years until ratings stabilised at 1-1.5 notches below their 2007 levels.

The loosening of bank rating standards in the pre-global financial crisis period was much the same for all geographical regions. Thus, S&P’s credit ratings for European banks loosened by 0.22 notch before the global financial crisis, for US and Canadian banks by 0.29 notch, and for RoW banks by 0.43 notch. The hardening of bank rating standards in the post-global financial crisis period was very intense for the US and Canadian banks and much less intense for the European and RoW banks. For example, S&P's credit ratings for European banks tightened by 0.53 notch after the global financial crisis, by 1.39 notches for US and Canadian banks, and by 0.11 notch for RoW banks.

Overall, for the period of our study, Moody's and S&P's showed a measure of alignment in their structural shifts in bank credit rating standards, and all three principal CRAs were unanimous in their hardening of bank credit rating standards for US and Canadian and European banks in the post-global financial crisis period. This can be attributed to the more severe effects that the collapse of the subprime mortgage market had on the balance sheets of the US banks.

Fitch, as the last entrant to the credit rating industry, seems to have followed the same downgrading trend as the other two CRAs but it was both less pessimistic and, more importantly, less volatile; this was probably in an attempt to differentiate itself from the other two agencies that dominate the credit ratings market.

Unlike the other two agencies, Fitch's published ratings incorporate a 'stabilising' factor, which was revealed by our analysis of the statistical significance of the coefficient associated with the variable 'Multiple Ratings'. It is interesting that in the presence of competition, Fitch gives higher credit ratings for US, Canadian, and RoW banks.

Our results show that all three CRA's exhibited adaptive rather than proactive behaviour as their overall tightening or relaxing of standards, beyond the information content of the publicly available data, was as a consequence to these major events, rather than a predictor. The two major agencies appear willing to undertake substantial revisions of their ratings signalling their preference for 'accuracy' and realism regarding the risk profile of banks in the presence of major 'negative' financial events. [14]

This study has meticulously documented the significant structural shifts in bank credit ratings, shedding light on crucial changes that have profound implications for financial stability across the globe. Beyond merely documenting these shifts, it is imperative to delve into the reasons behind these changes and explore the determinants that drive such shifts across different regions. Understanding these dynamics offers not only insights into the

[14] In the accompanying appendix we provide a preliminary (reduced form) economic explanation associating changes of the year coefficients to GDP shocks, and we provide encouraging statistical evidence.

changing landscape of financial risk assessment but also aids in anticipating future shifts and their potential impacts on global financial stability.

The determinants of changes in bank credit ratings are influenced by a complex interplay of factors, ranging from macroeconomic indicators to regulatory reforms, technological advancements, and even geopolitical events. Economic indicators such as GDP growth, inflation rates, and employment levels are foundational to the financial health of a region and, by extension, to the stability of its banking institutions. These indicators directly impact banks' risk profiles, influencing credit rating agencies' assessments and potentially leading to adjustments in credit ratings. Moreover, the aftermath of financial crises, notably the 2008 global financial crisis, has led to a paradigm shift in credit rating methodologies, with a more conservative approach being adopted to mitigate risk.

Regulatory frameworks and the evolution of these frameworks play a pivotal role in shaping credit ratings. The introduction of Basel III regulations, for example, has introduced more stringent requirements for banks in terms of capital adequacy, liquidity, and risk management. These regulatory changes have necessitated adjustments in credit rating methodologies to accurately reflect the heightened risk management standards, often resulting in tighter credit ratings for banks.

Technological advancements and changing market dynamics also significantly influence bank credit ratings. The advent of sophisticated risk assessment tools and real-time data analysis has enabled more dynamic adjustments to credit ratings, reflecting the rapid pace of change in the financial sector. Additionally, the rise of fintech companies and non-traditional financial services has introduced new competitive pressures on traditional banking institutions, impacting their risk profiles and, consequently, their credit ratings.

Geopolitical uncertainties and global economic trends further complicate the landscape of credit rating determinants. Events such as Brexit, trade wars, and geopolitical tensions introduce a layer of uncertainty that can affect financial markets and the creditworthiness of banks, especially those with significant exposure to the regions involved. Similarly, global economic downturns or upswings can lead to widespread adjustments in credit ratings, reflecting changes in the overall risk environment.

In conclusion, the structural shifts in bank credit ratings are driven by a diverse array of factors, each contributing to the dynamic nature of financial stability and risk assessment. This exploration into the determinants of credit rating shifts not only enhances our understanding of the current financial landscape but also underscores the importance of continuous research and analysis. As the global financial environment evolves, so too will the factors be influencing credit ratings, highlighting the need for vigilance and adaptability in the face of changing economic, regulatory, technological, and geopolitical landscapes.

A future research question is to examine the behaviour of the changes in rating standards due to the year indicators to capture. As such changes cannot be attributed to the information on the balance sheet these might be due to another information source. This analysis will contribute to the debate regarding the pro-counter cyclical behaviour of ratings, Bar-Isaac and Shapiro (2013).

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Appendix

Rating agencies try to estimate the long-term credit worthiness of a corporation independent of short-term business cycle effects. Nevertheless, ratings do correlate with the business cycle. Therefore, macroeconomic variables along with financial ratios and corporate governance characteristics are determinants of credit ratings. We test for the procyclical behaviour of the ratings , that are not based on the banks own financial characteristics by undertaking the estimation a testing of a simple vector autoregression system relating ratings changes to unanticipated macroeconomic changes.

We provide a preliminary investigation regarding the causes of the changes of the parameters associated with the annual dummies. To capture the observed adaptive behaviour of all the rating agencies to major economic/financial disruptions we propose a simple Vector Autoregressive model associating shocks to the economic environment to the changes of the estimated coefficients. Within the confines of this statistical structure, we test for the transmissions of shocks to our measure of the state of the economy and the changes of the coefficient estimates by agency and region. We estimate three VAR(1), test for the over identification restrictions imposed and subsequently test for the significance of the resulting impulse response functions. We attempt to establish the impact of unanticipated changes in the economic environment on the awarded credit ratings for banks, over and above the information contained in their own publicly available evidence. We do not claim that this is the only explanation but given the observed reactions of all CRAs it is deemed an avenue worth exploring albeit in terms of a reduced form statistical model. Our VAR model takes the following form:

$$\begin{bmatrix} d\log(gdp)_{i,t} \\ d(SP\_b)_{i,t} \\ d(MD\_b)_{i,t} \\ d(FT\_b)_{i,t} \end{bmatrix} = \begin{bmatrix} a11 & & & \\ a21 & a22 & & \\ a31 & & a33 & \\ a41 & & & a44 \end{bmatrix} \begin{bmatrix} d\log(gdp)_{i,t-1} \\ d(SP\_b)_{i,t-1} \\ d(MD\_b)_{i,t-1} \\ d(FT\_b)_{i,t-1} \end{bmatrix} + \begin{bmatrix} u_{gdp,i,t} \\ u_{SP\_i,t} \\ u_{MD\_i,t} \\ u_{FT\_i,t} \end{bmatrix}$$

Where i= Europe, US and Canada, Rest of the World (RoW), and t=1999-2015. The change in the coefficients associated with the time dummies are denoted by d(Agency coefficient)i,t.

We additionally impose the over identifying restrictions on the system's covariance matrix:

$$\Sigma_i = \begin{bmatrix} \sigma_{11,i} & & & \\ \sigma_{21,i} & \sigma_{22,i} & & \\ \sigma_{31,i} & & \sigma_{33,i} & \\ \sigma_{41,i} & & & \sigma_{44,i} \end{bmatrix}$$

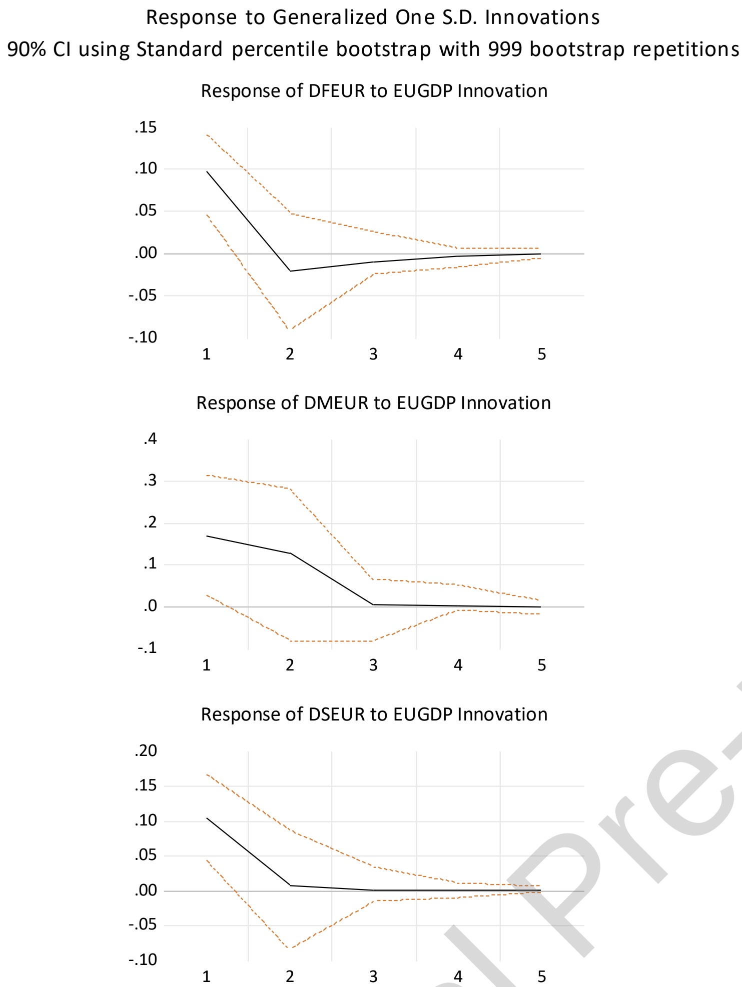
This formulation allows to test for the impact of regional GDP shocks to the ratings changes by each agency in isolation from all the others. We report the impulse response functions by region, along with the p-value for the validity of the overidentifying restrictions, in Figures A!, A2 and A3

In terms of data, For European GDP growth rate we use series (CLVMNACSCAB1GQEU28) from FRED, for the North American GDP growth we construct a weighted average of the USA and Canadian GDP using series (GDPC1) and (NGDPRSAXDCCAQ) from the same source. We generated an artificial series for the RoW GDP by regression World industrial production from the World Bank on the European and North American GDP measures and we added the residuals to the constant, thus creating a measure of RoW economic activity that is orthogonal to both EU and North America.

Figure A1: EUROPE

(i) Restrictions p-value 0.07

(ii) IRFs

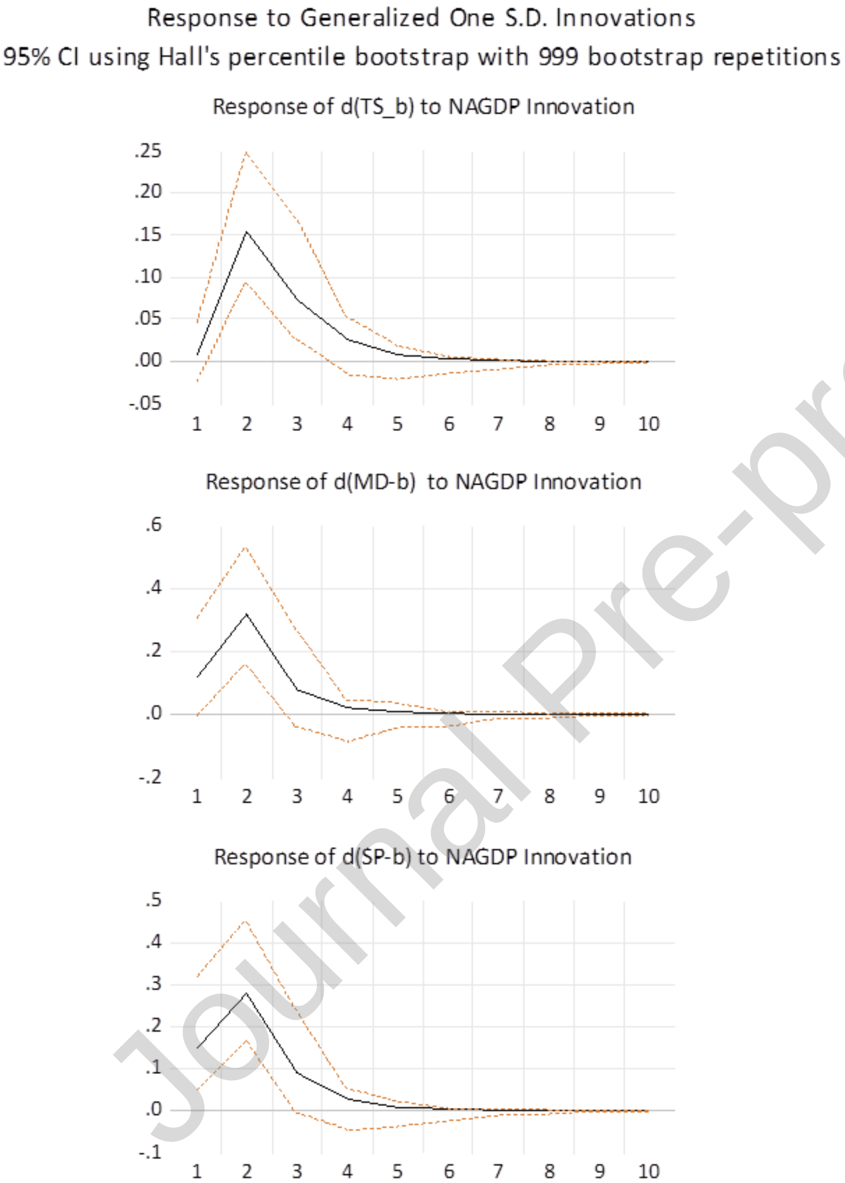


We find that the restrictions imposed are not rejected by the data and that all three agencies change in ratings can be partly explained by shocks to European GDP. The response is not immediate and the reactions of the agencies to the same shock differ. The most pronounced reaction is assonated with Moody's whilst Fitch and SP appear to react in a similar fashion. Overall the adjustment is rapid and monotonic, albeit at different speeds across agencies and does not display cyclical characteristics

Figure A2: NORTH AMERICA

(iii) Restrictions p-value 0.53

(iv) IRFs

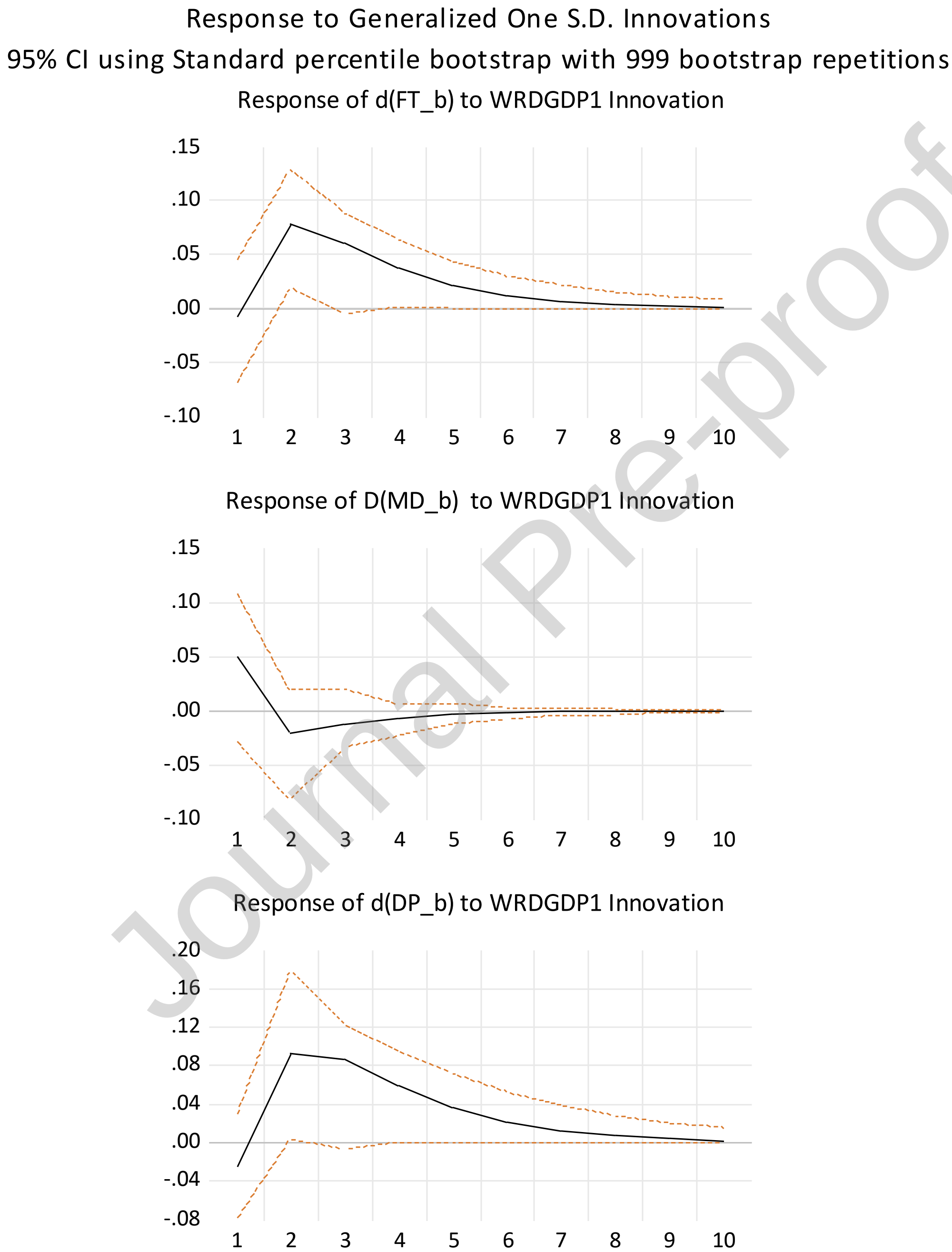


In comparison to the reaction to European shocks the reaction of all agencies in terms of their ratings are far stronger and more importantly longer lasting and peaking after two periods. As previously, Moody's reactions are exceeding those of S&P and almost twice as elevated than Fitch's reaction. Unlike the case in Europe the reaction of CRAs exhibits fluctuations their adjustment lasting longer compared to their behaviour when faced with shocks to the macroeconomic conditions in Europe.

Figure A3: RoW

(v) Restrictions p-value 0.15

(vi) IRFs



With the exception of Fitch and a marginal impact of the SP our results show that the agencies' responses to shocks, using our measures of economic activity, are rather muted although their shapes are bearing some similarities to the 'American' reactions. For the two significant cases, First and S&P the responses are not immediate, in anything the current shocks do not have an impact it is only after the second period that some reaction can be noticed.

In conclusion, we find statistical evidence that it is the unanticipated changes to the economic environment as captured by shock to regional GDPs provide for a partial explanation to the observed 'adaptive' behaviour of the credit rating agencies when awarding ratings to banks. Their reactions vary both across agencies and regions. The S&P ratings seem to be the most sensitive to such events across all three regions. By and large when it comes to Europe all CRA respond in very timely and immediate manner whilst there is a marked delay of responses when it comes to North America and the RoW.

The impact of the global economic/financial crisis from 2008 and the relatively rapid recovery, induced by the massive fiscal and monetary expansions can account for the behaviour of the CRAs. Unable to predict the crisis, there was a marked delay for the award of lower ratings followed by a more optimistic outlook after the recovery was underway. The faster than expected GDP recoveries or downturns, have a major impact on ratings over and above the dynamic changes of the data associated with each particular institution, the observed delays in rating's adjustment may be considered evidence of 'ratings stickiness'.

Tables

Table 1: Geographical Breakdown of Bank Location

Structure of world research for the three principal CRAs			
CRA	Fitch	Moody’s	Standard & Poor’s
Geographical breakdown	- Americas - Asia-Pacific - Emerging markets - Europe - Middle East and Africa - United States	- Asia Pacific - Europe, Middle East & Africa - Latin America & Caribbean - North America	- Americas - Europe, Middle East & Africa - Asia

Table 2: Credit Ratings per World Region/CRA

World Region	**Fitch**	**Moody's**	**S&P**	**Grand Total**
Europe	13,335	12,941	11,850	24,791
US & Canada	6,635	7,246	7,734	21,615
RoW	9,903	10,974	8,861	29,738
	30,173	31,161	28,445	89,779

Table 3: Rating Transformation Table

Fitch	Rating Scale Number	Moody's	Rating Scale Number	S&P	Rating Scale Number
AAA	17	Aaa	17	AAA	17
AA+	16	Aa1	16	AA+	16
AA	15	Aa2	15	AA	15
AA-	14	Aa3	14	AA-	14
A+	13	A1	13	A+	13
A	12	A2	12	A	12
A-	11	A3	11	A-	11
BBB+	10	Baa1	10	BBB+	10
BBB	9	Baa2	9	BBB	9
BBB-	8	Baa3	8	BBB-	8
BB+	7	Ba1	7	BB+	7
BB	6	Ba2	6	BB	6
BB-	5	Ba3	5	BB-	5
B+	4	B1	4	B+	4
B	3	B2	3	B	3
B-	2	B3	2	B-	2
CCC+	1	Caa1	1	CCC+	1
CCC	1	Caa2	1	CCC	1
CCC-	1	Caa3	1	CCC-	1
CC	1	Ca	1	CC	1
C	1	C	1	C	1
RD	1			R	1
D	1			SD	1
				D	1

Table 4: Summary Statistics for Bank Credit Ratings 2000-2015

	Fitch			Moody's			S&P		
	Mean	Std Dev	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Obs
World Sample	9.23	3.32	30,173	9.71	3.62	31,161	9.72	3.22	28,445
Europe	10.08	3.17	13,335	10.35	3.57	12,941	10.63	3.15	11,850
US & Canada	9.66	3.16	6,935	10.83	2.93	7,246	9.92	2.80	7,734
RoW	7.78	3.15	9,903	8.21	3.61	10,974	8.32	3.16	8,861

Table 5: Summary Statistics for Bank Credit Ratings for different periods

2000-5	Fitch			Moody's			S&P		
	Mean	Std Dev	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Obs
World Sample	9.35	3.44	8,409	10.31	3.22	7,878	9.91	3.21	7,678
Europe	10.06	3.62	3,361	11.55	2.43	2,906	11.07	3.09	3,028
US & Canada	10.18	2.57	2,750	11.11	2.62	2,717	10.11	2.59	2,741
RoW	7.33	3.24	2,298	7.75	3.32	2,255	7.80	3.18	1,909
2006-8	Fitch			Moody's			S&P		
	Mean	Std Dev	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Obs
World Sample	9.54	3.12	6,753	10.12	3.72	6,245	10.01	3.06	5,595
Europe	10.52	3.03	2,820	11.32	3.20	2,857	11.11	2.67	2,300
US & Canada	9.84	2.94	1,559	11.28	2.73	1,175	10.26	2.90	1,365
RoW	8.17	2.83	2,374	7.97	3.83	2,213	8.53	3.02	1,930

2009-15	Fitch			Moody's			S&P		
	Mean	Std Dev	Obs	Mean	Std Dev	Obs	Mean	Std Dev	Obs
World Sample	8.93	3.33	14,415	8.90	3.73	14,422	9.05	3.25	12,446
Europe	9.86	2.99	6,831	9.17	3.83	6,517	9.73	3.27	5,458
US & Canada	8.71	3.70	2,386	9.55	3.35	2,053	8.90	3.04	2,267
RoW	7.81	3.22	5,198	8.37	3.68	5,852	8.34	3.17	4,721

Table 6: Estimation results for Fitch / full world sample

Standard errors are calculated using cluster-correlated robust estimates of variance at the bank level, and the asterisks *, **, and *** correspond respectively to significance levels 10%, 5%, and 1%.

Variable	**Coefficient**	**Z stat**	$\frac{\textbf{Coefficient} \times \textbf{SD}}{\textbf{Rating Notch Length}}$	$\frac{\textbf{Coefficient}}{\textbf{Rating Notch Length}}$
Log of Assets	1.1130 ***	11.26	0.7292	
R.O.A.A.	0.1029 ***	2.75	0.2004	
Total Assets/Equity	-0.0001 ***	-9.37	-0.0160	
Net Loans/Total Assets	-0.0118 ***	-3.26	-0.1840	
Dep. & Funding/Total	-0.0016 ***	-3.53	-0.1605	
Other Op. Income/Avg	-0.0587	-1.39	-0.1142	
Country Rating	0.4868 ***	19.67	1.8747	
Multiple rating dummy	0.3996 ***	2.76		0.3730
Year Indicators				
2000	-0.4166 **	-2.38		-0.3888
2001	-0.4671 ***	-3.17		-0.4359
2002	-0.6198 ***	-4.50		-0.5785
2003	-0.8779 ***	-6.47		-0.8194
2004	-0.9042 ***	-6.91		-0.8440
2005	-0.9162 ***	-7.11		-0.8552
2006	-0.9194 ***	-7.16		-0.8582
2007	-0.8910 ***	-7.17		-0.8317
2008	-1.0046 ***	-7.86		-0.9377
2009	-1.1455 ***	-8.67		-1.0691
2010	-1.0591 ***	-8.08		-0.9885
2011	-1.0229 ***	-7.39		-0.9547
2012	-1.1139 ***	-7.38		-1.0397
2013	-1.1685 ***	-7.57		-1.0907
2014	-1.1991 ***	-7.75		-1.1192
2015	-1.1047 ***	-6.69		-1.0311
No. of observations	26,547			
Pseudo R^2	0.184			
Clusters of Banks	777			

Table 7: Estimation results for Moody's / full world sample

Standard errors are calculated using cluster-correlated robust estimate of variance at the bank level, and the asterisks *, **, and *** correspond respectively to significance levels 10%, 5%, and 1%.				
Variable	**Coefficient**	**Z stat**	$\frac{\text{Coefficient} \times \text{SD}}{\text{Rating Notch Length}}$	$\frac{\text{Coefficient}}{\text{Rating Notch Length}}$
Log of Assets	1.0334 ***	9.08	0.7936	
R.O.A.A.	0.2104 ***	4.26	0.4944	
Total Assets/Equity	-0.0025	-1.33	-0.8374	
Net Loans/Total Assets	0.0062	1.46	0.1227	
Dep. & Funding/Total	-0.0000	-1.53	-0.0389	
Other Op. Income/Avg	-0.1431 ***	-3.78	-0.4036	
Country Rating	0.4801 ***	19.26	2.2366	
Multiple rating dummy	-0.1276	-0.93		-0.1498
Year Indicators				
2000	-0.4020 **	-2.30		-0.4720
2001	-0.5142 **	-2.54		-0.6037
2002	-0.5386 **	-2.43		-0.6324
2003	-0.5256 **	-2.21		-0.6171
2004	-0.6386 ***	-2.65		-0.7498
2005	-0.6856 ***	-2.82		-0.8050
2006	-0.6861 ***	-2.72		-0.8056
2007	-0.1208	-0.46		-0.1419
2008	-0.2054	-0.77		-0.2412
2009	-0.4480 **	-1.65		-0.5260
2010	-0.6064 **	-2.25		-0.7120
2011	-0.8512 ***	-3.22		-0.9994
2012	-1.1454 ***	-4.31		-1.3448
2013	-1.2811 ***	-4.81		-1.5042
2014	-1.3658 ***	-5.15		-1.6037
2015	-1.2074 ***	-4.56		-1.4176
No. of observations	22,298			
Pseudo R^2	0.171			
Clusters of Banks	746			

Table 8: Estimation results for S&P / full world sample Standard errors are calculated using cluster-correlated robust estimate of variance at the bank level, and the asterisks *, **, and *** correspond respectively to significance levels 10%, 5%, and 1%.				
Variable	**Coefficient**	**Z stat**	$\frac{\text{Coefficient} \times \text{SD}}{\text{Rating Notch Length}}$	$\frac{\text{Coefficient}}{\text{Rating Notch Length}}$
Log of Assets	0.6431 ***	6.06	0.4786	
R.O.A.A.	0.1982 ***	3.75	0.4354	
Total Assets/Equity	-0.0001 ***	-9.78	-0.0255	
Net Loans/Total Assets	-0.0044	-1.05	-0.0890	
Dep. & Funding/Total	-0.0003	-0.38	-0.0746	
Other Op. Income/Avg	-0.1270 ***	-3.38	-0.5768	
Country Rating	0.5039 ***	19.50	2.0869	
Multiple rating dummy	-0.2149	-1.31		-0.2356
Year Indicators				
2000	-0.3312 *	-1.70		-0.3632
2001	-0.4041 *	-1.86		-0.4432
2002	-0.6615 ***	-2.82		-0.7255
2003	-0.9278 ***	-3.76		-1.0176
2004	-0.8977 ***	-3.59		-0.9846
2005	-0.7463 ***	-2.95		-0.8185
2006	-0.5882 **	-2.29		-0.6451

2007	-0.3868	-1.47		-0.4242
2008	-0.4600 *	-1.73		-0.5045
2009	-0.6652 **	-2.50		-0.7295
2010	-0.7794 ***	-2.97		-0.8547
2011	-0.8353 ***	-3.16		-0.9161
2012	-0.9253 ***	-3.46		-1.0148
2013	-1.0171 ***	-3.79		-1.1154
2014	-0.9883 ***	-3.70		-1.0839
2015	-0.9812 ***	-3.67		-1.0761
No. of observations	26,086			
Pseudo R^2	0.1585			
Clusters of Banks	669			

Table 9: Estimation results for European subsample per CRA

Standard errors are calculated using cluster-correlated robust estimate of variance at the bank level, and the asterisks *, **, and *** correspond to significance levels 10%, 5%, and 1%, respectively.

	Fitch				Moody's				S&P			
Variable	Coefficient	Z stat	Coefficient / Rating Notch	Coeffici / Rating Notch	Coefficient	Z stat	Coefficient / Rating Notch	Coeffici / Rating Notch	Coefficient	Z stat	Coefficient / Rating Notch	Coeffici / Rating Notch
Log		8.	0.7551			4.	0.6416			2.	0.3030	
R.O.A		3.	0.1321			4.	0.4127			3.	0.2748	
Total	-	-	-0.0351		-	-	-2.9006		-	-	-0.0514	
Net	-	-	-0.2103			2.	0.2651			1.	0.1075	
Dep. &	-	-	-0.2527		-	-	-0.1228		-	-	-0.3594	
Other	-	-	-0.0697		-	-	-0.0841		-	-	-0.0915	
Countr		17	2.3005			15	2.4287			17	2.4470	
Multipl	-	-		-0.1317		1.		0.3379	-	-		-0.0881
Year												
2000		0.		0.0414	-	-		-1.9202	-	-		-0.8389
2001	-	-		-0.0246	-	-		-2.2881	-	-		-1.0658
2002	-	-		-0.1412	-	-		-2.1174	-	-		-1.1511
2003	-	-		-0.5553	-	-		-1.9196	-	-		-1.5125
2004	-	-		-0.6475	-	-		-1.9759	-	-		-1.4902
2005	-	-		-0.6213	-	-		-2.1068	-	-		-1.4813
2006	-	-		-0.4944	-	-		-2.1121	-	-		-1.4408
2007	-	-		-0.4607	-	-		-1.2884	-	-		-1.0852
2008	-	-		-0.6892	-	-		-1.4442	-	-		-1.1696
2009	-	-		-0.9421	-	-		-1.7928	-	-		-1.4040
2010	-	-		-0.8292	-	-		-2.1949	-	-		-1.4738
2011	-	-		-0.7972	-	-		-2.5702	-	-		-1.7630
2012	-	-		-0.8112	-	-		-3.1690	-	-		-1.9547
2013	-	-		-0.8345	-	-		-3.4419	-	-		-2.0223
2014	-	-		-0.9374	-	-		-3.6796	-	-		-1.8934
2015	-	-		-0.7794	-	-		-3.2844	-	-		-1.8173
No. of	12,176				9,231				11,187			
Pseud	.2484				.2103				.2201			
Cluste	353				306				277			

Table 10: Estimation results for US & Canada subsample per CRA

Standard errors are calculated using cluster-correlated robust estimate of variance at the bank level, and the asterisks *, **, and *** correspond to significance levels 10%, 5%, and 1%, respectively.

	Fitch				**Moody's**				**S&P**			
Variab le	**Coeff icient**	**Z st at**	**Coefficient Rating Notch**	**Coeffici Rating Notch**	**Coeffic ient**	**Z st at**	**Coefficient Rating Notch**	**Coeffici Rating Notch**	**Coeffic ient**	**Z st at**	**Coefficient Rating Notch**	**Coeffici Rating Notch**
Log of		5.	1.4959			6.	1.4712			4.	1.0638	
R.O.A		3.	0.6035			3.	0.4659			5.	0.8041	
Total	-	-	-0.0797			0.	0.3579		-	-	-0.0279	
Net	-	-	-0.4680		-	-	-0.4881		-	-	-0.7781	
Dep. &	-	-	-0.3283			0.	0.0035			0.	0.0092	
Other	-	-	-0.1898		-	-	-0.6660		-	-	-0.6530	
Countr	-	-	-0.0889		(omitted					2.	0.2551	
Multipl		3.		1.3618	-	-		-0.7732		0.		0.1756
Year												
2000					-	-		-0.3397	-	-		-0.4814
2001	-	-		-0.0101	-	-		-0.4523	-	-		-0.6418
2002	-	-		-0.3428	-	-		-0.7360	-	-		-1.1502
2003	-	-		-0.5076	-	-		-1.0738	-	-		-1.3702
2004	-	-		-0.5943	-	-		-1.3804	-	-		-1.3449
2005	-	-		-0.6171	-	-		-1.3535	-	-		-1.2276
2006	-	-		-0.7629	-	-		-1.4051	-	-		-0.9807
2007	-	-		-0.8108	-	-		-0.6848	-	-		-0.9872
2008	-	-		-0.8914	-	-		-1.0847	-	-		-1.0080
2009	-	-		-1.2687	-	-		-2.1354	-	-		-1.9473
2010	-	-		-1.8870	-	-		-2.9683	-	-		-2.6712
2011	-	-		-2.1442	-	-		-3.2057	-	-		-2.5071
2012	-	-		-2.4784	-	-		-3.9026	-	-		-2.3458
2013	-	-		-2.5424	-	-		-3.8106	-	-		-2.4531
2014	-	-		-2.4615	-	-		-4.0080	-	-		-2.4912
2015	-	-		-2.4940	-	-		-3.8173	-	-		-2.4838
No. of	6,225				6,274				6,960			
Pseud	.135				.0701				.0842			
Cluste	162				185				174			

Table 11: Estimation results for RoW subsample per CRA

Standard errors are calculated using cluster-correlated robust estimate of variance at the bank level, and the asterisks *, **, and *** correspond to significance levels 10%, 5%, and 1%, respectively.

	Fitch				**Moody's**				**S&P**			
Varia ble	**Coeff icient**	**Z st at**	**Coefficient Rating Notch**	**Coeffici Rating Notch**	**Coeffi cient**	**Z st at**	**Coefficient Rating Notch**	**Coeffici Rating Notch**	**Coeffi cient**	**Z st at**	**Coefficient Rating Notch**	**Coeffici Rating Notch**
Log		5.	0.6400			5.	0.6794			4.	0.5487	
R.O.A		1.	0.2299			1.	0.2725			1.	0.4585	
Total	-	-	-0.6014		-	-	-2.3800		-	-	-0.1651	
Net		1.	0.1183			2.	0.2479		-	-	-0.0248	
Dep. &		0.	0.0452			3.	0.0815			0.	0.0000	

Other		0.	0.0704		-	-	-0.2288		-	-	-0.0670	
Countr		14	2.1684			12	2.6097			12	2.3845	
Multipl		5.		0.3828	-	-		-0.0166		0.		0.0102
Year												
2000					-	-		-0.1602	-	-		-0.7928
2001	-	-		-0.3828	-	-		-0.1450	-	-		-1.0044
2002	-	-		-0.7686	-	-		-0.0600	-	-		-1.3421
2003	-	-		-1.1568	-	-		-0.1365	-	-		-1.6834
2004	-	-		-1.2401	-	-		-0.2763	-	-		-1.7898
2005	-	-		-1.2949	-	-		-0.3194	-	-		-1.3585
2006	-	-		-1.4148	-	-		-0.3662	-	-		-1.1471
2007	-	-		-1.3447	-	-		-0.0721	-	-		-1.1086
2008	-	-		-1.3153	-	-		-0.0650	-	-		-1.2030
2009	-	-		-1.2301	-	-		-0.0441	-	-		-1.1307
2010	-	-		-1.2647		0.		0.0505	-	-		-1.2913
2011	-	-		-1.3610	-	-		-0.1346	-	-		-1.2074
2012	-	-		-1.4481	-	-		-0.1325	-	-		-1.1698
2013	-	-		-1.5977	-	-		-0.2473	-	-		-1.2844
2014	-	-		-1.6117	-	-		-0.3116	-	-		-1.3294
2015	-	-		-1.5935	-	-		-0.3402	-	-		-1.3812
No. of	8,146				6,793				7,939			
Pseud	0.2916				0.317				0.2909			
Cluste	262				255				218			

Table 12: Estimation results for Structural Breaks for the World sample

a. World sample: Wald test for intercepts

	b_1 2002-5	Coefficient/ Rating Notch Length	b_2 2006-8	Coefficient/ Rating Notch Length	b_3 2009-15	Coefficient/ Rating Notch Length	*p-value*
Fitch	-0.388	-0.365	-0.486	-0.458	-0.662	-0.623	0.000
Moody's	-0.354	-0.419	-0.072	-0.085	-0.733	-0.868	0.000
S&P	-0.633	-0.696	-0.290	-0.319	-0.697	-0.766	0.000

b. World sample: Wald test for slopes

	b_{02} -2001	b_{12} 2002-5	b_{22} 2006-8	b_{32} 2009-15	*p-value*
Fitch	-0.022	-0.022	-0.011	-0.003	0.030
Moody's	-0.062	-0.013	0.054	-0.036	0.000
S&P	-0.046	-0.001	0.013	-0.014	0.002

Table 13: Estimation results for Structural Breaks for the US & Canada subsample

a. US & Canada subsample: Wald test for intercepts

	b_1 2002-5	Coefficient/ Rating Notch Length	b_2 2006-8	Coefficient/ Rating Notch Length	b_3 2009-15	Coefficient/ Rating Notch Length	*p-value*
Fitch	-0.404	-0.510	-0.648	-0.817	-1.703	-2.148	0.000
Moody's	-0.549	-0.778	-0.517	-0.733	-1.927	-2.730	0.000
S&P	-0.792	-1.038	-0.573	-0.751	-1.629	-2.136	0.000

b. US & Canada subsample: Wald test for slopes

We report the *p*-value for the Wald χ^2 test for the hypothesis that all coefficients are equal.

	b_{02} -2001	b_{12} 2002-5	b_{22} 2006-8	b_{32} 2009-15	*p-value*
Fitch	-0.006	-0.018	-0.017	-0.038	0.372
Moody's	-0.034	-0.032	0.016	-0.042	0.142
S&P	-0.054	-0.003	-0.007	-0.011	0.254

Table 14: Estimation results for Structural Breaks for the European Subsample

a. European subsample: Wald test for intercepts							
	b_1 2002-5	Coefficient/ Rating Notch Length	b_2 2006-8	Coefficient/ Rating Notch Length	b_3 2009-15	Coefficient/ Rating Notch Length	*p-value*
Fitch	-0.574	-0.534	-0.625	-0.582	-0.976	-0.908	0.000
Moody's	-0.630	-0.721	-0.258	-0.295	-1.346	-1.539	0.000
S&P	-0.993	-0.939	-0.765	-0.722	-1.316	-1.249	0.000

b. European subsample: Wald test for slopes					
	b_{02} -2001	b_{12} 2002-5	b_{22} 2006-8	b_{32} 2009-15	*p-value*
Fitch	-0.008	-0.041	-0.029	0.001	0.014
Moody's	-0.229	-0.004	0.065	-0.065	0.000
S&P	-0.127	-0.021	0.029	-0.023	0.000

Table 15: Estimation results for Structural Breaks for the RoW subsample

a. RoW subsample: Wald test for intercepts							
	b_1 2002-5	Coefficient/ Rating Notch Length	b_2 2006-8	Coefficient/ Rating Notch Length	b_3 2009-15	Coefficient/ Rating Notch Length	*p-value*
Fitch	-1.095	-0.950	-1.371	-1.189	-1.467	-1.270	0.000
Moody's	-0.188	-0.146	-0.069	-0.054	-0.089	-0.069	0.821
S&P	-1.278	-1.025	-0.740	-0.593	-0.880	-0.705	0.000

b. RoW subsample: Wald test for slopes					
	b_{02} -2001	b_{12} 2002-5	b_{22} 2006-8	b_{32} 2009-15	*p-value*
Fitch	-0.165	-0.053	0.018	-0.024	0.014
Moody's	-0.034	-0.027	0.048	-0.021	0.000
S&P	n/a	n/a	n/a	n/a	n/a

Figures

Figure 1: Plot of year indicator estimates for the full world sample, 2000 to 2015, for each CRA

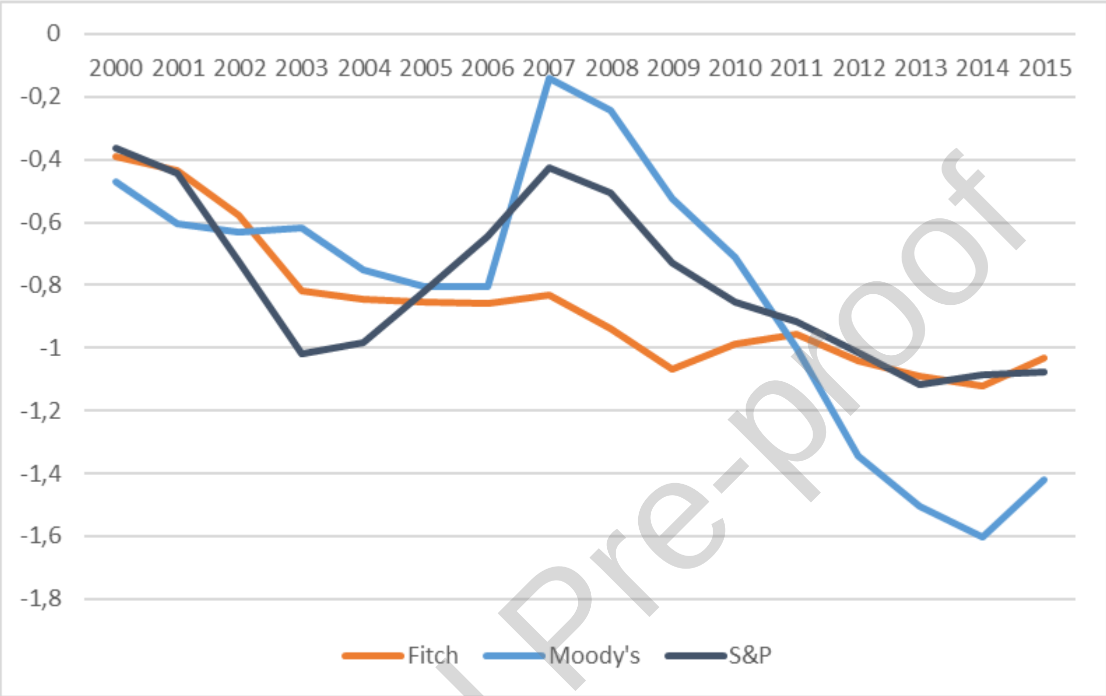


Figure 2: Plot of year indicator estimates for the European subsample, from 2000 to 2015, for each CRA

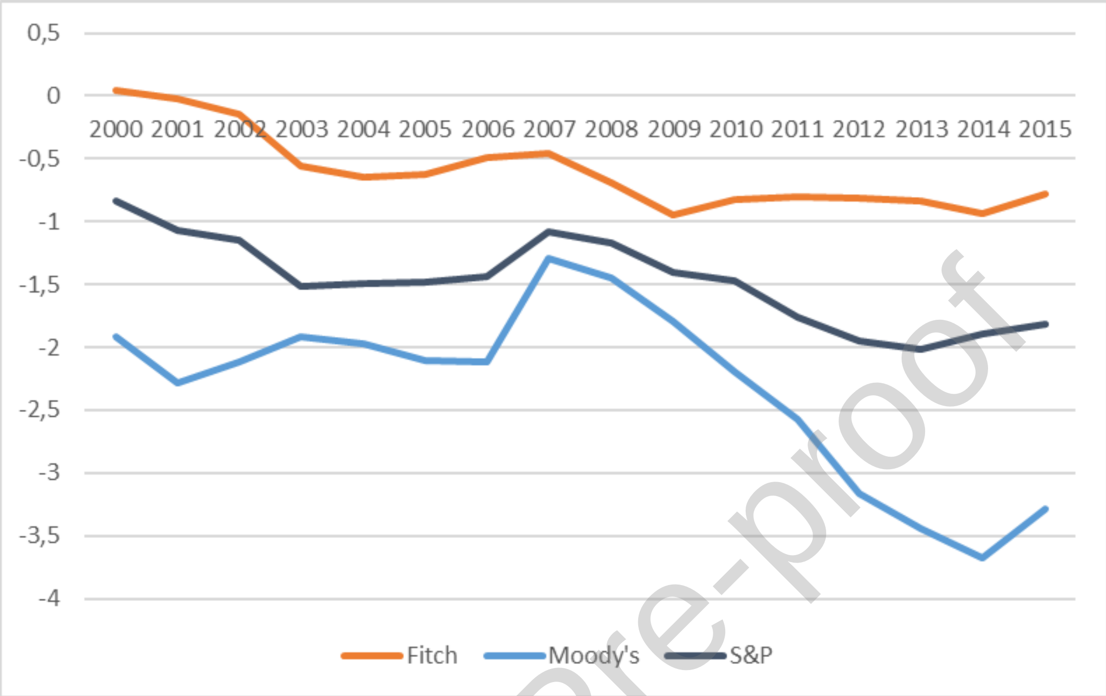


Figure 3 Plot of year indicator estimates for the US & Canada subsample, from 2000 to 2015, for each CRA

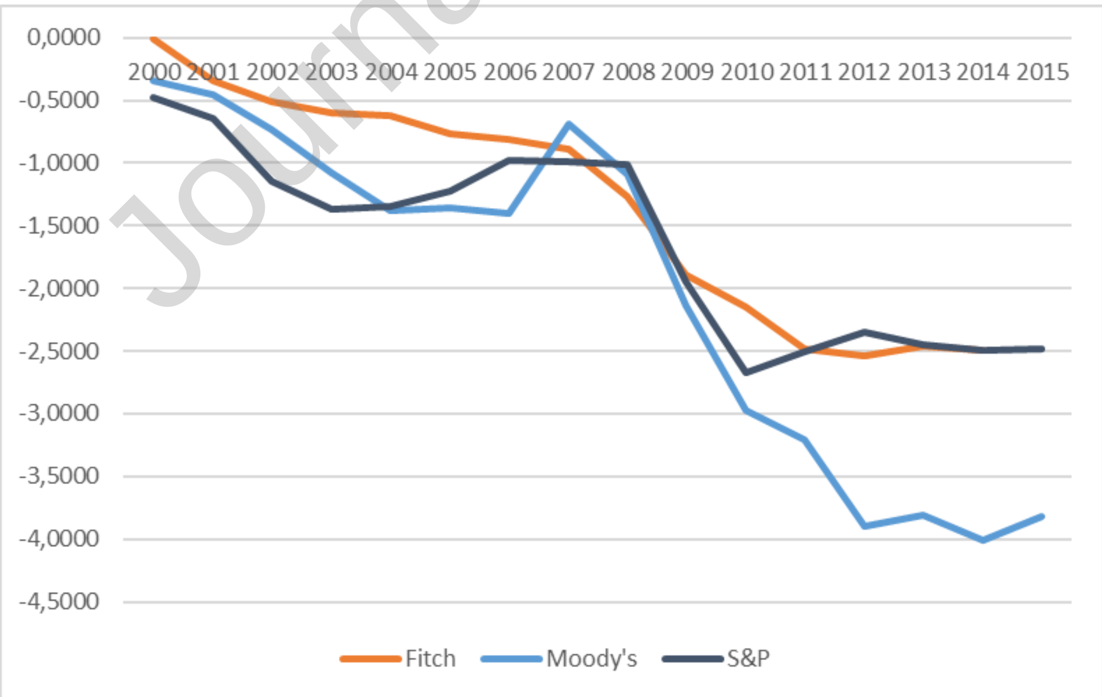


Figure 4: Plot of year indicator estimates for the RoW sample, 2000 to 2015, for each CRA