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Bank Asset and Informational Quality

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Abstract

We examine the relationship between bank asset and informational quality. We use a diversified panel of 699 banks from 84 countries and measure opacity (lack of informational quality) with rating disagreements between issuer-specific ratings by three credit rating agencies (S&P, Moody's and Fitch). Results from panel ordered logit regressions show that poor asset quality increases the probability of greater credit rating disagreements. Considering that the recent regulatory frameworks require from banks to reduce the worrying levels of non-performing loans and to increase transparency in their risk-taking, our findings have important policy implications.

Keywords: banks, opacity, split ratings, asset quality

JEL: G20, G21, G28

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1. Introduction

Banks do not always fully disclose their risks. In the immediate term, banks benefit from hiding negative information as they report higher profits and healthier asset quality than the real ones[2]. This reduces capital needs, enables the bank to maintain its reputation or even improves that and allows managers gain better compensation and credentials (Jensen and Meckling, 1976). However, these information asymmetries regarding the bank's risk-taking can have adverse effects on the bank and the broader financial system. A key source of bank risk is non-performing loans (henceforth NPLs) that increased significantly for many banks during the recent financial crisis. To deal with the asymmetric information about NPLs, bank supervisory authorities set new disclosure requirements that increase the transparency with which financial institutions publish their risks[3]. On the other hand, bank supervisors have taken steps to reduce the levels of NPLs that are preventing banks from operating normally, which appeared to be effective in many European countries. An interesting question therefore arises from such a context, that is, whether the reduction in NPLs could also improve bank transparency.

This paper aims to investigate whether poor asset quality prevents banks from being transparent by measuring opacity (lack of informational quality) with credit rating disagreements. A rating disagreement, also referred to as split rating, occurs when two rating agencies assign a different rating to the same asset (issue) or firm (issuer). When a bank is opaque and the public cannot assess the quality of the published information, credit rating agencies should disagree more about the creditworthiness of this bank compared to other institutions whose publicly available

[2] Niinimaki (2012) describes two methods with which banks hide loan losses.

[3] Basel Pilar 3 focuses on disclosure requirements: "The Basel Committee on Banking Supervision (BCBS) has long believed that it is important to encourage market discipline by way of meaningful disclosure of the key risks borne by internationally active banks" (BIS, 2019). Similarly, the European Banking Authority has published explicit disclosure requirements for non-performing and forborne exposures (EBA, 2018).

information is more transparent. Morgan (2002) introduced this measure of opacity and since then it has been widely used to proxy the lack of transparency in banking as well as in other industries (e.g., Hyytinen and Pajarinen, 2008; Iannotta, 2006). Livingston et al. (2007) show that firms that experience asset opacity issues are more likely to receive disagreed ratings from different agencies.

Opacity can have significant implications for any firm and for the financial markets. Opaque firms are harder to value and thus suffer from decreased market liquidity and higher price volatility, thereby more likely to be subject to greater haircuts and be forced to deleverage (Dudley, 2009). Livingston and Zhou (2010) show that investors price information opacity (measured by split ratings) in bond yields as a risk factor. Also, information asymmetries can lead to undervaluation of a firm's equity which makes it more expensive to raise capital (Myers and Majluf, 1984). Morgan (2002) suggests that banks are inherently more opaque compared to other types of firms due to their lack of physical fixed assets and the difficulty of monitoring opaque borrowers. This creates issues in the economy considering the importance of banks in the financial system. In the absence of a government that insures deposits and regulates the bank, bank opacity increases the exposure of the financial system to systemic risks such as bank runs. Jones et al. (2013) argue that opacity matters even in the presence of deposit insurance because it reduces the effectiveness of market discipline. Studying bank opacity in a sample that includes two crisis periods, Flannery et al. (2013) find some evidence that banks are unusually opaque during non-crisis periods and show that crises increase adverse selection costs when trading bank stocks compared to trading stocks issued by other types of firms. Blau et al. (2017) find that bank stocks have significantly higher price delay than non-bank stocks, which is partly driven by informational opacity.

Others, on the other hand, argue that bank opacity may have some short-run beneficial effects for the bank. In the bank opacity model of Jungherr (2018), for a given level of risk, opacity reduces the possibility of a bank run (as negative information is kept away from the public), while bank efficiency and stability are not maximized under full transparency. Berger et al. (2000) argue that differences in opacity within the banking industry help banks to generate persistence in profits, relative to other industries.

Although opacity is important for banks, only a few studies focus on the determinants of bank opacity as measured by split ratings. Morgan (2002) investigates the disagreement between S&P and Moody's ratings on bonds issued by US banks from 1983 to 1993. Morgan finds that a bank's asset composition has a significant effect on the probability of a split rating. More specifically, assets that are inherently associated with greater uncertainty, such as trading assets or loans, are related positively to split ratings, while fixed assets that contain less risk are inversely related to split ratings. Iannotta (2006) conducts a similar study for S&P and Moody's ratings on bonds issued by European banks and finds that riskier types of assets lead to rating splits. Iannotta (2006) also finds that the bank equity ratio increases the probability of split ratings, while Morgan (2002) finds the opposite in his analysis.

Bank assets can increase the bank's vulnerability when their quality is poor. As one of the most important elements of bank analysis, asset quality has attracted significant attention globally after the recent financial crisis. Banks are now required to report in detail their borrowers' ability to pay. The negative effects of poor asset quality on banks have been discussed extensively in literature, such as higher possibility of bank insolvency (e.g., Altman, 1977; Forgione and Migliardo, 2018; Martin, 1977; Wheelock and Wilson, 2000), deteriorated profitability (Brock and Rojas-Suarez, 2000; Garcia-Herrero et al., 2009), and reduction in bank cost efficiency (Berger and DeYoung, 1997).

The analyses of Morgan (2002) and Iannotta (2006) show that riskier types of assets can increase the probability of split ratings for banks and Livingston et al. (2007) report similar findings for other types of firms. Flannery et al. (2004) who measure opacity with market microstructure properties and analysts' earnings forecasts also show that bank asset types have different levels of opacity. Banks usually hold very few assets that are not risky and can be easily and accurately valued. Instead, banks hold risky financial assets and this asset structure may lead to agency issues among shareholders, managers and creditors. When these assets consist of many loans to small borrowers, monitoring becomes difficult for public investors (Diamond, 1984). Morgan (2002) argues that delegating monitoring to the bank is efficient but the bank might not always be transparent about the ability of its borrowers to repay their loans. Gao et al. (2019) provide evidence that opaque borrowers can have adverse effects on bank monitoring. Therefore, lending to opaque borrowers can lead to the bank hiding information from the public either actively or passively. In other words, poor asset quality may be associated with bank opacity.

Morgan (2002) and Iannotta (2006) provide some evidence that rating splits are positively associated to bad credit ratings. Bank credit ratings are affected by asset quality (e.g., Huang and Shen, 2015; Poon et al., 1999) but credit ratings and asset quality are two different concepts. Whereas credit ratings reflect the overall creditworthiness of the bank and its capacity to meet its financial commitments, asset quality measures such as problem loans are only partly associated with the bank's ability to pay back its creditors as the bank can turn to other sources of funding to cover its debt obligations in times of distress (e.g., raise capital). The strong focus of recent regulatory requirements on the reduction and transparent reporting of NPLs suggests that the effects of asset quality need to be investigated separately.

Although poor asset quality is inherently associated with higher risk and it is evident that riskier assets drive bank opacity, no study with direct measures of bank asset quality such as problem loans has provided evidence of this relationship. We aim to fill this gap by investigating the relationship between poor asset quality and three rating splits generated by the disagreements among issuer-specific credit ratings by S&P, Moody's and Fitch on a diverse global sample of banks. We posit that poor asset quality increases the probability of rating splits. Our analysis also focuses on whether poor asset quality is associated with increases in the probability of rating splits greater than 1.

The rest of the paper is structured as follows: Section 2 outlines the empirical methodology, Section 3 discusses the data, Section 4 presents the empirical results, Section 5 discusses the robustness checks and Section 6 concludes and discusses the policy implications of the findings.

2. Empirical Methodology

2.1 Measures of Opacity and Asset Quality

Opacity is measured as the absolute difference between pairs of ratings among three credit rating agencies[4]. The long-term Issuer Credit Ratings (ICR) by S&P, Moody's and Fitch are transformed from alphanumeric to numerical values that range from 1 to 17[5] (see Table 1). Since ratings from three credit rating agencies are available, three credit rating splits are constructed as follows:

[4] The binary measurement of rating disagreement that is used in other studies (= 1 when two ratings disagree, 0 otherwise) is not efficient here due to the large variability in rating disagreements. For instance, for investment grade banks, 30% of the SPLIT 3 observations are above 1 (see Table 5).
[5] Jiang (2008) and Shen et al. (2012) also use the same transformation of ratings in 17 numerical values.

$$SPLIT\ 1_{i,t} = \left|S\&P_{i,t} - Moody's_{i,t}\right| \tag{1}$$

$$SPLIT\ 2_{i,t} = \left|S\&P_{i,t} - Fitch_{i,t}\right| \tag{2}$$

$$SPLIT\ 3_{i,t} = \left|Moody's_{i,t} - Fitch_{i,t}\right| \tag{3}$$

Where *SPLIT 1*, *SPLIT 2* and *SPLIT 3* are the credit rating disagreements and *S&P*, *Moody's* and *Fitch* are the credit ratings by the respective agencies in numerical values for bank *i* at time *t*. The resulting split variables are ordered and range from 0 for no disagreement to 9 which is the greatest disagreement between two agencies in the sample.

<Insert Table 1 Here>

The main measure of asset quality is problem loans which is calculated as the sum of non-performing, impaired and other problem loans divided by net total loans. Literature has suggested that NPLs are a good indicator of asset quality (e.g., Meeker and Gray, 1987), however, the inclusion of impaired and other problem loans make problem loans a more comprehensive measure. The ratio of NPLs, net of guaranteed loans to loans before reserves is used as a robustness check. As an alternative to problem and non-performing loans, the ratio of loan loss reserves to gross loans is used. It is calculated as total loan loss and allocated transfer risk reserves divided by total loans and leases, net of unearned income and gross of reserve. Loan loss reserves is the amount that the bank keeps to cover estimated loan losses in case of defaults or nonpayment. The higher the amount of reserves, the more negative the bank's perception is of its borrowers' ability to fully pay back their loans. Therefore, higher values of this ratio indicate the bank's deterioration of asset quality.

2.2 Regression Framework

Considering the categorical nature of the rating disagreement variables, we employ random-effects ordered logit models with time and country dummies in the following form:

$$\Pr(Rating\ Disagreement_{i,t}) = F(Asset\ Quality_{i,t-1}, Controls_{i,t-1}, Year_{i,t}, Country_i) + \varepsilon_{i,t} \qquad (4)$$

Where Rating Disagreement is the rating split as described in equations (1), (2) and (3). Asset quality is measured in different models as problem loans, NPLs or loan loss reserves. Several bank-specific variables are used as controls. The return on average assets for profitability, the equity ratio for bank capital, the cost-to-income ratio for managerial quality, the natural logarithm of the total assets for bank size, the natural logarithm of the ZSCORE for bank risk, the intangible assets ratio, the liquidity ratio and a dummy variable that is equal to 1 when the bank is listed in the stock market and 0 otherwise. Table 2 summarizes all variables. Year and Country are the time and country dummies respectively. $\varepsilon_{i,t}$ is the unobservable error term which follows a logistic distribution with mean zero and variance $\pi^2/3$.

The likelihood-ratio test conducted in all regressions suggests that there is enough variability between banks to prefer a random-effects ordered logit over a standard ordered logit. The results remain consistent when changing the number of integration points in the quadrature approximation used by the random-effects models. In the regressions, only investment grade[6] banks are used, as inclusion of non-investment grade banks does not produce as statistically significant results. Also, regression results for non-investment-grade banks alone are not presented due to limited observations.

<Insert Table 2 Here>

[6] A bank is considered as investment grade in the sample when at least one credit rating agency has rated the bank as investment grade.

3. Data

3.1 Data Source and Sample Characteristics

The relationship between bank asset quality and credit rating disagreements is examined based on an unbalanced panel of 699 banks from 84 countries. Bank-specific data is sourced from the S&P Global Market Intelligence database and macroeconomic data is obtained from the International Monetary Fund (IMF). The sample ranges from 2005 to 2018. Calveras (2003) suggests that banks hide more information under tighter capital requirements which makes our sample period ideal for this study since capital requirements soared globally after the financial crisis. In contrast to other studies that measure opacity with the disagreement between two credit ratings (e.g., Iannotta, 2006; Morgan, 2002), we use three long-term Issuer Credit Ratings (ICR) from the three most renowned credit rating agencies (S&P, Moody's and Fitch). This offers the opportunity for further testing as three different credit rating splits are created instead of one that is the norm in related studies. These ratings constitute the agencies' forward-looking assessment regarding the bank's overall creditworthiness in contrast to ratings used in previous studies that are issue-specific and rate securities such as bonds issued by the bank.

Table 3 presents the distribution of rating split observations across the 84 countries in the sample during 2005-2018. The observations are distributed mainly across banks from North America, Europe and Asia-Pacific. Indicatively, some of the top countries in total rating split observations include USA (1650), United Kingdom (605), Italy (391), France (384), Australia (363), Russia (348) and Taiwan (320).

<Insert Table 3 Here>

3.2 Descriptive Analysis

Table 4 provides important insights to the rating disagreements. First, banks that have an average problem loans ratio above the sample median show a higher average absolute rating gap across all three rating splits than banks with problem loans below the median. Similarly, banks with more problem loans receive on average lower credit ratings. Also, the rating disagreement between Moody's and Fitch (SPLIT 3) has the highest values on average, while the rating disagreement between S&P and Fitch (SPLIT 2) has the lowest values on average. The Kappa statistic suggests that, in all cases, the three credit rating agencies did not make their determinations randomly.

<Insert Table 4 Here>

Table 5 presents the rating gap distribution for all three splits. Credit rating agencies appear to agree around 30-40% of the time, while a considerable proportion of the rating gaps is above 1. More specifically, for investment grade banks that are included in the regressions, rating gaps take the value 2 or more for 21.8% of SPLIT 1 (the rating disagreement between S&P and Moody's), 16.2% of SPLIT 2 and 27.1% of SPLIT 3.

<Insert Table 5 Here>

Figure 1 presents the three-year moving average of each rating split for the sample period, including the financial crisis and its aftermath. It is shown that SPLIT 1 and SPLIT 3 increase significantly during the financial crisis as greater uncertainty over the banks' risk-taking possibly led to more and wider rating disagreements. SPLIT 1 decreases after the financial crisis, while SPLIT 3 maintains its high values. SPLIT 2 has been relatively low compared with the other two, although it increases after the crisis. Overall, it appears that all three splits have been converging closer to 0.9 in recent times.

<Insert Figure 1 Here>

4. Empirical Results

Table 6 reports the results of random-effects ordered logit models with time and country dummies, in which problem loans are used as the main measure of bank asset quality for investment grade banks. The first three models include only problem loans as the explanatory variable and the three different rating splits as the dependent variables. In the next three models, eight bank-specific control variables are added.

<Insert Table 6 Here>

The results presented in Table 6 show that the coefficient of PL is positive and statistically significant throughout the six models with a small drop of significance for model (5) after the inclusion of control variables. This implies that, for investment grade banks, the deterioration of their asset quality increases the probability of a greater disagreement between two rating agencies. Morgan (2002) and Iannotta (2006) have shown that the asset mix is an important determinant of rating splits and bank uncertainty. Both studies find that the probability of a rating split increases when the bank holds riskier types of assets. Extending the work of Morgan (2002) and Iannotta (2006), our findings, in particular the positive and statistically significant coefficients of PL, suggest that the quality of a bank's risky assets is also likely to drive bank opacity. Public investors and rating agencies cannot easily and directly estimate the ability of borrowers, especially those with loans being due, to repay the bank as monitoring is delegated to the bank. Banks with more risky assets are more reluctant to be fully transparent. As a result, the inability to correctly value the loans of non-paying borrowers and the lack of trust in the bank's published information can lead to disagreements between rating agencies regarding the creditworthiness of the bank.

To test the findings with problem loans used as the asset quality measure, loan loss reserves and NPLs substitute problem loans in Tables 7 and 8 respectively. As expected, the coefficients for the NPLs are almost identical to those of PL as the two variables are highly correlated. It appears that the inclusion of impaired and other problem loans does not influence the PL coefficients. LLR coefficients are also in line with the initial findings. Five of the LLR coefficients are positive and highly statistically significant. However, the coefficient for LLR in model (5) is not statistically significant for SPLIT 2. Overall, evidence for the positive relationship between poor asset quality and rating splits is confirmed for SPLIT 1 and SPLIT 3.

The signs of the statistically significant coefficients for the control variables are mostly as expected. Profitability reduces the probability of a rating split between S&P and Fitch (SPLIT 2), while poor managerial quality is positively associated with SPLIT 1 and SPLIT 3. Surprisingly, listed banks appear to cause greater rating disagreements between S&P and Fitch (SPLIT 2).

<Insert Tables 7 and 8 Here>

Table 9 shows the percentage point increase of the probability for wider splits when the PL, LLR or NPL variables increase from the 10^{th} to the 90^{th} percentile, holding the rest of the variables at their median levels. The calculation is based on the coefficients of PL, LLR and NPLs from models (4), (5) and (6) in Tables 6, 7 and 8. For example, when PL increases from the 10^{th} to the 90^{th} percentile, the probability that SPLIT 1 will be wider than 1 increases by 12.11%. The findings presented in Table 9 suggest that asset quality is not only associated with rating disagreements but also with the extent to which they disagree. It suggests that the deterioration of asset quality can increase the probability of greater rating splits even when agencies disagree by 3 rating scales. For the effect of LLR on SPLIT 2 that its coefficient is not statistically significant in the regressions, the percentage point increase of the probability for all split widths is only marginal.

<Insert Table 9 Here>

5. Robustness tests

As the sample includes banks from vastly diverse countries that implement different regulations and are at various stages of financial and economic development, we conduct further robustness checks that are presented on Tables 10 and 11.

We first run regressions for geographical sub-samples. Table 10 shows the regression results for the relationship between problem loans and the three rating splits in USA, European Union and the Asia-Pacific region. The results confirm that SPLIT 1 is consistently positively associated with poor asset quality in all sub-samples. However, the same result for SPLIT 3 that was found in the overall sample appears to be driven by banks from the European Union since the coefficient for problem loans is not statistically significant in the other sub-samples.

Also, to control for time-variant country factors, we add three macroeconomic control variables (i.e. GDP growth, inflation growth and unemployment) since both rating splits and problem loans may be affected by national economic conditions. Table 11 shows the results of the extended regressions from Tables 6, 7 and 8 with the inclusion of the macroeconomic control variables. The coefficient for PL remains highly statistically significant for SPLIT 1 and SPLIT 3, while the coefficients for LLR and NPL drop marginally in statistical significance for SPLIT 1.

<Insert Tables 10 and 11 Here>

6. Conclusions & Policy Implications

Literature argues that banks hide information from the public when they hold more opaque types of assets, which leads to disagreements between rating agencies. However, the role of the quality of risky assets in bank uncertainty has been neglected so far. The aim of this paper has been to examine whether poor asset quality prevents banks from being transparent.

Using a diversified panel of 699 banks from 84 countries over the period of 2005-2018, we examine the relationship between asset quality and opacity as measured by splits among long-term Issuer Credit Ratings (ICR) by three credit rating agencies. We find evidence that poor asset quality is associated with bank uncertainty. More specifically, problem loans, loan loss reserves and NPLs are found to increase the probability of greater credit rating disagreements. This result is found to be robust for the disagreement between ratings by S&P and Moody's in all regressions, while banks from the European Union drive the same result for disagreements between Moody's and Fitch. The analysis of percentage point increases for the probability of wider splits when asset quality decreases further supports that poor asset quality influences the extent to which rating agencies disagree. In several cases, the percentage point increase of the probability for greater rating splits after a significant deterioration in asset quality is large for gaps greater than 1. We argue that this positive relationship between poor asset quality and rating splits exists possibly due to the tendency of banks to hide information from the public because of agency-related incentives or borrower opacity.

Our finding that poor asset quality increases the probability of rating splits has some important policy implications. While previous studies show that banks are inherently more opaque than firms from other industries, the greater opacity that risky bank assets such as loans are associated with should not be ignored. Instead, risky assets can be carefully managed and regulated since banks are important financial institutions for the economy as they transform risk and create liquidity. The recent regulatory frameworks that require banks to reduce their NPLs will probably help banks to be more transparent as agency problems will be decreased. Also, policies for greater transparency in the way NPLs are reported will likely help public investors and credit rating agencies to value more accurately bank assets. This will further reduce the frequency and width of rating disagreements and in turn reduce information asymmetries between banks and investors.

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Tables and Figures

Table 1
The transformation of credit ratings to numerical values

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

The table presents the rating scales of long-term Issuer Credit Ratings (ICR) by S&P, Moody's and Fitch and their numerical transformation. All ratings below B-/B3 take the value of 1 to ensure comparability across all three credit ratings.

Table 2
Descriptive statistics

Variable	Definition	Detailed Description	Mean	Std. Dev.	Min	Max	Obs.
Credit Rating Disagreement							
SPLIT 1	Credit Rating Disagreement 1	The absolute difference between long-term Issuer Credit Ratings (ICR) by S&P and Moody's	0.959	0.880	0.000	8.000	3764
SPLIT 2	Credit Rating Disagreement 2	The absolute difference between long-term Issuer Credit Ratings (ICR) by S&P and Fitch	0.792	0.823	0.000	7.000	3337
SPLIT 3	Credit Rating Disagreement 3	The absolute difference between long-term Issuer Credit Ratings (ICR) by Moody's and Fitch	1.077	0.994	0.000	9.000	3783
Asset Quality							
PL	Problem Loans	The sum of non-performing, impaired and other problem loans divided by net total loans	5.607	9.526	0.000	98.830	5150
LLR	Loan Loss Reserves	Total loan loss and allocated transfer risk reserves divided by total loans and leases, net of unearned income and gross of reserve	3.261	4.152	0.000	83.837	5393
NPL	Non-Performing Loans	Non-performing loans, net of guaranteed loans, divided by loans before reserves	5.404	8.545	0.000	90.343	4589
Bank-Specific Control Variables							
ROAA	Return on Average Assets	Net Income/Average Assets	0.762	1.600	-34.690	33.814	5366
EQRAT	Equity Ratio	Total Equity/ Total Assets	8.808	4.157	-35.043	60.335	5489
MQ	Managerial Quality	Operating Expenses/ Operating Income	56.028	20.380	-172.261	380.818	5437
LNTA	Bank Size	Natural logarithm of total assets	17.680	1.617	12.457	21.981	5479
LNZSCORE	Bank Risk	Natural logarithm of the ZSCORE which is calculated as the sum of EQRAT and ROAA divided by the standard deviation of ROAA	3.121	1.046	-3.682	17.047	5309
INTANGLIBLES	Intangible Assets	Total Intangible Assets/ Total Assets	0.820	1.317	0.000	16.808	5315
LIQUIDITY	Bank Liquidity	Liquid Assets/ Total Assets	29.709	14.891	0.635	167.913	4977
LISTED	Ownership Status	= 1 if bank is listed in the stock market, 0 otherwise	0.536	0.499	0.000	1.000	5520

(Continued on next page)

Table 2 ***(continued)***

Variable	Definition	Detailed Description	Mean	Std. Dev.	Min	Max	Obs.
Macro Control Variables							
GDPG	Real GDP Growth	Annual percentage change of real GDP	2.523	3.001	-15.100	25.100	5498
INFG	Inflation Growth	Annual percentage change of the average consumer price index (CPI)	3.110	3.602	-3.700	59.200	5279
UNEMP	Unemployment	The number of unemployed people as a percentage of the total labor force	7.002	4.289	0.400	27.500	4955

The sample consists of an unbalanced panel of 699 banks from 84 countries and covers the years from 2005 to 2018. The ratings have been transformed into numerical values as shown on Table 1. Asset quality and control variables are in percentage points (%), apart from LNTA, LNZSCORE and LISTED.

Table 3
Distribution of rating split observations across countries in the sample

Country	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*	Country	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
Argentina	0	0	15	Liechtenstein	11	0	0
Australia	150	103	110	Luxembourg	38	35	28
Austria	42	30	45	Malaysia	61	18	25
Azerbaijan	3	6	2	Malta	0	2	0
Bahrain	12	21	13	Mexico	47	57	57
Bangladesh	1	0	0	Mongolia	9	0	7
Belarus	14	16	9	Morocco	4	8	6
Belgium	67	64	52	Netherlands	54	67	65
Bermuda	9	9	11	New Zealand	63	44	44
Brazil	113	85	86	Nigeria	15	39	18
Bulgaria	0	10	2	Norway	26	14	14
Canada	49	55	49	Oman	8	8	9
Chile	49	30	28	Panama	6	25	0
China	89	77	106	Peru	24	34	22
Colombia	20	20	43	Philippines	12	9	48
Costa Rica	2	2	12	Poland	22	16	69
Croatia	2	12	2	Portugal	44	41	45
Cyprus	4	5	19	Qatar	25	26	33
Czech Republic	35	21	28	Romania	4	1	21
Denmark	57	33	33	Russia	127	71	150
Dominican Republic	0	0	6	Saudi Arabia	67	58	72
Egypt	17	15	12	Singapore	41	32	39
Finland	36	17	17	Slovakia	0	0	7
France	125	136	123	Slovenia	5	5	29
Georgia	2	6	11	South Africa	23	22	44
Germany	90	93	110	South Korea	112	89	95
Greece	40	34	33	Spain	103	81	97
Guatemala	9	11	6	Sri Lanka	0	5	6
Hong Kong	80	41	102	Sweden	56	57	39
Hungary	13	0	15	Switzerland	28	18	12
Iceland	0	4	0	Taiwan	137	115	68
India	94	48	65	Thailand	74	67	83
Indonesia	24	34	49	Togo	1	1	1
Ireland	53	40	40	Trinidad and Tobago	7	0	0
Israel	26	18	17	Tunisia	6	6	6
Italy	128	134	129	Turkey	33	30	116
Japan	131	82	83	USA	539	597	514
Jordan	0	9	0	Ukraine	4	4	21
Kazakhstan	22	20	8	United Arab Emirates	37	32	83
Kenya	1	0	0	United Kingdom	189	205	211
Kuwait	31	26	50	Uzbekistan	17	9	0
Lebanon	15	9	14	Vietnam	30	13	24
				All Countries	3764	3337	3783

Table 4
Differences Among Ratings and Rating Disagreements

		Average Ratings			Kappa Statistic			Average Absolute Gap			Correlation Between Ratings		
		S&P	*Moody's*	*Fitch*	*S&P and Moody's*	*S&P and Fitch*	*Moody's and Fitch*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*	*S&P and Moody's*	*S&P and Fitch*	*Moody's and Fitch*
Sample Total		10.048	10.103	10.149	0.245	0.344	0.230	0.959	0.792	1.077	0.940	0.946	0.916
Banks with Problem Loans	Above Median	9.010	8.927	9.356	0.266	0.324	0.221	0.966	0.859	1.171	0.940	0.948	0.908
	Below Median	11.129	11.437	11.116	0.214	0.359	0.231	0.951	0.718	0.962	0.918	0.926	0.911
Investment Grade	Yes	10.417	10.464	10.487	0.227	0.337	0.225	0.971	0.782	1.066	0.919	0.925	0.893
	No	4.004	3.551	4.579	0.301	0.262	0.127	0.791	0.913	1.224	0.823	0.796	0.776

S&P, Moody's and Fitch are the transformed credit ratings by the respective rating agencies (see Table 1). Kappa Statistic is a measure of interrater agreement (See Morgan (2002)). Average absolute gap is the mean of each rating split. Banks are divided in subsamples of banks with average problem loans above and below the sample median (2.51%) and of banks that are rated by at least one of the three rating agencies as investment grade or not.

Table 5
Rating Gap Distribution

		SPLIT 1				*SPLIT 2*				*SPLIT 3*			
Gap =		0	1	2	3+	0	1	2	3+	0	1	2	3+
Sample Total		0.316	0.470	0.170	0.044	0.411	0.424	0.136	0.029	0.300	0.425	0.206	0.069
Banks with Problem Loans	Above Median	0.327	0.462	0.162	0.050	0.385	0.427	0.149	0.039	0.288	0.412	0.199	0.101
	Below Median	0.306	0.479	0.178	0.037	0.440	0.421	0.121	0.018	0.315	0.440	0.216	0.029
Investment Grade	Yes	0.309	0.472	0.175	0.043	0.415	0.424	0.136	0.026	0.304	0.424	0.204	0.067
	No	0.413	0.441	0.091	0.055	0.370	0.429	0.138	0.063	0.244	0.429	0.240	0.087

Banks are divided in subsamples of banks with average problem loans above and below the sample median (2.51%) and of banks that are rated by at least one of the three rating agencies as investment grade or not.

Table 6
Random-Effects Ordered Logit Models with Problem Loans (PL) as measure of Asset Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	SPLIT 1	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
PL	0.041***	0.079***	0.047***	0.040***	0.039**	0.057***
	(0.010)	(0.015)	(0.010)	(0.012)	(0.017)	(0.012)
ROAA				0.071	-0.324***	-0.193**
				(0.095)	(0.103)	(0.087)
EQRAT				0.036	-0.032	0.005
				(0.030)	(0.038)	(0.033)
MQ				0.010***	-0.005	0.016***
				(0.004)	(0.005)	(0.005)
LNTA				-0.112	-0.113	-0.073
				(0.073)	(0.104)	(0.088)
LNZSCORE				-0.268**	-0.125	-0.023
				(0.114)	(0.144)	(0.138)
INTANGIBLES				0.041	-0.131*	-0.053
				(0.063)	(0.077)	(0.074)
LIQUIDITY				-0.009	0.008	0.005
				(0.006)	(0.007)	(0.006)
LISTED				0.040	0.718**	-0.005
				(0.199)	(0.291)	(0.247)
Year Dummies	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES
Observations	2786	2488	2798	2413	2203	2455
N. of Banks	380	364	409	352	340	379
Pseudo R2	0.159	0.214	0.169	0.162	0.218	0.162
Log Likelihood	-2766.62	-2191.8	-2989.82	-2388.32	-1943.48	-2653.51

SPLIT 1, SPLIT 2 and SPLIT 3 are the dependent variables and each one is the absolute difference between each pair of the three credit rating agencies (S&P, Moody's and Fitch). The explanatory variables are all in their 1-year lagged form. Standard errors are in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 7

Random-Effects Ordered Logit Models with Loan Loss Reserves (LLR) as measure of Asset Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	SPLIT 1	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
LLR	0.125***	0.112***	0.123***	0.095***	0.022	0.140***
	(0.030)	(0.035)	(0.028)	(0.034)	(0.041)	(0.032)
ROAA				-0.0004	-0.354***	-0.172
				(0.093)	(0.100)	(0.087)
EQRAT				0.009	-0.045	-0.027
				(0.030)	(0.034)	(0.034)
MQ				0.008**	-0.005	0.016***
				(0.004)	(0.004)	(0.004)
LNTA				-0.134	-0.077	-0.065
				(0.073)	(0.101)	(0.087)
LNZSCORE				-0.183	-0.171	0.012
				(0.116)	(0.142)	(0.139)
INTANGIBLES				0.044	-0.147**	-0.102
				(0.063)	(0.075)	(0.073)
LIQUIDITY				-0.014**	0.008	0.000
				(0.006)	(0.007)	(0.006)
LISTED				0.014	0.688**	0.059
				(0.205)	(0.288)	(0.246)
Year Dummies	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES
Observations	2876	2578	2888	2478	2278	2532
N. of Banks	394	377	420	364	350	388
Pseudo R2	0.159	0.203	0.166	0.161	0.210	0.160
Log Likelihood	-2878.07	-2315.37	-3135.47	-2472.01	-2036.44	-2776.35

SPLIT 1, SPLIT 2 and SPLIT 3 are the dependent variables and each one is the absolute difference between each pair of the three credit rating agencies (S&P, Moody's and Fitch). The explanatory variables are all in their 1-year lagged form. Standard errors are in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 8
Random-Effects Ordered Logit Models with Non-Performing Loans (NPL) as measure of Asset Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	SPLIT 1	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
NPL	0.045***	0.090***	0.055***	0.041***	0.048**	0.056***
	(0.012)	(0.017)	(0.012)	(0.014)	(0.020)	(0.014)
ROAA				0.058	-0.285***	-0.216**
				(0.097)	(0.102)	(0.088)
EQRAT				0.038	-0.020	0.009
				(0.031)	(0.038)	(0.034)
MQ				0.011***	-0.005	0.016***
				(0.004)	(0.005)	(0.005)
LNTA				-0.098	0.006	-0.085
				(0.080)	(0.105)	(0.093)
LNZSCORE				-0.308**	-0.149	-0.130
				(0.121)	(0.146)	(0.148)
INTANGIBLES				0.034	-0.149	-0.060
				(0.064)	(0.076)	(0.075)
LIQUIDITY				-0.010	0.008	0.002
				(0.006)	(0.007)	(0.006)
LISTED				-0.046	0.649**	-0.057
				(0.209)	(0.283)	(0.256)
Year Dummies	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES
Observations	2475	2234	2499	2123	1967	2174
N. of Banks	343	331	372	317	310	344
Pseudo R2	0.161	0.198	0.165	0.161	0.199	0.160
Log Likelihood	-2472.07	-2024.7	-2710.84	-2120.49	-1793.5	-2383.74

SPLIT 1, SPLIT 2 and SPLIT 3 are the dependent variables and each one is the absolute difference between each pair of the three credit rating agencies (S&P, Moody's and Fitch). The explanatory variables are all in their 1-year lagged form. Standard errors are in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 9
The percentage point increase of the probability for wider splits when banks increase their PL, LLR or NPL from the 10^{th} to the 90^{th} percentile.

	PL			LLR			NPL		
	SPLIT 1	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
Gap > 0	2.12%	8.74%	15.51%	1.82%	3.50%	20.62%	2.07%	13.64%	9.96%
Gap > 1	12.11%	4.07%	1.89%	14.97%	0.72%	2.66%	12.23%	1.43%	10.51%
Gap > 2	2.89%	0.23%	0.15%	5.32%	0.04%	0.22%	3.09%	0.08%	1.19%
Gap > 3	0.38%	0.01%	0.02%	0.88%	0.00%	0.03%	0.39%	0.00%	0.15%

The table presents the percentage point increase of the probability for wider splits when the problem loans (PL), loan loss reserves (LLR) or non-performing loans (NPL) variables increase from the 10th to the 90th percentile, holding the rest of the variables at their median levels. The calculation uses the PL, LLR and NPL coefficients from models (4), (5) and (6) from Tables X, Y and Z. Results for Gap > 4 are not reported as those percentage point increases are very close to zero.

Table 10
Random-Effects Ordered Logit Models with Problem Loans (PL) as measure of Asset Quality for different geographical subsamples

	USA			European Union			Asia-Pacific		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SPLIT 1	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
PL	0.553***	0.092	0.169	0.030***	0.002	0.031***	0.432***	0.214	0.094
	(0.117)	(0.123)	(0.127)	(0.010)	(0.017)	(0.011)	(0.145)	(0.253)	(0.161)
ROAA	0.261	-0.325	0.516	0.117	-0.196	-0.268***	-0.039	-0.078	-0.272
	(0.322)	(0.322)	(0.359)	(0.117)	(0.135)	(0.102)	(0.497)	(0.686)	(0.475)
EQRAT	-0.089	0.082	0.056	0.003	-0.109	-0.020	-0.008	-0.340	-0.089
	(0.066)	(0.079)	(0.083)	(0.034)	(0.055)	(0.044)	(0.095)	(0.172)	(0.110)
MQ	0.023	-0.007	0.050***	0.006	-0.008	0.006	-0.007	-0.002	0.016
	(0.015)	(0.014)	(0.016)	(0.004)	(0.005)	(0.005)	(0.015)	(0.022)	(0.018)
LNTA	-0.362*	0.540	0.156	-0.002	-0.321**	-0.334***	-0.382*	-1.289***	0.455*
	(0.188)	(0.249)	(0.246)	(0.087)	(0.132)	(0.099)	(0.217)	(0.381)	(0.247)
LNZSCORE	-0.485*	-0.223**	-0.691	-0.147	-0.077	-0.027	0.512	-0.005	0.332
	(0.284)	(0.338)	(0.436)	(0.109)	(0.169)	(0.140)	(0.429)	(0.647)	(0.488)
INTANGIBLES	0.098	-0.048	-0.096	-0.256**	-0.519	0.205	1.336***	1.170*	0.525
	(0.096)	(0.112)	(0.119)	(0.125)	(0.170)	(0.133)	(0.429)	(0.606)	(0.482)
LIQUIDITY	-0.023	-0.016	0.004	-0.012***	-0.005	0.004	0.039**	0.099***	0.015
	(0.016)	(0.019)	(0.019)	(0.005)	(0.008)	(0.006)	(0.018)	(0.029)	(0.014)
LISTED	-0.858	-0.435	0.499	-0.074	1.232***	0.257	1.025*	1.324	-1.656***
	(0.628)	(0.797)	(0.885)	(0.207)	(0.343)	(0.261)	(0.583)	(0.862)	(0.636)
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	418	441	388	854	811	895	703	520	616
N. of Banks	55	61	52	121	120	134	96	76	92
Pseudo R2	0.187	0.212	0.222	0.112	0.171	0.116	0.317	0.335	0.303
Log Likelihood	-386.07	-384.01	-359.96	-918.93	-757.18	-1083.25	-545.48	-336.72	-476.14

SPLIT 1, SPLIT 2 and SPLIT 3 are the dependent variables and each one is the absolute difference between each pair of the three credit rating agencies (S&P, Moody's and Fitch). The explanatory variables are all in their 1-year lagged form. Standard errors are in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 11
Random-Effects Ordered Logit Models with macro controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SPLIT 1	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*	*SPLIT 1*	*SPLIT 2*	*SPLIT 3*
PL	0.035***	0.025	0.049***						
	(0.012)	(0.017)	(0.012)						
LLR				0.079**	-0.006	0.117***			
				(0.034)	(0.041)	(0.032)			
NPL							0.035**	0.033	0.047***
							(0.014)	(0.021)	(0.014)
GDPG	-0.003	-0.053	-0.010	-0.002	-0.048	-0.017	0.001	-0.062*	-0.017
	(0.028)	(0.034)	(0.026)	(0.028)	(0.034)	(0.026)	(0.029)	(0.035)	(0.027)
INFG	-0.083	-0.021	-0.005	-0.074	0.006	0.019	-0.099*	-0.010	-0.011
	(0.051)	(0.056)	(0.043)	(0.050)	(0.055)	(0.042)	(0.054)	(0.057)	(0.044)
UNEMP	0.045	0.127***	0.061	0.056	0.140***	0.057	0.070*	0.113**	0.050
	(0.037)	(0.045)	(0.039)	(0.037)	(0.044)	(0.039)	(0.038)	(0.046)	(0.041)
Bank-Specific Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2244	2054	2295	2305	2125	2368	1954	1818	2015
N. of Banks	326	315	349	338	325	358	291	285	315
Pseudo R2	0.150	0.215	0.155	0.149	0.208	0.153	0.150	0.194	0.151
Log Likelihood	-2254.75	-1814.03	-2506.55	-2336.26	-1903.59	-2626.82	-1984.60	-1663.75	-2238.33

SPLIT 1, SPLIT 2 and SPLIT 3 are the dependent variables and each one is the absolute difference between each pair of the three credit rating agencies (S&P, Moody's and Fitch). The explanatory variables are all in their 1-year lagged form. Standard errors are in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Figure 1. Credit rating disagreements over time
The figure reports the three-year moving average of the mean of each rating split.