Why Bank Ratings Split: Evidence from Fitch and Moody's

Changchun Hua *
Asian Public Policy Program, Hitotsubashi University
2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo, Japan
Telephone: +81-80-6509-5515
chua@st.ics.hit-u.ac.jp

Li-Gang Liu
Economic Research Division,
Research Department, Hong Kong Monetary Authority
55/F, IFC II, 8 Finance Street, Central, Hong Kong
lliu@hkma.gov.hk

* Changchun Hua is the corresponding author.

Abstract

To explain rating splits, the literature has proposed the information asymmetry hypothesis, the self-selectivity hypothesis, the rating model difference hypothesis and the random error hypothesis. While the fist two hypotheses mainly explain rating splits from the perspective of issuers, the last two hypotheses try to clarify rating differences from the perspective of raters. This paper attempts to combinedly examine these hypotheses in explaining bank rating splits between Moody's and Fitch, using an unbalanced panel data consisting of 781 banks during the period of 1998-2004. The data shows that the disagreement on bank financial strength between Fitch and Moody's is not rare but quite frequent and persistent. Furthermore, rating splits have asymmetric or lopsided distribution that Fitch generally assigns higher ratings, compared to Moody's. Using the two-stage approach, empirical studies finds that there is lack of evidence for sample selection bias in all regressions, which implies that banks' self-selectivity may not account much for bank rating splits. Furthermore, the information asymmetry hypothesis only gains partial support from the data. This hypothesis generally holds in emerging markets but not in mature markets, suggesting that the relationship between bank asset opaqueness and bank rating splits may diminish when financial system, information disclosure and financial infrastructure improves. This empirical evidence implies that bank rating splits may not really inherent in banks. The lopsided rating differences may mainly be due to the difference in rating models, such as different factors considered by raters, non-identical weighting system or different standards.

Key words:
Rating split　Information asymmetry　Sample selection bias　Ordered probit model

JEL classification:　C35, D82, G21

1. Introduction

Ratings have been extended to assess bank intrinsic safety and soundness by Moody's Investors Service (Moody's) and Fitch Ratings (Fitch), named as Moody's bank financial strength rating (MBFSR) and Fitch Individual Rating (FBIR), respectively. These ratings generally represent the two raters' summary measurements of the likelihood that a bank will run into financial difficulties and require assistance from its owners, industry group, or the authorities (Estrella et al, 2000; Moody's, 2006). When these two agencies rate a same bank, however, it is not always the case that they assign the same ratings. Why they assign different ratings to a same bank is of great interest to financial regulators, investors and other rating users. As these ratings are gaining greater acceptance in the marketplace, this issue is more and more important. This paper is to investigate the causes of bank rating splits between Moody's and Fitch from two perspectives—banks and rating agencies.

This study collects a panel of dataset consisting of 781 banks and deposit institution during the period 1998-2004. In the sample, 395 banks also obtain FBIR. With this dataset, the existing four main hypotheses—the information asymmetry hypothesis, the random error hypothesis, the self-selectivity hypothesis and the rating model hypothesis—that may explain the rating splits are examined. Empirical evidence shows that FBIR is systematically higher than MBFSR, which is probably the result of the differences in rating models.

In what follows, relevant literature and hypotheses of past studies is reviewed. Section 3 will present empirical methodology and discuss variables for regressions, followed by the data description of Section 4. Section 5 provides the empirical results and analyses and section 6 concludes.

2. Relevant Literature and Hypotheses

The line of research on rating splits, since Ederington (1986), has been trying to explain why rating agencies sometimes differ on the credit risk of bonds or sovereign from the point view of issuers and raters, respectively. From the point view of issuers, studies (e.g., Morgan, 2002) contend that the split rating reflects disagreement between rating agencies due to uncertainty created by the opacity of the issuing firms' assets, which is often viewed as information asymmetry hypothesis in the literature. Furthermore, rating splits may also possibly be the result of issuers' decision to solicit an optional rating, namely the self-selection behavior obtaining ratings from other rating agencies (Cantor and Packer, 1997). In terms of rating agencies, rating splits may arise due to the differences in rating models (factors considered by raters and their weights in the rating models) or/and subjective random errors in the rating process. These can be regarded as the rating model hypothesis and the random error hypothesis, respectively.[1] These views will be reviewed here and tested in the following sections.

Information asymmetry, self-selectivity and rating splits: Issuers' side

Theoretical works (Ramakrishnan and Thakor, 1984; Millon and Thakor, 1985) suggest that information asymmetry provides rationales for rating agencies to exist or for an issuer to solicit a rating. It also, however, could be an important source of rating splits since raters may form different opinions about the creditworthiness of the same issuer under the information asymmetry circumstances. This is possible even though their rating standards and methodologies do not differ systematically from each other. When rating agencies assess the creditworthiness of an issuer, they are probably not able to locate certain points for its creditworthiness. Instead, the possible creditworthiness is more likely to be a range. Rating splits may occur when the range of creditworthiness lies crossing the cutoffs. When the information availability or quality of an issuer is poorer, raters will probably have trouble in estimating its creditworthiness, which in turn may generate a larger range of the creditworthiness. The larger range of possible creditworthiness has higher possibilities of crossing the borderline between two notches, and therefore, raters have more chances to assign different ratings.

The role of information asymmetry in triggering rating splits was proposed in Morgan

[1] Some other reasons are also suggested in the literature in this respect, but they probably are only present in some special cases. For instance, for the case of rating splits between different countries' rating agencies, home bias may be an important source of rating differences (Shin and Moore, 2003).

(2002) and further examined in Livingston, Naranjo and Zhou (2005) and Haggard, Jain, Martin, and Pereira (2006). Morgan (2002) argued that banks are black boxes and their risks are hard to observe from outside the bank due to the opacity of their assets. Given this observation, rating splits should occur more often over bank bond issues compared to those of other industries if the information asymmetry hypothesis holds. In terms of split frequency and level, the author indeed found that Moody's and S&P disagree more with each other over banks than other industries (e.g., manufacturing, mining, services, etc.), except for the insurance industry that has higher uncertainty. This paper further explored the source of uncertainty inside the bank by running the regression of the split level (the absolute value of rating differences) on eight categories of bank assets and other potential explanatory variables. Estimation results suggest that loans and leases, cash and deposits, and trading assets increase the likelihood of disagreements, while the more fixed assets (premises and other real assets) tend to resolve the uncertainty. In addition, bank capital level also appears to help mitigate uncertainty and reduce rating splits, as expected in theory.

Livingston, Naranjo, and Zhou (2005) also confirmed that issuers with more information asymmetry problems are more likely to receive split bond ratings. They further proposed that if information asymmetry hypothesis holds, bonds with initial split ratings will be more likely to experience rating changes as time passes by. Moreover, the pattern of changes in ratings should to some extent bring convergence across rating agencies, although rating splits may largely remain. This is possible because the privation information of issuers will eventually become available to rating agencies. As the private information is revealed, raters will probably be able to understand better about the creditworthiness and update their assessments, triggering more rating changes and convergence among rating agencies. Their data and empirical tests widely support their arguments, providing further evidence for the information asymmetry hypothesis. Haggard, Jain, Martin, and Pereira (2006) explored this hypothesis by linking firm information quality—the precision of financial signals emanating from the firm's information system—and bond rating splits. Consistent with the information asymmetry hypothesis, they did find firms with lower measured information quality have a higher incidence of split ratings using a large sample of over 3,500 issues during 1981-2003.

Furthermore, another view from the perspective of issuers but completely different from the abovementioned hypothesis is that rating splits can be caused by the self-selectivity behavior. Not all issues or issuers are rated by all rating agencies, and therefore, rating splits may also be a result of sample selection, which is referred to as self-selectivity hypothesis here. As pointed out by Estrella (2000), credit ratings measure the relative likelihood of default instead of absolute defaulting probabilities, and are ordinal and relative rankings of the ability to service debt or the creditworthiness of issuers. Rating splits between agencies may occur due to different samples, especially when the sample means are different from the population ones. Moreover, these samples generally are the result of self-selection by issuers. For instance, some issuers choose to be rated by certain rating agency probably because they know that that agency provides a more favorable rating treatment to firms in an industry with their specific characteristics (Cantor and Packer, 1997). As such, self-selection may also be another source of rating splits.

This hypothesis can be explained more straightforwardly with the following econometric equations, as stated in Cantor and Packer (1997). The split expectation of two ratings in the hypothetical population (*P*) can be written as

$$E[r_1 - r_2 \mid P] = \alpha + E[\mathbf{x\beta} \mid P] \tag{1}$$

while the observed difference mean based on the sample (*S*) is

$$E[r_1 - r_2 \mid S] = \alpha + E[\mathbf{x\beta} \mid S] + E[\varepsilon \mid S] \tag{2}$$

where α is constant that may vary between agencies and $\mathbf{x}$ is a vector of observable information of issues/issuers. Including α and $\mathbf{x}$ is to capture the effects of rating models or other factors than sample selection on splits in the two ratings. If sample selection were entirely random, the conditional expectation of ε in *eq.* (2) would be zero and the conditional mean of $\mathbf{x}$ would equal its unconditional mean. In this case, observed rating splits would be caused by other sources, for instance, different rating standards or weightings. However, if the sample selection were nonrandom, the mean of $\mathbf{x}$ in the sample may differ from the one in population, which in turn causes the sample mean of $r_1 - r_2$ to vary from the population mean. Furthermore, if sample selection were related to ε, estimates of α and β would also be biased.

Cantor and Packer (1997) examined the role of sample selection in explaining rating splits between optional agencies (Fitch and Duff & Phelps) and mandatory agencies (Moody's and S&P) using a sample of 871 corporation bonds with outstanding ratings as of year-end 1993. The two-step procedure is applied to estimate the decision to obtain a third rating (Fitch or Duff & Phelps) and the determinants of rating splits. The primary issue of interest is the significance and scale of the inverse Mills ratio estimated from the first-stage probit regressions in the second-stage OLS or ordered probit regressions. The inverse Mills ratio measures the extent to which an issuer appears in the sample rated by the optional agency unexpectedly, based on their observed characteristics. Estimation results show that the inverse Mills ratio is generally significant in the second-stage regressions except for some cases, indicating the existence of self-selectivity. Large rating differences, however, after controlling for sample selection, implying that sample selection bias does not appear to explain much of rating splits.

Pottier and Sommer (1999) also examined reasons for differences in insurer financial strength ratings across agencies (S&P, Moody's, and Best), controlling for the sample selection bias. Furthermore, they also followed Ederington (1986) to test the differences in rating models of S&P and Moody's by restricting the cutoff values to be the same for the two models. Estimations find no evidence of sample selection bias in the rating difference regressions, indicating that rating splits across agencies do not seem to be driven by self-selection issues. Instead, the statistic test finds that rating agencies differ systematically from each other in the relative importance given to the different factors they consider, although the standards do not appear to differ.

Rating models, random error and rating splits: raters' side

From the perspective of rating agencies, Ederington (1986) documented that bond rating splits between two rating agencies could be attributed to different standards of creditworthiness, varied weighting and factors in creditworthiness estimations, or random differences of opinion on credit risk. With a hypothetical and simple rating process framework, Morgan (2002) proposed a theoretical model to demonstrate that the lopsided rating splits could be the result of different standards. The model assumes that there exist (reputation) costs for rating agencies if they misrate (either overrate or underrate) a bond, and the cost structure of underrating *vs*. overrating is mostly dependent on raters' conservativeness. The model predicts that the lopsided rating splits will occur when raters have different conservativeness, with the more conservative rater underrating more often. Thus, the rating model hypothesis holds that rating splits are mainly caused by non-identical weighting and/or non-identical classification schemes employed by rating agencies (Moon and Stotsky, 1993). The random error hypothesis, however, argues that there are no systematic differences between the rating agencies, and split ratings generally stand for random variations in judgment on credit risk, particularly when it lies close to the borderline between two ratings (Ederington, 1986).

Using 493 industrial bonds issued during 1975-80 and rated B or above by both Moody's and S&P, Ederington (1986) examined the rating determinant models and ran the restricted regressions that assign the same values for the cutoffs of the two agencies. The likelihood ratio test suggests that the restriction for the cutoff values is reasonable, and furthermore, both the individual and joint tests for the coefficients find no evidence that there is a systematic difference in factors or factors' weightings between the two rating models. This implies that the random error hypothesis may hold for the splits in industrial bond ratings of Moody's and S&P. Cantor and Packer (1996) also found that the sovereign credit ratings assigned by Moody's and S&P broadly share the same rating criteria although they have different weights for three explanatory variables.

Moon and Stotsky (1993), however, argued that the splits in municipality bond ratings assigned by Moody's and S&P are mainly due to rating model differences (the determinant factors, weightings, and rating classifications). They modeled the decision of a municipality to obtain a bond rating as well as the determinants of municipality's rating assigned by the two major rating agencies in a quadvariate-equation system. After obtaining the estimates of the system, several tests were implemented to examine how the two rating models differ from each other. Their results contrast with Ederington (1986) and support the rating model hypothesis; namely, split ratings appear to reflect differences in the weight attached to specific determinants of the ratings as well as differences in the way the bonds are classified. Similar results are also found by Pottier and Sommer (1999) for splits in insurer financial strength ratings assigned by Moody's, S&P, and A.M. Best.

As any single hypothesis can not alone fully elucidate splits in ratings in the literature, a more accurate explanation of rating splits may be some combinations of these potential causes. Indeed, these hypotheses are not necessarily mutually exclusive. This study will try to test these hypotheses for the splits of bank financial strength rating.

3. Empirical Specifications

3.1 Empirical study design and methodology

The existing literature suggests that one can explore reasons why rating splits from two perspectives—issuers and raters. From the point view of issuers, their decision regarding the optional rating and their asset opaqueness may cause rating splits. On the other hand, from the perspective of raters, rating differences among them can be triggered by their rating model differences or randomly subjective error. Thus, similar to Cantor and Packer (1997), this study will conduct a two-stage approach to examine why bank ratings split from the perspectives of both banks and raters. Both stages apply probit random effects estimations, with the assumption of no individual effects.[2] Specifically, in the first-stage probit regression, the likelihood of a bank to solicit an optional rating is examined. The second-stage estimation will run probit regressions of rating splits or rating differences on several sets of explanatory variables, together with inverted Mills ratio estimated from the first stage regression.

Let *d* denote banks' optional rating decision (1 being rated by both agencies, 0 otherwise)

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[2] Such assumption may not be reliable, but it would otherwise be computationally difficult to estimate models for limited dependent variables with panel data. Verbeek and Vijman (1992) suggested that the Heckit methodology can be applied with this assumption.

and y represent dependent variables of rating splits or differences. When the effect of bank asset opaqueness on rating splits is examined, dependent variables are the dummy SPLIT (1 when rating splits and 0 otherwise) and the absolute rating differences, i.e., |FBIR-MBFSR|. When the difference between two rating models is examined, dependent variables are DRating (-1 for FBIR<MBFSR, 0 for FBIR=MBFSR, and 1 for FBIR>MBFSR) and the difference between FBIR and MBFSR, namely FBIR-MBFSR. The second-stage regression, therefore, will generally apply ordered probit random effects estimation method except when the dependent variable is the dummy SPLIT, in which case the binary probit random effects estimation method will apply.

The banks' decision equation to obtain an optional rating can be written as follows,

$$\begin{aligned} d_{it}^{*} &= \boldsymbol{\alpha}'\mathbf{z}_{it} + u_{it} \\ d_{it} &= 1 \text{ if } d_{it}^{*} > 0, \text{ and } d_{it} = 0 \text{ if } d_{it}^{*} < 0 \end{aligned} \tag{3}$$

where $d*$ is a continuous, unobserved latent variable, which can be interpreted as the propensity to obtain an optional rating. $\mathbf{z}$ represents a vector of independent variables (including constant) in banks' decision equation to obtain an optional rating. The error term u is assumed to follow the normal distribution with mean 0 and variance σ_u^2.

The rating split equation can be generally expressed as follows,

$$y_{it}^{*} = \boldsymbol{\beta}'\mathbf{x}_{it} + e_{it} \tag{4}$$

where $e_{it} \sim N(0, \sigma_e)$. y^{*} is a continuous, unobserved latent variable, which can be interpreted as the hypothetic different opinions of raters on bank financial strength. $\mathbf{x}$ is a vector of explanatory variables (including constant) for rating splits. As shown above, the dependent variable y in this study has four forms: SPLIT, |FBIR-MBFSR|, DRating, and FBIR-MBFSR. When y is SPLIT, $y_{it} = 1$ if $y_{it}^{*} > 0$ and $y_{it} = 0$ otherwise; when y is one of other three dependent variables, $y_{it} = k$ if $\mu_{k-1} < y_{it}^{*} \leq \mu_k$, where μ's are cut-off values.

Rating splits, y_{it}, is observed only when banks also choose to be rated by Fitch, i.e., $d_{it} = 1$. If a bank's decision to obtain an optional rating also depends on its private information on rating differences between Moody's and Fitch, in addition to exogenous characteristics $\mathbf{z}$, the random variable u and e may also be correlated. Let their covariance be $\sigma_{e,u}$. In this case, the simple estimation of *eq*.(4) using the sub-sample would be inconsistent due to the sample selection bias, as shown in the following equation:

$$E(y^* \mid \mathbf{x}, d = 1) = E(y^* \mid \mathbf{x}, u > -\boldsymbol{\alpha}'\mathbf{z}) = \boldsymbol{\beta}'\mathbf{x} + E(e \mid u > -\boldsymbol{\alpha}'\mathbf{z}) = \boldsymbol{\beta}'\mathbf{x} + \frac{\sigma_{e,u}}{\sigma_u^2}\lambda(v) \qquad (5)$$

where λ is inverted Mills ratio, $\frac{\phi(v)}{\Phi(-v)}$, evaluated at $v = -\frac{\boldsymbol{\alpha}'\mathbf{z}}{\sigma_u}$ ($\phi(\cdot)$ and $\Phi(\cdot)$ are, respectively, the density and distribution functions for a standard normal variable). The inverted Mills ratio measures the extent to which a bank chooses to be rated by both agencies unexpectedly and monotonically decreases with the probability that a bank appears in the sub-sample expectedly, $\Phi(-v)$, based on the observed characteristics $\mathbf{z}$ (Heckman, 1979; Cantor and Packer, 1997). *Eq*.(5) shows that without accounting for selection bias, the estimation would be inconsistent. Thus, the second-stage regression can be shown as follows,

$$y_{it}^* = \beta' x_{it} + \gamma\widehat{\lambda}_{it} + error_{it} \qquad (6)$$

where $\widehat{\lambda}$ is estimated inverted Mills ratio from the first-stage regression *eq*.(3). *Eq*.(6) can be estimated with random effects binary or ordered probit model. Under null hypothesis of no selection bias, $H_0 : \gamma = 0$, a standard *t*-test on $\widehat{\gamma}$ is a valid test (Wooldridge, 2002). If $\gamma \neq 0$, then it is necessary to correct the covariance matrix of estimated parameters in *eq*.(6).

3.2 Variables selection

Banks' decision to obtain an optional rating

As documented in Cantor and Packer (1997), the existing literature provides very limited guidance, especially from the theoretical point view, on factors that may influence issuers' decisions to obtain an optional rating. Some empirical studies (e.g., Cantor and Packer, 1997; Pottier and Sommer, 1999) have shown that uncertainty, size and basic financial ratios may be important determinant factors in explaining issuers' decisions. Following these studies, this paper will estimate the first-stage equation of banks' decisions to be rated by Fitch while they have been rated by Moody's. The estimation results will be used in the second-stage studies to account for the self-selectivity effects on bank rating splits and differences.

As modeled in Ramakrishnan and Thakor (1984) and Millon and Thakor (1985), rating agencies exist since they have the advantage of information scale of economics in alleviating information asymmetry. This implies that the demand for ratings is caused by the uncertainties of issues or issuers. Banks are like black boxes with an opaque operating process, causing uncertainty and different opinions about their true value (Morgan, 2002). Thus, banks choose to be rated by an optional rating agency may also due to the uncertainty regarding their financial strength. As analyzed in Morgan (2002), loans and securities holdings are two major categories of financial assets that cause uncertainties in a bank. Thus, this study uses two variables—the loan asset ratio (*LNTAR*) and the securities holdings asset ratio (*SecTAR*)—to proxy for the level of the uncertainty in the bank. It is expected that these two ratios are positively correlated with the likelihood of soliciting an optional rating, holding other factors constant.

The potential benefit of obtaining an additional rating may be lower costs of capital, deposits, and other debt for a bank. In this case, a larger bank would have greater benefit if they obtain an additional rating. Thus, the bank size (logarithms of bank assets, *Size*) is also included in the regression to capture the potential benefits of an optional rating. Furthermore, as mentioned in Cantor and Packer (1997), different rating agency may favor various financial characteristics of an issuer, which may induce those issuers with certain characteristics favored by the optional rating agency to solicit the optional rating. As such, this study also includes the standard CAMEL financial ratios—capital ratio (equity/total assets, *ETAR*), non-performing loans ratio (NPLs/loans, *NPLR*), inefficiency ratio (expense/income, *ExpIncR*), returns on average assets (profit after tax/average assets, *ROAA*), and liquidity ratio (liquidity assets minus interbank deposits/total assets, *Liquidity*).

In addition, banks with different governance mechanisms may behave differently in choosing to obtain an optional rating, although they have similar uncertainties and financial characteristics. Thus, governance mechanism proxies—government owned banks (*SOB*), foreign banks (*FOB*), and publicly listed banks (*Publiclist*)—are also included in the regression. Furthermore, bank operating environment (*BHI*, *DIS*, *EntryREG*, *ActREG*, and *CapREG*) may also affect banks' decision to obtain an optional rating, and therefore, they are also included in the regression.[3] Finally, year dummies (*Y00*, *Y01*, *Y02*, and *Y03*) are also included in the decision equation to capture time effects on the banks' decision.

Bank asset opaqueness and rating splits

As suggested by financial intermediary theories and lender-borrower relationship theories, financial assets (e.g., loans, securities holdings, equity investments, etc.) *per se* are full of uncertainties due to information asymmetry. These financial assets end up with piles of papers (e.g., loan documents, securities, and cash), lacking physical visibility, proper verification and sensible judgment regarding their condition and quality. Since the majority of bank assets generally are financial assets, banking in nature is opaque. This opacity generates fundamental uncertainty for both investors of banks and rating agencies (Morgan, 2002). This, in turn, creates the demand for ratings by the investors of banks, and meanwhile, also causes rating splits among rating agencies.

The uncertainty over bank assets varies across financial asset categories as they may have different natures and various degrees of opacity. Loans (logarithm of loans, *Loan*), for instance, involve the complicate lender-borrower relationship under the circumstances of information asymmetry (Freixas and Rochet, 1997). As also admitted by Moody's (1993), the assessment of a bank's asset quality is both the most important and the most difficult element of bank analysis. Thus, the information asymmetry hypothesis expects that the possibility of rating

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[3] Herfindahl index here is calculated using bank assets data, namely, *BHI*=the sum of the square of each bank asset as percentage of banking sector total assets. The smaller values indicate that a banking sector is less concentrated and more competitive. Explicit scheme (*DIS*) takes values of 0 (no explicit deposit insurance scheme), 1 (explicit deposit insurance scheme), and 2 (blanket guarantee). Higher values of DIS indicate that the scheme protects deposits more explicitly and firmly. The entry restriction (*EntryREG*) ranges in value from 0 to 8, with higher values representing more restrictiveness. Bank activity restrictions (*ActREG*) are regulations on the ability of banks to engage in securities underwriting, brokering and dealing, insurance underwriting and selling, as well as real estate investment, development and management. This variable ranges in value from 1 to 4, with higher values indicating greater restrictiveness. Capital stringency regulation (*CAPREG*) refers to regulations on minimum capital ratios, definitions of capital, risk-based guidance, among others.

splits on a bank is positively correlated with the volume of loans in the bank. Furthermore, securities holdings mainly include government securities, other debt securities, shares, and other variable-yield securities, which may be held only for a short period. Although their volume can be measured easily, the market value of securities assets changes fast and their trading is difficult to scrutinize, which also adds uncertainties for analysts. Equity investments (logarithm of equity investments, *Equityasset*) contain a bank's investments in non-consolidated subsidiaries and other affiliates, which can be another source of uncertainty and opacity as they are mostly connected with third parities.

Cash and Deposits in other banks (logarithm of cash plus deposits in other banks, *Cash&DPBK*) are basically less uncertain and opaque, which, therefore, are expected to be less likely to cause disagreements among rating agencies. As emphasized in Morgan (2002), banks' fixed assets (logarithm of fixed assets, *fixedasset*) may help resolve uncertainty since they are generally visible and verifiable.[4] Compared to other financial assets, therefore, fixed assets are hypothesized to be negatively correlated with rating splits. The final main category of bank assets considered here is intangible assets (logarithm of intangible assets, *Intangibles*), mainly consisting of consolidation differences, goodwill, formation expenses and intangible fixed assets. This category of asset is often viewed to add opaqueness to a bank (Flannery, Kwan, and Nimalendran, 2004; Livingston, Naranjo, and Zhou, 2005).

Clearly, asset transparency may be closely related to market maturity, market competition degree, and banking regulatory framework. When market maturity largely differs, the same volume of assets may not necessarily indicate the same opacity. The interactions between asset categories and market maturity (*IndusCY*) are included to capture the effect of market maturity on asset transparency. In general, the operating environment of a bank may also affect asset opaqueness. Therefore, the market competition degree (*BHI*) and regulatory framework—entry restriction (*EntryREG*), activity restriction (*ActREG*), capital adequacy regulation (*CapREG*), and deposit insurance scheme (*DIS*)—are also included in the regression to control for the environmental effects on the opacity of banks. In addition, similar to other

[4] However, Flannery, Kwah, and Nimalendran (2004) included fixed asset as part of the opacity of a bank, together with investments in unconsolidated subsidiaries, intangible assets, and other assets in balance sheet.

studies, this paper also includes the average ratings of Moody's and Fitch (*RatingAVG*) to control for the risk level of banks. Higher risk levels (lower average ratings) are expected to cause more rating splits between the two rating agencies.

Bank rating models and rating differences

From the perspective of rater, rating differences may be caused either by rating models (factors, factors weighting, and cutoffs) or subjective random errors (Ederington, 1986; Morgan, 2002). To test this hypothesis, therefore, this study uses factors that are considered in rating determinant models to explain rating differences, accounting for banks' self-selectivity bias. According to Moody's and Fitch's statements, factors that raters consider in assigning bank ratings basically cover two major aspects, namely banks' own specifics and their operating environments. The former is mainly composed of bank risks, capital, profitability, franchise value, and governance mechanisms, among others, while the latter consists of banking sector structure, regulatory framework, and macroeconomic stability.

Specifically, bank risks can mainly be disaggregated into credit risk, liquidity risk, market risk, operating risk, and other risks (Bessis, 2002; Koch and MacDonald, 2006). To capture how rating agencies weigh each bank risk differently, some financial ratios are used to be proxies for risks. Credit risk is proxied by the quality of loans—non-performing loans ratio (*NPLR*), while the liquidity risk is indicated by the ratio of liquid assets minus interbank deposits to total assets (*Liquidity*). The market risk level of a bank is represented by its market risk exposure—the ratio of securities holding position to total assets (*SecTAR*). The operational risk usually refers to the possibility of unexpected losses or expenses due to malfunctioned internal control or external events, which is represented by efficiency risk (*ExpIncR*) and the business line mix (*BusinessMix*).[5] In addition, the ratio of off-balance sheet items to total assets (*OffBSTAR*) is also used to as a proxy for bank credit, liquidity, market and operational risks that originate from off-balance sheet activities.

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[5] Business mix (*BusinessMix*) is calculated by summing the square of the ratio of each part income (interest income, commission income, fee income, trading income, and other operating income) to total income. In order to have a normal distribution, logarithmic transformation is done for this variable. The lower the business mix, the more diversified the business.

Furthermore, capital level and profitability of a bank are two main lines of defense against the abovementioned risks. As such, capital ratio (*ETAR*) and profitability (*ROAA*) are also included in the regression. As emphasized by both agencies, bank franchise value is also an important factor in assigning ratings. To indicate a bank's franchise value, two proxies—the business diversification (*BusinessMix*) and earnings stability (*sdROAA*, the standard deviation of *ROAA* in three years)—are used here. In addition, governance mechanism plays an important role in mitigating agency problems, which certainly is an important factor in determining ratings. Several proxies for governance, therefore, are used in this study, including government ownership (*SOB*), foreign ownership (*FOB*), and public-listed status (*Publiclist*). Also, this study includes the scale and scope proxies—the logarithms of total assets (*Size*) and a binary variable of bank holding company (*BHC*)—in the regression to account for their effects on rating assignments.[6]

Bank operating environment factors considered in this study mainly cover banking sector structure, regulatory framework, and macroeconomic growth and stability. Specifically, banking sector structure factors include banking sector competition degree (*BHI*), government ownership share in the market (*BSOBR*), and foreign ownership share in the market (*BFOBR*).[7] Bank regulatory framework factors consist of entry regulation (*EntryREG*), activity restriction (*ActREG*), capital adequacy regulation (*CAPREG*), supervisory agency independence (*SuperIndep*), and deposit insurance scheme (*DIS*, *MHI*, and *DISPower*).[8] Banking distress period (*BDepress*) is also included to examine how the two agencies treat banking crisis differently in terms of individual bank ratings.[9] Furthermore, average GDP annual growth rate

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[6] Bank holding company operates the widest scope in the banking sector, which is essentially a shell organization that owns and manages subsidiary banks and firms (Koch and MacDonald, 2006). Thus, the dummy *BHC* (1 when bank holding company and 0 otherwise) may capture the impact of different scopes on ratings.

[7] Government ownership share and foreign ownership share in the market are calculated by dividing the aggregate assets of government owned banks and foreign banks by the total banking assets, respectively.

[8] Supervisory agency independence (*SuperIndep*) takes values 1, 2, and 3, with higher values indicating higher dependence degree of the supervisory agency. Deposit insurance scheme design (*MHI*) is to indicate the moral hazard caused by the scheme. It is the first principal component of nine factors (e.g., insurance coverage, management, premium, fund, source of fund, etc.), and it explains around 84.5 percent of the total variation in these nine variables. Deposit insurance agency's power (*DISPower*) reflects whether the agency has the authority to intervene banks, whether the agency can take legal actions against banks, and whether the legal actions have been taken. This variable takes values from 1 to 4, with higher values indicating stronger power.

[9] Banking depression dummy variable takes one if there is a serious banking depression and zero otherwise, and it is defined in greater detail in Caprio and Klingebiel (2003).

(*gGDP*) and standard deviation of growth rate (*sdgGDP*) are included in the regression to represent macroeconomic stability.

Finally, Market maturity (*IndusCY*) and time dummies are included to control for different standards across markets and years that can not be explained above. Moreover, for the same financial ratios regarding bank risks, capital, profitability and franchise value, raters may attach different weights in assigning ratings for mature and emerging markets. Indeed, Moody's (2006) explicitly mention this point in their rating methodology. Thus, in addition to the abovementioned financial ratios, the interactions between these ratios and market maturity dummy (*IndusCY*) are also included to capture the different importance in mature *vs*. emerging markets.

4. Data Description

The sample used in this study is unbalanced panel data, consisting of 781 banks during the period 1998-2004. These banks were rated by Moody's at least for one year in the studied period. Moreover, among them 395 banks also obtained ratings from Fitch. Bank ratings and financial information of the sampled banks are obtained from Bankscope, the primary data source of this paper.[10] This is augmented with country information such as banking sector structure, regulatory and supervisory framework, and macro economy. Part of banking sector structural data such as bank average size, Herfindahl index, and market ownership are also calculated using the aggregate data in Bankscope. For macroeconomic data, they are obtained from the International Financial Statistics (IFS) of the International Monetary Fund. And the data for regulatory and supervisory framework are obtained from Demirguc-Kunt, Karacaovali, and Laeven (2005) and regulatory surveys conducted by Barth, Caprio and Levine in the World Bank.[11] As the three-year average values of financial and economic variables and the median values of binary variables are used in the analysis, the effective studied period in this study is 2000-2004. MBFSR and FBIR are mapped into eight numerical scores in the Table 1, with 0

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[10] Most of the information is based on consolidated accounting data. When unavailable, the unconsolidated information is used. The accounting data in Bankscope are globally formatted and denominated in US dollar.

[11] Barth, Caprio and Levine conducted surveys regarding bank regulation and supervision. The databases are available at the World Bank's website. The approach to construct variables for regulatory and supervisory framework is described in detail in Barth, Caprio, and Levine (2001).

denoting the lowest rating, E, and 8 representing the highest rating A.[12]

The disagreement between the two rating agencies is quite frequent and persistent, as suggested by Tables 2-5. The cross-tabulation between MBFSR and FBIR in Table 2 describes how agencies differ from each other to the detail of each rating categories. For instance, of the banks with rating A assigned by Moody's, four are rated by half-notch lower to A/B, and one are rated by one-notch lower to B by Fitch. The cross-tabulation suggests that rating splits occur more often than non-splits. Furthermore, the dynamics of rating splits illustrated in Table 3 shows that around 68.5 percent of co-rated cases with rating splits maintained the stability, suggesting that the majority of rating splits persisted during 2000-2004. This feature can also be seen from the percentage of cases with rating splits in the whole co-rated sample in Tables 4 and 5. Of the 1,681 co-rated cases during 2000-2004, around 70 percent had rating splits. In terms of different markets and regions, this percentage is also at average around 70 percent. All these numbers provide strong evidence for large existence of rating splits. Moreover, the percentage of rating splits ranged from 66 to 78 percent during 2000-2004, and there is no decreasing trend, which also provides evidence for the persistency of rating splits.

To measure formally how often the two raters agree with each other, Kappa statistic is calculated.[13] Its value ranges from -1 (complete disagreement) to 1 (perfect agreement) via 0 (no agreement above that expected by chance). For the whole sample, the Kappa coefficient is around 0.19, suggesting that the agreement between Moody's and Fitch on the creditworthiness of banks is very slight. By comparing this statistic in each year, one can find that it had lowest value, about 0.09, in 2000, indicating that the two agencies rarely agreed with each other that year. Considering this statistic in different markets, it seems that the two rating agencies had more disagreements on the creditworthiness of banks in the mature markets compared to developing markets, but this difference is very marginal, only 0.007. For the developing markets, African countries had lowest Kappa statistic, around -0.065, followed by Middle East

[12] If MBFSR and FBIR are changed in a year, the latest ratings are used.
[13] Kappa statistic is a widely used measure of interobserver variability. It is calculated based on the difference between observed agreement compared to how much agreement would be expected to be present by chance alone or expected agreement (Cohen, 1960). Thus, it can be thought of as the chance-corrected proportional agreement, which is obvious superior to the simple agreement percentage.

countries, 0.031, and Asian countries, 0.089. These statistics suggest that Moody's and Fitch have poor agreements regarding the financial strength of banks in these countries. All these suggest that rating splits are substantial.

However, the split level—the absolute value of rating differences—is relatively moderate in the sample. For the whole sample, the split level is around half notch at average. As shown in Tables 4 and 5, out of 1,168 split cases, 781 cases (around 67 percent) have rating splits of half notch, and 334 cases (about 29 percent) have rating splits of one notch. The rating differences exceeding one notch occurred 53 times, less than 5 percent of total split cases. The maximal difference between MBFSR and FBIR is two-notch, as shown in Table 2. This, however, took place only twice: a bank with rating D by Moody's obtained a rating B from Fitch, and another bank rated E by Moody's was assigned a rating C by Fitch. This split structure does not vary much as time passes, but does have variations for different markets and regions, as shown in Table 4.

Another feature of rating splits that is worthwhile to mention here is that, in general, Fitch seems assign higher ratings compared to Moody's. As shown in Table 5, more than 80 percent of rating split cases occurred because Fitch assigned higher ratings than Moody's did, especially for developing countries. Around 87 percent of splits in the developing markets have lower ratings from Moody's, while for the mature markets, this kind of splits only occupy about 79 percent. The extreme case is that in all the rating splits for the banks of the Western Hemispherical developing countries, Fitch assigned higher ratings. In terms of each year, it seems that this pattern, since 2001, has been continuing and getting more evident. The percentage of rating splits due to higher ratings assigned by Fitch was 77.5 percent in 2001, and it grew to 86.4 percent in 2004, in spite of increasing sample size.

The descriptive statistics of selected financial variables are listed in Table 6. In terms of total assets and disaggregated asset categories, rated by both agencies at average are larger compared to banks only rated by Moody's, suggesting that larger banks tend to solicit an optional rating. When banks are co-rated by both agencies, those banks with split ratings tend to be smaller than those without rating splits, and furthermore, bank size seems decrease as rating splits get larger. The table also suggests that when Moody's rates higher, asset size is generally larger. In terms of asset quality, Table 6 shows that at average, banks rated by both agencies tend to have lower non-performing loans ratios, around 5 percent, while banks only rated by Moody's have about 8 percent. In general, however, Table 6 does not show clear patterns for different groups in terms of financial ratios. For instance, liquidity, efficiency, profitability, and capital ratios do not differ largely across groups.

Table 1 Transformation of letter to numeric variable for ratings

Moody's	Fitch	Interpretation	Mapping
A	**A**	*Superior intrinsic financial strength*: highly valuable and defensible business franchises, outstanding financial fundamentals, and a very predictable and stable operating environment.	8
A-,B+	**A/B**		7
B	**B**	*Strong intrinsic financial strength*: valuable and defensible business franchises, good financial fundamentals, a predictable and stable operating environment, and no major concerns.	6
B-,C+	**B/C**		5
C	**C**	*Adequate intrinsic financial strength*: limited but still valuable business franchises, possessing one or more problems with financial fundamentals or the operating environment.	4
C-,D+	**C/D**		3
D	**D**	*Modest intrinsic financial strength* (potentially requiring some outside supports): a weak business franchise, deficient financial fundamentals in one or more respects, or an unpredictable and unstable operating environment.	2
D-,E+	**D/E**		1
E	**E**	*Very modest intrinsic financial strength* (very serious problems, either requiring or being likely to require external supports): a weak and limited business franchise, materially deficient financial fundamentals in one or more respects, or a highly unpredictable or unstable operating environment.	0

Notes: Moody's appends '+' and '-' to each category (from E up to A) to distinguish intermediate categories while Fitch only uses the slash to express intermediate categories. To make it comparable, this study rescales Moody's intermediate categories according to Fitch's methodology.

The Interpretations of ratings are from websites of Moody's and Fitch.

Table 2 The cross-tabulation of bank ratings (2000-2004)

Fitch	**Moody's**									
	A	**A-,B+**	**B**	**B-,C+**	**C**	**C-,D+**	**D**	**D-,E+**	**E**	**No Moody's**
A	21	17	4	6	0	0	0	0	0	53
A/B	4	52	90	33	8	0	0	0	0	117
B	1	59	129	195	92	26	1	0	0	392
B/C	0	10	28	76	76	103	2	0	0	390
C	0	0	3	36	52	117	25	6	1	185
C/D	0	0	0	7	8	75	35	37	1	117
D	0	0	0	1	3	19	39	59	8	170
D/E	0	0	0	0	1	6	13	52	9	46
E	0	0	0	0	0	0	2	16	17	9
No Fitch	0	23	74	236	232	359	232	310	136	

Table 3 The cross-tabulation of rating updates for banks with rating splits (2000-2004)

Moody's rating updates	**Fitch's rating updates**			
	Downgrade	**Stable**	**Upgrade**	**Total**
Downgrade	20 (1.7%)	27 (2.3%)	0 (0.0%)	47 (4.0%)
Stable	41 (3.5%)	800 (68.5%)	83 (7.1%)	924 (79.1%)
Upgrade	8 (0.7%)	164 (14.0%)	25 (2.1%)	197 (16.9%)
Total	69 (5.9%)	991 (84.8%)	108 (9.2%)	1168 (100.0%)

Table 4 The distribution of rating splits by year (2000-2004)

Year	**(1) Obs.**	**(2) Partial Correlation**	**(3) [a] Kappa statistic**	**Splits**		**FBIR>MBFSR**		**Split Level (|FBIR-MBFSR|)**		
				(4) No.	**(5) =(4)/(1)**	**(6) No.**	**(7) =(6)/(4)**	**(8) Half notch**	**(9) One notch**	**(10) Over one notch**
2000	261	0.817	0.091	203	78%	167	82%	127	61	15
2001	313	0.836	0.202	213	68%	165	78%	143	61	9
2002	343	0.831	0.200	236	69%	184	78%	156	70	10
2003	369	0.853	0.231	244	66%	200	82%	166	70	8
2004	395	0.859	0.199	272	69%	235	86%	189	72	11
Total	1,681	0.840	0.190	1,168	70%	951	81%	781	334	53

Note: [a] Kappa-statistic= (Observed agreement - expected agreement)/(1 - expected agreement).

Table 5 The distribution of rating split by development degree and geography (2000-2004)

Regions	(1) Obs.	(2) Partial correlation	(3) Kappa statistic	Splits		FBIR>MBFSR		Split Level (|FBIR-MBFSR|)		
				(4) No.	(5) =(4)/(1)	(6) No.	(7) =(6)/(4)	(8) Half notch	(9) One notch	(10) Over one notch
Industrial Countries	1,147	0.781	0.149	795	69%	626	79%	557	200	38
Developing Countries	534	0.757	0.157	373	70%	325	87%	224	134	15
Africa	19	0.065 [a]	-0.065 [a]	13	68%	11	85%	9	4	0
Asia	165	0.754	0.089	124	75%	106	85%	54	57	13
Europe	154	0.679	0.192	94	61%	72	77%	80	14	0
Western Hemisphere	93	0.839	0.203	60	65%	60	100%	42	18	0
Middle East	103	0.597	0.031[a]	82	80%	76	93%	39	41	2

Note: [a] These coefficients are not significant; however, other partial correlation and Kappa statistics are significant at least at the level of 5%.

Table 6 Selected variable means of banks rated at least by Moody's

Selected variables	Full sample	Rated by		Split		FBIR-MBFSR		Split level (|FBIR-MBFSR|)		
		Moody's only	both agencies	No	Yes	>0	<0	Half notch	One notch	Over one notch
lnLOAN	15.88	15.32	16.41	16.81	16.23	15.90	17.69	16.38	15.95	15.88
lnTOTSE	13.21	12.05	14.31	14.92	14.04	13.70	15.54	14.01	14.21	13.45
lnEINVEST	13.83	13.77	13.89	13.98	13.86	13.73	14.40	13.89	13.81	13.76
lnCASHDP	13.40	12.90	13.88	14.23	13.72	13.29	15.62	13.83	13.56	13.15
lnINTANG	14.35	14.28	14.42	14.46	14.40	14.35	14.63	14.43	14.34	14.34
lnFIXA	12.09	11.57	12.58	13.02	12.39	12.02	14.02	12.60	12.04	11.45
Size	16.45	15.90	16.98	17.39	16.80	16.45	18.33	16.95	16.52	16.33
LNTAR	0.56	0.54	0.58	0.57	0.58	0.59	0.54	0.58	0.57	0.63
NPLR	0.06	0.08	0.05	0.06	0.04	0.03	0.06	0.04	0.03	0.02
Liquidity	0.14	0.15	0.13	0.13	0.13	0.13	0.11	0.13	0.13	0.06
OffBSTAR	0.55	0.63	0.47	0.38	0.51	0.55	0.33	0.46	0.56	1.04
SecTAR	0.19	0.18	0.20	0.19	0.20	0.20	0.19	0.20	0.20	0.18
BusinessMix	-0.39	-0.38	-0.40	-0.42	-0.39	-0.39	-0.43	-0.41	-0.35	-0.43
ExpIncR	0.88	0.90	0.87	0.91	0.85	0.83	0.94	0.86	0.83	0.86
ETAR	0.08	0.08	0.07	0.07	0.08	0.08	0.06	0.08	0.08	0.08
ROAA	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.02
sdROAA	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00

Note: these data are calculated on the basis of the three-year average values.

5. Empirical Results and Analyses

5.1 Bank optional rating decision

The estimation result for banks' decisions on the optional rating is presented in Table 7. The χ^2 statistics for testing the joint significance of explanatory variables suggest that the optional rating decision model as a whole is statistically significant. McFadden's pseudo R^2 shows that the model can explain around 61% of the variations of bank selections in the sample, and the overall reclassification accuracy is around 66%. Furthermore, most coefficients of selected variables are significant and the signs are generally consistent with *a priori* anticipations. These suggest that the model reasonably fit the data.

As shown in the table, variables that are proxies for uncertainties, the loan-asset ratio (*LNTAR*) and the securities holding asset ratio (*SecTAR*), have significantly positive coefficients, which suggests that banks with higher uncertainty tend to solicit ratings from both Moody's and Fitch. This is in general consistent with the uncertainty hypothesis. Furthermore, bank size is significantly and positively correlated to the likelihood of obtaining an optional rating, indicating that larger banks are more likely to solicit both ratings. Given that larger banks may receive greater benefits by choosing to be rated by both agencies, this result is not surprising. Furthermore, larger banks may have higher uncertainty, which induces them to obtain an optional rating.

The coefficients of *CAMEL* financial ratios—equity, non-performing loans, efficiency, returns on average assets, and liquidity ratios—are all statistically significant. Furthermore, their signs suggest that banks with better performance tend to be rated by both Moody's and Fitch. All governance mechanism proxies—government ownership, foreign ownership and publicly listed banks—have statistically significant and negative coefficients. This shows that controlling for other factors, government-owned banks and foreign banks are less likely to obtain an optional rating, compared to domestic private banks. In addition, compared to unlisted banks, listed banks tend to have smaller possibility to solicit an optional rating.

With regard to regulatory framework, estimations suggest that, in general, bank regulations have influence on the decision of banks rated by Moody's to obtain another rating from Fitch. Specifically, banks in countries with explicit deposit insurance scheme tend to obtain a second rating. Stricter entry and activity restrictions are likely to discourage banks to go for another rating, while capital adequacy regulation may increase the possibility of a bank being rated by both agencies. Market competition degree seems have no effects on the decision as its coefficient is not statistically significant.

Table 7 Random effects binary probit estimation for bank optional rating decision (2000-2004)

Independent variable	**Dependent variable=Orating [a]**	
	Coeff.	(sd)
Constant	-46.17***	(7.68)
LNTAR	14.87***	(2.90)
SecTAR	6.31***	(1.83)
SIZE	2.48***	(0.42)
ETAR	9.79**	(4.59)
ROAA	28.07*	(16.2)
NPLR	-6.33*	(3.35)
ExpIncR	-2.68*	(1.46)
Liquidity	12.55***	(2.30)
SOB	-7.78***	(1.43)
FOB	-3.73***	(0.77)
Publiclist	-0.87**	(0.38)
BHI	-3.01	(2.73)
DIS	3.28***	(0.65)
EntryREG	-0.28**	(0.13)
ActREG	-1.57***	(0.37)
CapREG	0.76***	(0.16)
Y00	-4.17***	(1.10)
Y01	-2.06***	(0.70)
Y02	-0.36	(0.55)
Y03	-0.28	(0.63)
Obs.	2513	
Log-likelihood	-582.78	
Model χ^2	1803.22	
AIC	9.36	
McFadden's Psuedo-R^2	0.61	
Correct prediction	65.6%	

Notes: [a] 0 and 1; 1 indicates the decision to go for an optional rating and 0 indicates not.
*, **, *** denote the significance level of 10%, 5% and 1%, respectively.

5.2 Self-selectivity, asset opaqueness and bank rating splits

The information asymmetry hypothesis predicts that, to some extent, uncertainty over bank risk—and therefore bank rating splits—is inherent in banks, which may reflect the asset opaqueness. This hypothesis is investigated here by running regressions of SPLIT and the split level (|FBIR-MBFSR|) on banks' assets, controlling for other factors as well as accounting for sample selection bias. Estimation results are listed in Table 8, and each dependent variable has four models. Model (1) contains the least number of explanatory variables, only including bank asset categories and year dummies. Model (2) adds the interaction terms between market maturity (*IndusCY*) and bank assets, which can account for the situation that the same volume asset may represent different risk level in different markets. Model (3) further includes some bank operating environmental variables, such as market competition degree and regulatory framework. Model (4) is constructed to test sample selection bias by including the estimated inverted Mills ratio, $\hat{\lambda}$, that is estimated from the first-stage probit regression.

As shown in the table, the null hypothesis, $\lambda = 0$, can not be rejected for both dependent variables, suggesting that self-selectivity may not account much for rating splits. Furthermore, the table also shows that regression results are generally consistent among different models as well as between the two dependent variables, except for some variables in model (1). Among all models, model (1) has the least fitness, suggesting that it might not be proper without distinguishing the effect of different market maturities. Models (2)-(4) have very similar results regarding each category of bank asset, and models (3)-(4) have almost the same results for market competition and regulatory framework. The overall reclassification accuracy is around 70 percent for SPLIT and 47 percent for the split level, |FBIR-MBFSR|.

How various categories of assets influence rating splits between Moody's and Fitch is of primary interest here. To avoid multicollinearity problem, the securities holdings are excluded from the regressions. Estimation results show that only loans and fixed assets are consistently statistically significant, but they have different effects on rating splits in different markets. In emerging markets, loans are positively correlated to the likelihood of rating splits, while fixed assets tend to mitigate the disagreements between raters, which is consistent with the prediction of the information asymmetry hypothesis. In mature markets, however, loans tend to reduce the probability of rating splits, and the mitigation effect of fixed assets on rating splits is near zero.[14] This suggests that bank rating splits are unlikely driven by the asset opaqueness, which is not fully consistent with the information asymmetry hypothesis. To summarize these findings, one may conjecture that bank rating splits can be caused by the opaqueness of assets; however, as market gets more mature (more transparent information disclosure system, better financial infrastructures, etc.), this causal relationship may be broken. In other words, bank rating splits are not really inherent in banks, and therefore, the information asymmetry hypothesis only, to some extent, gains support here.

Table 8 also shows that the general risk level, indicated by average ratings, do not really cause the disagreements between Moody's and Fitch. Furthermore, it seems that the market competition degree may increase the likelihood of bank rating splits as Herfindahl index is significantly and negatively correlated with SPLIT or the split level. Interestingly, the explicit insurance scheme tends to help mitigate the disagreements between the rating agencies. Stricter entry and capital restrictions tend to magnify the disagreements between Moody's and Fitch, while activity restrictions seem have not impact. Finally, compared to other years, it is confirmed here that the two rating agencies did have more disagreements in 2000.

[14] The coefficients of each asset category for mature markets are the sum of coefficients of two corresponding variables since there are the interaction terms between market maturity (*IndusCY*) and each category of asset.

Table 8 Random effects probit estimation results for bank rating splits (2000-2004)

Independent variables	Dependent variable=SPLIT [a]				Dependent variable=|FBIR-MBFSR| [b]			
	(1) Coeff. (sd)	(2) Coeff. (sd)	(3) Coeff. (sd)	(4) Coeff. (sd)	(1) Coeff. (sd)	(2) Coeff. (sd)	(3) Coeff. (sd)	(4) Coeff. (sd)
Constant	7.48** (3.79)	8.52** (3.88)	8.30** (4.01)	8.38** (4.01)	4.50 (3.40)	3.78 (3.37)	3.41 (3.49)	3.44 (3.50)
Loan	-0.14 (0.10)	0.90*** (0.23)	0.87*** (0.25)	0.87*** (0.25)	0.01 (0.09)	0.94*** (0.18)	0.90*** (0.19)	0.91*** (0.19)
Equityasset	-0.02 (0.19)	-0.45 (0.95)	-0.53 (0.98)	-0.52 (0.98)	0.06 (0.18)	0.08 (0.66)	0.07 (0.69)	0.08 (0.69)
Cash&DPBK	0.03 (0.04)	-0.04 (0.09)	-0.04 (0.09)	-0.05 (0.09)	0.02 (0.03)	-0.03 (0.08)	-0.03 (0.08)	-0.03 (0.08)
Fixedasset	-0.23** (0.10)	-0.84*** (0.22)	-0.82*** (0.23)	-0.82*** (0.23)	-0.35*** (0.08)	-0.80*** 0.16	-0.78*** 0.16	-0.79*** 0.16
Intangibles	-0.12 (0.25)	-0.30 (0.91)	-0.20 (0.93)	-0.22 (0.93)	-0.03 (0.21)	-0.56 0.64	-0.51 0.66	-0.52 0.66
RatingAVG [c]	0.07 (0.05)	0.00 (0.06)	-0.03 (0.06)	-0.03 (0.06)	0.00 (0.04)	-0.04 (0.04)	-0.05 (0.05)	-0.04 (0.05)
Loan * IndusCY		-1.50*** (0.27)	-1.41*** (0.28)	-1.41*** (0.28)		-1.31*** (0.21)	-1.21*** (0.22)	-1.21*** (0.22)
Equityasset * IndusCY		0.50 (0.97)	0.65 (0.99)	0.64 (0.99)		0.09 (0.68)	0.17 (0.71)	0.17 (0.71)
Cash&DPBK * IndusCY		0.12 (0.10)	0.11 (0.10)	0.11 (0.10)		0.07 (0.09)	0.07 (0.09)	0.07 (0.09)
Fixedasset * IndusCY		0.82*** (0.25)	0.78*** (0.26)	0.78*** (0.26)		0.57*** (0.18)	0.53*** (0.19)	0.53*** (0.19)
Intangibles * IndusCY		0.38 (0.89)	0.16 (0.91)	0.17 (0.91)		0.81 (0.62)	0.63 (0.64)	0.64 (0.64)
BHI			-4.06*** (1.46)	-3.98*** (1.46)			-4.69*** (1.33)	-4.64*** (1.34)
DIS			-0.56* (0.30)	-0.56* (0.30)			-0.49** (0.25)	-0.49** (0.25)
EntryREG			0.14* (0.08)	0.14* (0.08)			0.11* (0.06)	0.11* (0.06)
ActREG			-0.07 (0.15)	-0.07 (0.15)			(0.04) (0.11)	0.03 (0.11)
CapREG			0.08* (0.05)	0.08* (0.05)			0.07** (0.03)	0.07** (0.03)

Y00	0.57*** (0.14)	0.54*** (0.14)	0.55*** (0.14)	0.55*** (0.14)	0.66*** (0.10)	0.68*** (0.11)	0.67*** (0.11)	0.67*** (0.11)
Y01	-0.01 (0.13)	0.00 (0.13)	0.03 (0.14)	0.03 (0.14)	0.07 (0.10)	0.09 (0.10)	0.10 (0.11)	0.10 (0.11)
Y02	0.03 (0.15)	0.03 (0.15)	0.03 (0.15)	0.03 (0.15)	0.10 (0.12)	0.12 (0.12)	0.12 (0.12)	0.12 (0.12)
Y03	-0.12 (0.18)	-0.12 (0.18)	-0.12 (0.18)	-0.12 (0.18)	-0.07 (0.14)	-0.06 (0.14)	-0.06 (0.14)	-0.06 (0.14)
$\hat{\lambda}$				0.0001 (0.0002)				0.0001 (0.0002)
Obs.	1681	1681	1676	1387	1681	1681	1676	1387
Log-likelihood	-800.9	-786.1	-777.5	-777.5	-1492.3	-1473	-1457.7	-1457.7
McFadden's Psuedo-*R^2*	0.19	0.18	0.18		0.20	0.189	0.185	
AIC	1.35	1.32	1.31	1.32				
Correct prediction	69.1%	68.8%	70.6%	70.9%	46.4%	47.2%	47.9%	47.4%

Notes: The coefficients of SPLIT regressions are random effects binary probit estimators, and the coefficients of |FBIR-MBFSR| regressions are random effects ordered probit estimators. The regression (4) of each dependent variable applies two-step procedure to account for sample selection bias. The inverted Mills ratios are estimated from the decision equation to solicit an optional rating.

[a] SPLIT=0 if MBFSR=FBIR; SPLIT=1 if MBFSR ≠ FBIR.

[b] 0, 1, 2, 3+

[c] Average of FBIR and MBFSR; higher values indicates stronger financial strength.

*, **, *** denote the significance level of 10%, 5% and 1%, respectively.

5.3 Self-selectivity, rating model differences and rating splits

As shown by the distribution of rating splits, a palpable feature of bank rating splits in the sample is lopsided disagreement, namely one agency generally assign higher ratings than the other agency does. Table 5 shows that over 80 percent of rating split cases have higher ratings from Fitch. This pattern of splits can hardly driven by randomly subjective error; otherwise, it should be more symmetric disagreement. The potential causes can be threefold in the literature. First, as theoretically argued by Morgan (2002), the lopsided disagreement can arise when two agencies are different in conservativeness. Second, as empirically pointed out by Moon and Sotsky (1993) and Pottier and Sommer (1999), split ratings may appear because rating agencies may systematically consider different factors or adopt different weighting systems for the same factors they consider in assigning ratings. Finally, this lopsided distribution of rating splits may also be caused by self-selectivity behavior of banks (Cantor and Packer, 1997). The first two potential causes are generally referred to as the rating model difference hypothesis.

To test these hypotheses, the rating differences between Fitch and Moody's in conceptual (DRating) term and numeric term (FBIR-MBFSR) are regressed on a set of rating determinant factors, accounting for self-selectivity bias. The regression of DRating is to examine factors that may determine the probability for FBIR to be higher than MBFSR, while the regression of the numeric difference between them is to explore factors that may affect the likelihood of the difference in each scale between the two ratings. Each dependent variable has two models—one controls for sample selection bias and the other one does not—and estimation results are presented in Table 9. As shown in the table, estimation results are generally consistent between models, except for some variables. The overall reclassification accuracy is around 65 percent for DRating and 46 percent for the numeric difference, FBIR-MBFSR.

With regard to financial ratios, credit risk (*NPLR*) seems to be viewed more important by Fitch, while market risk (*SecTAR*) seems to be attached less weight by Fitch, compared to Moody's. These weighting differences may not vary across markets as their interaction terms are rarely statistically significant. In terms of operational risk, however, the weighting difference is dependent on markets. The opposite signs of efficiency risk (*ExpIncR*) coefficients in different maturity markets show that Fitch assigns higher weights for efficiency risk in emerging markets but lower weights in mature markets, compared to Moody's. Similarly, business mix coefficients also have opposite signs in different maturity markets. As discusses in previous sections, business mix (*BusinessMix*) can be proxy for both operational risk and franchise value due to diversified businesses. The opposite signs may imply that Fitch favors higher concentrated business in emerging markets as the control of operational risk there is relative weaker, but prefers business diversification in mature markets as this can benefit banks in the long run given that the operational risk can be duly controlled there.

The statistic significance for equity ratio and profitability does not appear in both all regressions, and therefore, it should be explained with cautions. Other financial ratios, e.g., liquidity ratio, off-balance sheet risk, and earning stability, do not have significant coefficients. Moreover, bank size is consistently negatively correlated with two dependent variables, implying that Fitch does not give extra points for larger banks as Moody's does. Furthermore, publicly listed banks seems gain less if they go for Fitch individual rating, compared to Moody's financial strength rating. The government ownership does not have significant coefficients in all regressions, and thus need to be considered carefully. The two rating agencies seem not have disagreements regarding foreign ownership and bank holding companies.

Regarding bank operating environmental factors (including banking sector structure, regulatory framework, and macroeconomic stability), the two rating agency may not disagree with each other, as these variables are hardly significant in the regressions. Furthermore, the null hypothesis, $\lambda = 0$, can not be rejected for both dependent variables, implying that self-selectivity issue may not account much for the lopsided disagreement between the two rating agencies. In other words, the private information regarding rating agencies that banks hold seems not really help them get better treatments by Fitch when they go for a second rating.

Table 9 Random effects ordered probit estimation results for rating model differences (2000-2004)

Independent variables	Dependent variable=DRating [a]				Dependent variable=FBIR-MBFSR [b]			
	(1)		(2)		(1)		(2)	
	Coeff.	(sd)	Coeff.	(sd)	Coeff.	(sd)	Coeff.	(sd)
Constant	19.5***	(3.05)	19.0***	(3.14)	18.80**	(2.23)	18.2***	(2.28)
NPLR	-7.3***	(2.76)	-7.4***	(2.74)	-5.68**	(2.45)	-5.84**	(2.45)
Liquidity	-1.34	(1.36)	-0.99	(1.39)	-0.22	(0.92)	-0.04	(0.93)
OffBSTAR	0.18	(0.28)	0.16	(0.24)	0.24	(0.32)	0.23	(0.28)
SecTAR	5.10**	(2.11)	5.36**	(2.16)	3.51**	(1.37)	3.65***	(1.37)
BusinessMix	1.56*	(0.89)	1.61*	(0.89)	1.65**	(0.70)	1.64**	(0.70)
ExpIncR	-2.78**	(1.26)	-2.77*	(1.25)	-2.5***	(0.91)	-2.5***	(0.91)
ETAR	0.82	(6.55)	1.30	(6.78)	-0.44	(4.69)	-0.13	(4.88)
ROAA	-1.99	(17.72)	-1.20	(17.48)	-0.66	(13.0)	0.35	(12.9)
sdROAA	-3.24	(10.66)	-4.66	(10.63)	-4.08	(7.44)	-4.89	(7.46)
NPLR*IndusCY	-5.67	(5.57)	-5.88	(5.66)	-1.79	(3.60)	-1.76	(3.59)
Liquidity*IndusCY	0.21	(1.74)	0.00	(1.75)	0.04	(1.23)	0.01	(1.22)
OffBSTAR *IndusCY	-0.12	(0.36)	-0.11	(0.34)	-0.23	(0.35)	-0.23	(0.32)
SecTAR*IndusCY	-4.06	(2.48)	-4.36*	(2.54)	-2.41	(1.68)	-2.67	(1.69)
BusinessMix *IndusCY	-3.04**	(1.22)	-3.06**	(1.23)	-1.93**	(0.91)	-1.88**	(0.91)
ExpIncR*IndusCY	4.61**	(2.22)	4.68**	(2.25)	5.05***	(1.34)	5.03***	(1.34)
ETAR*IndusCY	18.37*	(9.43)	18.48*	(9.49)	7.64	(5.74)	7.27	(5.90)
ROAA*IndusCY	13.55	(34.9)	15.45	(36.0)	50.7***	(20.4)	50.6***	(20.6)
sdROAA*IndusCY	-17.49	(22.4)	-16.69	(22.0)	-17.67	(12.7)	-17.53	(12.5)
Size	-0.8***	(0.11)	-0.8***	(0.12)	-0.6***	(0.08)	-0.6***	(0.08)
SOB	1.32	(1.04)	1.14	(1.06)	1.7**	(0.68)	1.46**	(0.71)
FOB	0.30	(0.49)	0.25	(0.51)	0.12	(0.41)	0.08	(0.42)
Publiclist	-1.0***	(0.35)	-1.0***	(0.36)	-0.8***	(0.28)	-0.8***	(0.28)
BHC	2.08	(2.86)	2.12	(2.98)	2.54	(1.84)	2.57	(1.82)
BHI	2.00	(3.01)	2.07	(3.04)	-1.03	(2.49)	-1.07	(2.51)
BSOBR	-2.60	(1.77)	-2.45	(1.80)	-2.57*	(1.47)	-2.53*	(1.48)
BFOBR	-0.36	(0.78)	-0.39	(0.79)	-0.42	(0.56)	-0.47	(0.56)
BDEPRESS	0.38	(0.38)	0.40	(0.39)	0.30	(0.28)	0.31	(0.28)
EntryREG	0.21	(0.14)	0.19	(0.14)	0.12	(0.11)	0.12	(0.11)
ActREG	0.05	(0.27)	0.06	(0.26)	0.12	(0.18)	0.15	(0.18)
CapREG	0.04	(0.06)	0.06	(0.06)	0.07	(0.05)	0.08*	(0.05)
SuperIndep	-0.02	(0.28)	-0.02	(0.28)	-0.23	(0.23)	-0.25	(0.23)
DIS	-0.64	(0.61)	-0.53	(0.68)	-0.56	(0.45)	-0.51	(0.46)
MHI	-0.19	(0.13)	-0.20	(0.14)	-0.13	(0.10)	-0.14	(0.10)
DISPower	-0.13	(0.24)	-0.15	(0.23)	-0.11	(0.17)	-0.11	(0.18)
gGDP	-0.07	(0.05)	-0.06	(0.05)	-0.04	(0.04)	-0.03	(0.04)

sdgGDP	-0.06	(0.06)	-0.05	(0.06)	-0.05	(0.04)	-0.04	(0.04)
IndusCY	-5.60**	(2.49)	-5.41**	(2.50)	-5.4***	(1.47)	-5.3***	(1.47)
Y00	0.47**	(0.20)	0.38*	(0.22)	0.5***	(0.15)	0.40**	(0.16)
Y01	-0.38**	(0.19)	-0.44**	(0.21)	-0.28**	(0.14)	-0.32**	(0.15)
Y02	-0.45**	(0.19)	-0.46**	(0.19)	-0.35**	(0.15)	-0.36**	(0.15)
Y03	-0.38*	(0.23)	-0.38	(0.24)	-0.28	(0.17)	-0.28	(0.17)
$\hat{\lambda}$			0.07	(0.07)			0.05	(0.05)
Obs.	1326		1326		1326		1326	
Log-Likelihood	-760.8		-760.1		-1274.3		-1273.8	
McFadden's Psuedo-*R*²	0.22				0.20			
Correct prediction	65.91%		65.46%		45.93%		45.93%	

Notes: The coefficients are random effects ordered probit estimators. The regression (2) of each dependent variable applies two-step procedure to account for sample selection bias. The inverted Mills ratios are estimated from the regression of the decision to solicit optional rating.

[a] DRating= -1 if FBIR<MBFSR; DRating=0 if FBIR=MBFSR; Drating=1 if FBIR >MBFSR.

[b] The value of FBIR-MBFSR is truncated within the range [-3, 3], namely -3, -2, -1, 0, 1, 2, 3.

*, **, *** denote the significance level of 10%, 5% and 1%, respectively.

6. Conclusion

Past studies have proposed the information asymmetry hypothesis, the self-selectivity hypothesis, the rating model difference hypothesis and the random error hypothesis in explaining rating splits. While the fist two hypotheses mainly explain rating splits from the perspective of issuers, the last two hypotheses try to clarify rating differences from the perspective of raters. Specifically, the information asymmetry hypothesis predicts that rating splits are inherent in the uncertainty of issuers due to the opacity of the industry, and the self-selectivity hypothesis proposes that the private information that issuers have may help them get better treatments if they go for an optional rating. When it comes to raters, the rating difference can arise due to non-identical factors used in assigning ratings, and/or different weighting systems attached to those factors, and/or non-identical classification schemes (the rating model difference hypothesis). Or simply, rating splits are caused by randomly subjective errors of raters, which can be referred to as the random error hypothesis.

This paper attempts to research bank rating splits between Moody's and Fitch and to combinedly study several hypotheses of rating splits proposed in the literature, using an unbalanced panel data consisting of 781 banks during the period of 1998-2004. The data shows that the disagreement on bank financial strength between Fitch and Moody's is not rare but quite frequent and persistent. Furthermore, rating splits have asymmetric or lopsided distribution that Fitch generally assigns higher ratings, compared to Moody's. In general, such situation is hardly driven only by random errors, implying to reject the random error hypothesis. Other three hypotheses are empirically examined in a two-stage regression framework, in which case the self-selectivity bias can be tested.

Empirical studies generate some interesting findings. First, there is lack of evidence for sample selection bias in all regressions, which implies that banks' self-selectivity may not account much for bank rating splits. In other words, the private information held in banks does not help them get better treatments by obtaining an optional rating. Second, the information asymmetry hypothesis only gains partial support from the data. This hypothesis generally holds in emerging markets but not in mature markets, suggesting that the relationship between bank asset opaqueness and bank rating splits may diminish when financial system, information disclosure and financial infrastructure improves. This empirical evidence implies that bank rating splits may not really inherent in banks. Third, the lopsided rating differences may mainly be due to the difference in rating models, such as different factors considered by raters, non-identical weighting system or different standards. Finally, banking sector structure and regulatory framework may have influence on rating splits, but do not cause lopsided disagreement. The lopsided splits are mainly the result of raters' disagreement regarding bank specifics. In sum, asymmetric rating splits appear to reflect rating model differences, especially about bank specifics. Thus, it is interesting to pursue a further study on that which rating model is more consistent with revealing true bank soundness and safety.

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