Is there a difference in treatment between solicited and unsolicited bank ratings and, if so, why? [1]

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Abstract

This paper analyses the effect of soliciting a rating on the rating outcome of banks. This type of analysis sheds light on an important policy question, namely whether there is a difference in treatment between banks which request a rating and those which do not. Using a sample of Asian banks rated by Fitch Ratings, I find evidence that unsolicited ratings tend to be lower than solicited ones after accounting for differences in financial and non-financial characteristics between banks. This downward bias does not seem to be explained by the "self-selection hypothesis", which states that banks with more favourable private information self-select into the solicited group because they can obtain higher ratings by doing so. Rather, unsolicited ratings appear to be lower because they are only based on public information and, as a result, they tend to be more conservative than solicited ones. This is shown by testing the "public disclosure hypothesis", which states that the difference in treatment between solicited and unsolicited ratings disappears when banks with an unsolicited rating release enough public information to compensate for the absence of private information. Overall, the findings of this study have important policy implications for the reform of the credit rating industry and for the Third Pillar of the New Basel Accord.

Keywords: unsolicited ratings, treatment effect, switching regression, public disclosure

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1 Introduction

Several facts have recently drawn public attention to the work and functioning of credit rating agencies. First and foremost, their failure to predict the Asian crisis and a wave of corporate scandals such as Enron, WorldCom or Parmalat. Second, the potential procyclicality of their assessments and their increasing role in the regulatory mechanism of financial markets. Third, a number of issues related to the transparency and integrity of the rating process. Among those issues, the practice of unsolicited ratings has prompted controversy among issuers, credit rating agencies and regulators alike. Unsolicited ratings are formally defined as "ratings that credit rating agencies conduct without being formally engaged to do so by the issuer" (IOSCO, 2003). As such, and contrary to solicited ratings, unsolicited ratings do not imply the payment of a rating fee and do not involve any formal meetings between the credit rating agency and the entity being rated.[2] These meetings typically provide an opportunity for credit rating agencies to get an overview of a company's activities and to obtain more information than what is disclosed in its published annual reports. Fight (2001) reports excerpts of a survey conducted by Cantwell & Company which indicate that more than 90% of companies release either selected or substantial non-public information to their rating agency during these meetings.

The controversy surrounding unsolicited ratings stems from the fact that many issuers complain that these "unwanted" ratings tend to be lower, *ceteris paribus*, than ratings which are solicited and paid for. Obviously, this perceived downward bias may be due to the fact that issuers with more favourable private information request a rating or to the fact that credit rating agencies assign more conservative ratings in the absence of private information. However, this perceived bias could also indicate that credit rating agencies are guilty of strong arm tactics aiming at expanding their market share aggressively. Many issuers indeed believe that unsolicited ratings are used by credit rating agencies to blackmail them into paying for and participating in a rating process in the hope of obtaining a higher solicited rating. A recent example of such alleged abuses of power are the successive downgrades of Hannover Re, one of the world's largest reinsurance companies, by Moody's Investors Service Inc. ("Moody's"). Hannover Re was

[2] Golin (2001) insists that most credit rating agencies nevertheless attempt to invite the participation of the rated entity, either through submission of questionnaires, informal visits, or informal reviews of the draft report.

initially approached by Moody's in 1998 to subscribe to its rating services, but declined the offer since it was already paying fees to Standard and Poor's ("S&P") and A.M. Best Company ("A.M.") - a smaller credit rating agency - for this purpose. Despite being turned down, Moody's decided to go ahead and rate Hannover Re at no charge. Although Moody's initial unsolicited rating was Aa2, only one notch below that given by S&P, it was subsequently lowered to Aa3 (January 2001) and then A2 (November 2001). In March 2003, Moody's further downgraded Hannover to junk status (Baa1), while both S&P and A.M. continued to give the insurance company a rating well above investment grade. Moody's final downgrade sparked a 10% drop in the insurer's stock and surprised many analysts given that there was no new information in the public domain justifying this. Hannover Re's comments were that Moody's decisions were "pure blackmail" and that company's officials had being told on many occasions that if they paid for a rating, it "could have a positive impact" on the grade. Hannover Re further pointed out that, since S&P was already making headway in Germany and throughout Europe in rating the insurance business, Moody's decision to assign an unsolicited credit rating probably represented a fast way to play catch-up (Wall Street Journal, 2004).

In spite of the huge controversy surrounding unsolicited ratings,[3] credit rating agencies strongly defend this practice. Their main arguments can be summarised as follows. First, unsolicited ratings should be seen as a service to investors and market participants who frequently make requests for coverage of institutions that are unwilling to undergo the rating process or pay the fee (Standard and Poor's, 2003). Second, unsolicited ratings contribute to open up competition among credit rating agencies as they allow smaller agencies to compete with the "Big Three": Moody's, S&P and Fitch Ratings ("Fitch"). Some of these smaller agencies, well established by now, would have found it very difficult to start their business without initially issuing some unsolicited ratings (Dominion Bond Rating Service, 2001). Third, unsolicited ratings prevent firms from "rating shopping", a practice whereby firms only request an additional rating when they expect an improvement on their existing rating (Moody's, 2004). Finally, credit rating agencies do not issue higher solicited ratings to keep existing customers or lower unsolicited ratings to attract new customers as it would imply that they are willing to jeopardise their reputation in order to benefit from a temporary increase in revenues (Golin, 2001).

[3] For a review of other alleged abuses of power, see Hill (2004).

This paper contributes to the ongoing debate about the use or abuse of unsolicited ratings by investigating whether there is a difference in treatment between Fitch' solicited and unsolicited bank ratings and, if so, why. Using individual ratings of Asian banks, I find that Fitch assigns the same weight to rating determinants reflecting public information in the solicited and unsolicited groups. This result gives some credence to Fitch's claim that the methodology for its unsolicited bank ratings is "nearly the same" as for its solicited bank ratings (Fitch, 2001). However, I also find that unsolicited bank ratings tend to be lower than solicited ones after controlling for rating determinants reflecting public information. The difference in treatment between both types of ratings is economically significant, as it represents between 0.8 and 1.2 notches on a 1 to 9 rating scale. This result questions Fitch's attitude to refuse any regulation of unsolicited ratings (cf. section 2.1).

Several explanations are consistent with a systematic difference in treatment between solicited and unsolicited ratings. This paper tests two hypotheses put forward by credit rating agencies, investors and academics. The first one is the "self-selection hypothesis". This hypothesis states that solicited ratings tend to be higher than unsolicited ones because they are the result of self-selection based on private information, i.e. issuers (here, banks) with more favourable private information request a rating since they can obtain a higher rating by disclosing their private information to the rating agency. Under the self-selection hypothesis, I expect issuers with more favourable private information to self-select into the solicited group. This hypothesis is tested using a treatment effect model and an endogenous switching regression model, which both extend the standard model of sample selection due to Heckman (1979).

A rejection of the self-selection hypothesis would be consistent with two different interpretations: unsolicited ratings are lower in order to persuade issuers to pay for a higher solicited rating; alternatively, unsolicited ratings are lower because they are only based on public information and, as a result, they tend to be more conservative than solicited ones. The latter interpretation is supported by contract theory. An important result in this area, known as the "full-disclosure theorem", states that issuers always disclose good information in equilibrium when private information can be certified once disclosed and three additional conditions hold (see Bolton and Dewatripont, 2005). As a result, issuers who choose not to disclose private information (i.e. not to ask for a rating) inevitably reveal that they are of the bad type and credit rating agencies assume the worst by assigning lower unsolicited ratings.

A way to test that lower unsolicited ratings are due to the absence of private information consists in verifying the second hypothesis, which I call the "public disclosure hypothesis". This hypothesis states that the difference in treatment between solicited and unsolicited ratings disappears when issuers with an unsolicited rating release enough public information to compensate for the absence of private information. In other words, issuers who choose not to request a rating and who disclose little *public* information receive a low unsolicited rating, since in this case the disclosure of additional *private* information via a contractual relationship would contribute to lower the credit rating agency's uncertainty about their true quality. However, issuers who choose not to request a rating but who disclose extensive *public* information do not receive a low unsolicited rating, since in this case the extra value of *private* information is low and there is thus no reason for the credit rating agency to err on the side of caution.[4]

Testing the public disclosure hypothesis is of particular interest in the case of Fitch's ratings since a former official of BankWatch[5] acknowledges that *"It is true that unsolicited ratings are often more conservative than solicited ratings. The reason is not that agencies are attempting to punish companies that decline to pay for a rating, but that where there is doubt, the agencies will tend to err on the side of caution. Correspondingly, the more information provided to the agencies, the more transparent the disclosure process, the more comfort agency analysts will feel in giving the company the benefit of the doubt (...) In the same manner, where in the case of an unsolicited rating, the issuer has not been very forthcoming with information, or places the burden of extracting that information on the agency analyst, it is not surprising that the agency analyst will tend to err on the side of conservatism, and properly so. As a matter of practice, less disclosure tends to be associated with higher risk. In the context of risk assessment, disclosure is not only the means by which the assessment is performed, it is also arguably a positive credit consideration in itself*" (Golin [2001], pp. 534-535). Many market participants also believe that the absence of private information combined with low public disclosure explains the downward bias in unsolicited ratings. For instance, the investment bank Merrill Lynch noted that the low unsolicited ratings assigned to four major Egyptian banks by Moody's in 1997 were mainly due to "poor transparency of financial accounts" along with "lack of cooperation regarding non-public information"

[4] Thus, the public disclosure hypothesis assumes some degree of substitutability between *private* and *public* information, which is not necessarily unrealistic.
[5] BankWatch is the credit rating agency which initiated the practice of unsolicited bank ratings in Asia prior to its absorption by Fitch (see section 3.1).

(Egypt State Information Service, 1997). The public disclosure hypothesis is tested via a bank disclosure index similar to the one used by Baumann and Nier (2003).

The results of this paper do not support the self-selection hypothesis since I do not find that banks with more favourable private information self-select into the solicited group. Rather, the results appear to be consistent with the public disclosure hypothesis since I find that banks which do not request a rating, but which disclose extensive public information, do not receive a lower unsolicited rating. The latter finding is interesting because the marginal impact that public disclosure has on the relationship between soliciting a rating and the actual rating outcome is ambiguous in theory. The marginal effect of public disclosure may be positive if issuers who do not request a rating and who disclose extensive public information receive the benefit of the doubt (public disclosure hypothesis). However, public disclosure may also confirm negative perceptions or intuitions about issuers who choose not to be rated, hence its marginal impact may be negative. This study shows that the first effect dominates the second.

The remainder of the paper is organised as follows. The background to unsolicited ratings and the relevant literature are reviewed in Section 2. Section 3 presents a brief history of Fitch's unsolicited ratings as well as the sample used in this study. Section 4 describes the econometric framework used in the analysis. Section 5 investigates whether there is a difference in treatment between Fitch's solicited and unsolicited bank ratings and, if so, whether the self-selection hypothesis or the public disclosure hypothesis can account for it. The last section concludes and offers some relevant policy implications.

2 Background to research and review of the literature

2.1 Background to research

Prior to the 1970s, credit rating agencies used to charge bondholders a fee for obtaining rating information and thereby provided unsolicited rather than solicited ratings. The shift from a business model that was subscription-fee based to one that charged issuers for the privilege of obtaining a rating occurred mainly because of the spread of low-cost photocopying and the desire of issuers to reassure investors of the quality of their issuances (White, 2001). However, in 1991, Moody's reintroduced the practice of unsolicited ratings and other agencies quickly followed in the mid-1990s.

Even though the vast majority of credit ratings are still assigned on a solicited basis, unsolicited credit ratings currently represent a sizeable portion of the total number of ratings. According to the Cantwell survey (Fight, 2001), unsolicited ratings represented between 6% (S&P) and 26.6% (Fitch) of the total number of credit ratings assigned in industrial countries in 2000. In another survey conducted by Baker and Mansi (2002), US firms with an unsolicited rating averaged 10.6% of the total number of firms with a credit rating in 1999. In Europe, the phenomenon of unsolicited ratings is believed to be substantially smaller (Basel Committee, 2000). In fact, issuers located in developing countries appear to be the main targets of unsolicited ratings. Evidence from *Bankscope* for instance indicates that almost 80% of S&P's unsolicited bank ratings were assigned in Africa, South America and Asia (excluding Japan) in February 2005.

Interestingly, credit rating agencies do not talk about solicited versus unsolicited ratings but use a softer terminology. In 1996, S&P started issuing unsolicited ratings under the name "public information ratings", mainly to companies in the insurance and banking sectors. These ratings, which appear with a "pi" subscript in its publications, are assigned by broad numerical categories without a + or − modifier (i.e. AAA, AA...). Contrary to S&P, Moody's policy has long been not to disclose whether a rating was solicited or not. Due to market pressure, it finally announced in 1999 that it would identify in its initial rating assignment announcements the unsolicited ratings for which the issuer had declined its invitation to participate in the assignment process (Moody's, 1999). Since January 2000, the following statement appears in the first press release accompanying the assignment of an unsolicited rating by Moody's: "This rating was initiated by Moody's. The issuer did not participate in the assignment process". However, there is no additional designation after this and unsolicited ratings are also not reported in Moody's regular publications. Fitch, the third biggest player in the credit rating industry, issues unsolicited ratings under the name "shadow ratings" to various types of financial instruments and entities. Most of these unsolicited ratings are not disclosed to the public, except for those assigned to banks, which are the subject of this paper.

Data for the banking sector show that the number of unsolicited ratings has dropped over the last years. Banks with a public information rating accounted for 9% of banks with a local currency rating from S&P in February 2005, down from 18% five years earlier. Fitch has also decreased its issuance of shadow ratings in proportion of the total number of bank individual ratings, from 14% in February 2002 to 9% three years later.

While no data are available for Moody's, it insists that it has almost completely curtailed its assignment of unsolicited ratings (Moody's, 2003).

Despite their relatively low frequency and the recent decrease in their number, unsolicited ratings have come under the attention of several regulatory bodies as part of wider investigations into the role and function of credit rating agencies. In 2003, the US Securities and Exchange Commission ("SEC") issued a report where it expressed its concerns about credit rating agencies engaging in specified practices with respect to unsolicited ratings (e.g., sending a bill for an unsolicited rating, sending a fee schedule and "encouraging" payment, indicating that a rating might be improved with the cooperation of the issuer). The SEC also mentioned that it would explore whether only credit rating agencies that issue clearly labelled unsolicited ratings should be granted the status of Nationally Recognized Statistical Rating Organizations (SEC, 2003). In 2004, the International Organization of Securities Commissions ("IOSCO") published a "Code of Conduct for Credit Rating Agencies" that sets out a series of measures that agencies should incorporate into their own codes of conduct. In particular, the code asks credit rating agencies to "disclose whether the issuer participated in the rating process" and to identify each rating not initiated at the request of an issuer as such (IOSCO, 2004). Interestingly, Fitch's reply was that it did "not believe that it is necessary or appropriate to require the disclosure of whether a rating is initiated or whether the issuer has cooperated in the rating process" and that such requirements "interfere in the editorial process of the rating agencies" (Fitch, 2004a). Finally, the Committee of European Securities Regulators ("CESR") also recently recommended that credit rating agencies disclose whether they initiate their credit ratings and whether the issuer participates in the rating assessment process (CESR, 2005).

2.2 Review of the literature

This paper is related to the literature on unsolicited credit ratings, which can be divided into four groups of papers. The first set of papers (Poon [2003a], Poon [2003b] and Poon and Firth [2004]) attempts to control for sample selection to see whether there is a difference in treatment between solicited and unsolicited ratings. The second set of papers (Butler and Rodgers [2003] and Gan [2004]) stresses the role of private vs. public information in explaining differences in treatment between solicited and unsolicited ratings. Since these first two groups of papers are most closely related to this study, I will compare them to my paper in detail. The third set of papers (Byoun and Shin [2003] and Güttler et al. [2005]) is concerned with the stock market reaction to unsolicited ratings. Finally, the fourth set of papers (Cantor and Packer [1997] and Feinberg et al. [2004]) compares the ratings of several credit rating agencies with different degrees of reliance on unsolicited ratings.

The first group of papers focuses on different samples of unsolicited ratings assigned to banks and insurance companies by S&P and Fitch[6] but adopts the same econometric approach, i.e. a standard model of sample selection which accounts for self-selection into solicited status. Sample selection is indeed a concern, since there may be systematic reasons why issuers with a rating choose to request one. Failure to control for this will yield inconsistent parameter estimates (Heckman, 1979). The results of these papers provide conflicting evidence of sample selection in credit ratings: Poon (2003a) and Poon and Firth (2004) find evidence that issuers with worse financial characteristics self-select into the solicited group while Poon (2003b) finds evidence that issuers with better financial characteristics self-select into the solicited group. Since these papers use a standard model of sample selection instead of a treatment effect model or an endogenous switching regression model (cf. section 4), they are unable to estimate the impact of soliciting a rating while simultaneously controlling for the selection bias. As a result, they rely on a matching technique to investigate whether unsolicited ratings are lower than solicited ones *ceteris paribus*. This technique consists in pairing solicited and unsolicited issuers with similar financial profiles in order to eliminate the selection bias. Poon (2003a), Poon (2003b) and Poon and Firth (2004) pair between one-twentieth and one-third of issuers by matching their sovereign rating and four financial ratios from the key financial areas considered to be important in determining credit ratings. The results of the matching sub-samples indicate that unsolicited ratings are still lower than solicited ones after controlling for differences in financial profile and sample selection. Though the above findings are interesting, it is important to highlight that they are based on a minority of the sample firms with no more than five common characteristics. Moreover, Heckman et al. (1998) point out that matching is not, in general, guaranteed to reduce sample selection bias and that it may even increase it.

[6] Poon (2003a) uses S&P's ratings of 265 insurance companies in 15 mostly developing countries; Poon (2003b) considers S&P's ratings of 171 banks in 20 mostly developing countries; Poon and Firth (2004) use Fitch's ratings of 951 banks in 82 countries. The latter paper is based on a sample that includes non-Asian banks, which is incorrect since Fitch does not assign unsolicited bank ratings outside Asia (see section 3.1).

The second group of papers focuses on US bonds rated by Moody's and S&P. Since both agencies do not distinguish between solicited and unsolicited ratings in the US market, these papers rely on estimated fees paid to rating agencies to infer if issuers have or not asked for a rating and how many rating agencies they have hired.[7] Butler and Rodgers (2003) use cross-sectional regressions to see if high rating fees – assumed to proxy for solicited status – are associated with ratings which are more favourable to the issuer. They also interact several financial variables with a "high rating fee" dummy in order to isolate the marginal effect that soliciting a rating has on how ratings are affected by firm fundamentals. The authors find that solicited ratings are not higher *ceteris paribus* and that the marginal effect of soliciting a rating is to decrease the impact that most financial variables have on credit ratings. They interpret these findings as evidence that credit rating agencies do not suffer from a conflict of interest and that soliciting a rating induces them to place less weight on public information in favour of some private information. These results should be interpreted with caution as the authors have chosen to exclude bonds with zero rating fees from their sample in order to control for sample selection. Since almost every zero rating fees bond is unsolicited, this is likely to create an even bigger selection problem in their sample.

Gan (2004) investigates the question of whether there is a difference in treatment between solicited and unsolicited ratings by relying on an *ex ante* and an *ex post* approach. The *ex ante* approach consists in a cross-sectional regression that looks at whether unsolicited ratings are lower than solicited ones while controlling for issuers' characteristics. The *ex post* approach consists in a cross-sectional regression that looks at whether unsolicited ratings perform better than solicited ones after the issuance of the rating while controlling for issuers' characteristics. Gan finds a statistically significant difference between the rating assigned to solicited and unsolicited issuers in her *ex ante* regression but no statistically significant difference between their subsequent performance – measured by Altman's Z-score – in her *ex post* regression. This result leads Gan to reject what she calls the "punishment hypothesis", which states that, if issuers were truly discriminated against, they should not only receive lower credit ratings *ex ante* but they should also exhibit stronger performance *ex post*. Gan concludes that her results are rather consistent with a self-selection bias based on private information

[7] This approach requires the choice of a rating fee threshold above (below) which ratings are considered to be solicited (unsolicited). Gan (2004) relies on fee schedules estimates while Butler and Rodgers (2003) split their sample into two groups of bonds: those with high rating fees (assumed to be solicited) and those with median or low rating fees (assumed to be unsolicited).

without, however, explicitly testing that firms with more favourable private information self-select into the solicited group.

In light of the above-mentioned studies, the main contributions of this paper are threefold. First, this paper investigates whether there is a difference in treatment between solicited and unsolicited bank ratings using a sample where both types of ratings are identified as such. I believe that this represents an advantage over Butler and Rodgers (2003) and Gan (2004), who are unable to distinguish clearly between solicited and unsolicited ratings. Second, this study addresses the issue of self-selection carefully through the use of a treatment effect model and an endogenous switching regression model. These models allow to measure treatment effects and program effectiveness while simultaneously controlling for sample selection (Greene, 2003). As a result, this paper improves on Poon (2003a), Poon (2003b) and Poon and Firth (2004) who use Heckman's standard model of sample selection and on Butler and Rodgers (2003) and Gan (2004) who do not adequately or explicitly control for sample selection ("self-selection hypothesis"). Third, this study tests whether the difference in treatment between solicited and unsolicited ratings disappears when banks with an unsolicited rating release enough public information to compensate for the absence of private information ("public disclosure hypothesis"). This hypothesis has not yet been tested in the literature. In the remainder of this section, I briefly discuss some studies on unsolicited ratings which are less closely related to this paper.

The third group of papers uses credit ratings of non-US issuers to study the stock market reaction to unsolicited ratings. Byoun and Shin (2003) analyse a sample of firms rated by S&P between 1996 and 2002 of which a majority are from Japan. They set up a model in which unsolicited ratings bring about market reaction due to signalling effects: bad firms choose not to signal in equilibrium and their quality is revealed by their unsolicited rating. Consistent with the implications of the model, they find that many unsolicited ratings are rated speculative grade, while most solicited ratings are rated investment grade. Furthermore, they find negative market reactions to downgrade announcements and positive market reactions to upgrade announcements for unsolicited ratings but only positive market reactions to upgrade announcements for solicited ratings. They interpret this result as being consistent with the model implication that the market reacts strongly to news about unsolicited ratings. Güttler et al. (2005) focus on a majority of Asian firms rated by S&P between 1996 and 2004 and restrict their sample to shifts from an unsolicited to a solicited status. Their main finding is that stock returns react negatively to the announcement of a downgrade but do not react to the announcement of an upgrade following a change in the solicitation status. The authors take this finding as evidence that the market believes that unsolicited ratings suffer from a downward bias, i.e. the market only reacts to downgrades because they reveal new information, while it does not react to upgrades because they represent a natural correction after a shift from an unsolicited to a solicited status.

Finally, the fourth set of papers compares the ratings of several credit rating agencies with different degrees of reliance on unsolicited ratings. Cantor and Packer (1997) compare corporate credit ratings of two agencies publishing both solicited and unsolicited ratings in the US (Moody's and S&P) with those of two agencies mainly issuing solicited ratings in the US (Fitch and Duff & Phelps). They find that corporate credit ratings issued by Moody's and S&P tend to be lower on average than those assigned by Fitch and Duff & Phelps and that this result does not reflect a sample selection bias, i.e. firms do not engage in "rating shopping" by seeking a rating from more favourable agencies. Feinberg et al. (2004) also find that credit rating agencies with both solicited and unsolicited ratings tend to issue lower ratings on average although they do not control for sample selection. In addition, they find that credit rating agencies publishing mostly solicited ratings are less likely to be downgrade leaders and to assign more severe downgrades than rating agencies which issue both solicited and unsolicited ratings. These results suggest that agencies relying extensively on solicited ratings may be more reluctant to upset issuers.

3 Brief history and sample

3.1 History of Fitch's unsolicited bank ratings

Fitch started to issue unsolicited bank ratings after its acquisition of Thomson BankWatch in October 2000. Prior to its absorption by Fitch, BankWatch – then the largest bank credit rating agency in the world – used two types of rating scales in emerging markets, the so-called "intra-country issuer rating" and "credit evaluation rating" scales. The latter scale mainly applied to unsolicited ratings of smaller institutions or banks in Asia. However, BankWatch did not to always disclose whether a rating was paid for or not. In an effort to promote transparency, Fitch announced that ratings that were part of BankWatch's credit evaluation scale and that were not solicited would be appended with an "s" (shadow) following their integration into its rating system in order to indicate that they were mainly based on public information. Fitch nevertheless insisted that the methodology behind these "shadow" (unsolicited) ratings and the more traditional "full due diligence" (solicited) ratings was almost the same and that their definition and scale were identical (Fitch, 2001).

Figure 1 reports the number of solicited and unsolicited bank ratings in the sample countries (see section 3.2) between April 2001 and September 2004. The issuance of unsolicited ratings started in June 2001 and was completed five months later, in November. Unsolicited ratings initially totalled 113, more than twice the number of solicited ratings (54). The number of unsolicited ratings remained stable until mid-2002 before decreasing toward the end of the period surveyed. As of September 2004, the number of banks with an unsolicited rating was 93 and the number of banks with a solicited rating was 76 in the sample countries. Interestingly, eleven banks moved from an unsolicited to a solicited status between 2001 and 2004 (the rest of the decrease in the number of unsolicited ratings being mainly attributable to mergers, acquisitions and liquidations). Out of these eleven banks, five benefited from a one notch increase in their rating following the announcement that they had started to pay a rating fee, whereas none had its rating lowered. Two banks also stopped paying for their rating over the period considered and they both immediately had their rating downgraded by one notch. Of course, these figures do not control for changes in financial profiles and for a selectivity bias, i.e. banks may start requesting (giving up) a rating when their financial fundamentals start improving (deteriorating).

It should also be noted that Fitch's unsolicited bank ratings are individual ratings, which differ from the more well-known debt ratings. Individual ratings focus on the ability of issuers to satisfy their obligations in general, irrespective of the terms of any particular debt obligation. They thus differ from debt ratings, which attempt to assess the risk that an issuer will not repay a specific security or class of securities, e.g. long-term debt. In addition, individual ratings do not take into account external support that an issuer might receive from a parent company or from its country of incorporation, which means in practice that they are not constrained by a sovereign ceiling like debt ratings. In a nutshell, bank individual ratings attempt to assess the overall creditworthiness of a bank on a standalone basis.[8] The purpose of bank individual ratings is also different from bank debt ratings. Debt ratings are used almost exclusively by investors and regulators, while the primary customers of individual ratings are commercial banks which need to set lines of credit with financial institutions they are dealing with, especially in trade finance transactions such as letters of credit.

3.2 Sample

The bank individual ratings and the corresponding financial information used in this study were obtained from *Bankscope* and *Fitch Research.* The initial sample consisted of Fitch's ratings of Asian banks as of January 31, 2004 (cf. Table 1).[9] The sample was further restricted to ratings of banks located in countries that have both solicited and unsolicited ratings (these countries are shown in *italics* in Table 1).

Among the sample countries, Taiwan, India and Hong Kong are the countries with the highest number of bank individual ratings, with respectively 39 banks (23.1% of observations), 32 banks (18.9% of observations) and 18 banks (10.7% of observations). Unsolicited ratings constitute the majority of ratings in the sample countries with 95 banks (56.2% of observations). Solicited ratings account for the remainder of the sample with 74 banks (43.8% of observations). The number of solicited and unsolicited ratings is roughly equal in two countries (Hong Kong and Taiwan) while the other sample countries have a vast majority of solicited ratings (Indonesia, Macau, Malaysia, the Philippines and South Korea) or unsolicited ratings (Bangladesh, China, India and Vietnam). Obviously, a plausible explanation for this imbalance is that banks located in countries with weakly developed banking markets hardly borrow in the international interbank market and, as a consequence, do not require an individual rating. Another possible explanation is that banks located in countries with very different regulatory systems and/or accounting standards prefer to be rated by local credit rating agencies (Poon, 2003a).

Table 2 lists the frequency and percentage of solicited and unsolicited ratings by rating level for the 169 sample banks. Note that, contrary to Fitch's debt ratings which use the standard AAA to D rating scale, Fitch's individual ratings rest on an A to E

[8] Individual ratings are also known as "financial strength" ratings at Moody's and Capital Intelligence. Their complete definition is provided in the Appendix.

[9] The panel structure of the data is not exploited in this paper since there are only thirteen solicitation changes between 2001 and 2004 (cf. section 3.1).

classification with intermediate categories i.e. A/B, B/C, C/D and D/E. The rating category with the highest number of sample banks is the D category (40 banks or 23.7% of observations) while no sample bank falls in the A category. Less than a third of the sample banks (49 banks or 29% of observations) obtain C ratings or above, meaning that their overall creditworthiness is adequate to (very) strong. The remaining sample banks (120 banks or 71% of observations) are classified below C, meaning that their overall creditworthiness is somewhat weak to very weak. Solicited ratings mostly fall into the B/C to D categories whereas unsolicited ratings are concentrated in the C to E categories. The fact that unsolicited ratings are more concentrated across the rating scale tends to confirm the perception of many issuers that these ratings are less accurate than solicited ones (Baker and Mansi, 2002).

Table 3 compares the mean and standard deviation of some financial and non-financial characteristics in the solicited and unsolicited groups (the t-statistic for mean equality is given in the last column). As Fitch asks for a minimum of three years' annual data and a maximum of five years' when assigning a new rating, this paper uses the five-year average (1999 to 2003) of variables if available and their three-year average (2001 to 2003) if not. The variables in the table were selected according to Fitch's bank rating methodology (Fitch, 2004b), which indicates that Fitch bases its bank individual ratings on a number of quantitative and qualitative factors that can be classified into nine categories: (1) risk management; (2) funding and liquidity; (3) capitalisation; (4) securitisation; (5) earnings and performance; (6) market environment; (7) diversification of business and franchise; (8) management and strategy and (9) corporate governance. Using this classification, the variables which exhibit the strongest correlation with Fitch's individual ratings are reported in Table 3.[10] In addition, Fitch also emphasises its need for a detailed breakdown of banks' balance sheet and income statement when assigning a rating. This particular requirement is captured by a disclosure index, which can be found at the bottom of Table 3. The disclosure index records whether or not banks provide information on 147 items in their published financial statements as mentioned in *Bankscope*.[11] The 147 items include balance sheet items (97), income statement items (37) and note items (13). The disclosure index is normalised between 0 and 100.

[10] Table 1A in the Appendix shows the definition, unit and summary statistics of each variable.
[11] The disclosure index used in this study is similar to and highly correlated with the disclosure index used by Baumann and Nier (2003). The main difference is that Baumann and Nier's index is restricted to 18 core categories, some of them arbitrarily weighted.

Looking at the variables in the first five categories of Table 3, banks with an unsolicited rating have better asset quality (i.e. lower impaired loans/gross loans) but are less liquid and less capitalised than banks with a solicited rating. The difference between the performance of the solicited and unsolicited groups (as measured by the return on assets and the cost to income ratio) is not found to be statistically significant, while no variable related to the securitisation category could be found in *Bankscope*. The variables in the last five categories of Table 3 provide information about mostly non-financial characteristics of banks. Banks which request a rating are more likely to have a financial statement which is consolidated (62.2% in the solicited group vs. 44.2% in the unsolicited group) and which has been approved by the auditors without qualification (88.3% in the solicited group vs. 77.2% in the unsolicited group). There are more commercial banks in the unsolicited group (94.7%) than in the solicited one (77.0%) while non-banking credit institutions all have a solicited rating. Interestingly, the sovereign credit rating and the diversification/franchise variables do not differ significantly across solicited status. Corporate governance variables show that banks with an unsolicited rating are located in countries with worse corporate governance practices than banks with a solicited rating. Moreover, banks requesting a rating have a statistically higher degree of involvement of individuals and/or families in their ownership (4.3% of equity owned by this type of shareholders in the solicited group vs. 0.4% in the unsolicited group), while banks that choose not to be rated have stronger ties to the State (28.3% of equity owned by this type of shareholders in the unsolicited group vs. 9.1% in the solicited group). In addition, banks rated on a solicited basis have significantly more subsidiaries (7.0) than banks rated on an unsolicited basis (3.2). This result does not seem to proxy for a size effect since the difference between the means of the "total deposits" variable in the solicited and unsolicited groups was not significant. Finally, the last row of Table 3 indicates that banks with a solicited rating disclose significantly more public information than banks with an unsolicited rating. However, the difference between the level of public disclosure of the two groups is very small (1.8%), meaning that banks with a solicited rating disclose on average only 2.6 items (out of a possible 147) more than banks with an unsolicited rating.

Overall, the evidence presented in Table 2 indicates that unsolicited ratings tend to be more frequently assigned at the lower end of the rating scale than solicited ones, while Table 3 shows some differences in the characteristics of the solicited and unsolicited groups. In order to answer the question of whether the differences in financial and non-financial characteristics or a sample selection bias can account for the lower unsolicited ratings, I now turn to the econometric analysis.

4 Econometric framework

4.1 Ordinary least squares

To test whether banks with a solicited rating and those with an unsolicited rating obtain the same rating *ceteris paribus*, I first use a simple ordinary least squares regression. The analysis is based on a regression of the form:

$$Rating_i = X_i\beta + \delta Solicited_i + \varepsilon_i \qquad (1)$$

where $Rating_i$ corresponds to the individual rating of bank i coded on a 9 (A) to 1 (E) scale, X_i is a matrix of financial and non-financial characteristics that explain the individual rating of bank i and $Solicited_i$ is a dummy variable that equals one if bank i has requested an individual rating and zero otherwise. Although the dependent variable in equation (1) takes nine different discrete values, this paper treats *Rating* as a continuous variable, essentially for two reasons. First, researchers often treat discrete variables as continuous when the range of values that they take is large enough and when the gaps between successive values are equivalent (e.g. Abrevaya and Hausman, 1999). Since individual are divided into nine categories and the common practice is to standardise rating categories into numbers, *Rating* may be thus reasonably treated as a continuous variable. Second, the existing literature on the determinants of credit ratings indicates that this type of analysis is not particularly sensitive to the choice between ordinary least squares and ordered probit, a statistical model for discrete random variables (see for instance Pottier and Sommer, 1999).[12]

Looking at equation (1), the coefficient of $Solicited_i$, δ, measures the so-called treatment effect. The "treatment" in this context is whether or not banks have requested an individual rating from Fitch. The null hypothesis to be tested is whether $\delta = 0$, i.e. whether soliciting a rating has no effect on the rating itself once controlling for relevant

[12] As a robustness check, I have estimated equation (1) using ordinary least squares and ordered probit. The results, which are shown in the Appendix (Table 2A), indicate that both methods classify the same variables as significant and have very similar prediction rates.

bank characteristics. One issue that arises in this setup is the potential endogeneity of the variable $Solicited_i$ i.e. the possibility that $\mathrm{E}(\varepsilon_i \mid Solicited_i) \neq 0$, yielding biased and inconsistent least squares estimates. For instance, if the typical bank which chooses to request a rating would have a relatively high rating whether or not it asked to be rated, there will be a positive correlation between $Solicited_i$ and ε_i. In this case, the least squares estimates of δ will actually overestimate the treatment effect. Therefore, I use two extensions of the standard model of sample selection due to Heckman (1979) to account for potential self-selection into solicited status (see for instance Greene, 2003).

4.2 Treatment effect model

The treatment effect model complements the outcome equation (1) with the following latent model:

$$Solicited_i^* = W_i\gamma + u_i \tag{2}$$

$$Solicited_i = 1 \text{ if } Solicited_i^* > 0\text{, 0 otherwise} \tag{3}$$

where W collects all variables in X plus any other variables that affect the decision to request an individual rating but not the rating itself. The model further assumes that X and W are exogenous and that ε and u follow a bivariate normal distribution with mean vector zero and covariance matrix $\mathbf{\Omega}$ equal to:

$$\Omega = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon u} \\ . & \sigma_u^2 \end{bmatrix} \tag{4}$$

where σ_ε^2 is the variance of the error term in the outcome equation, σ_u^2 the variance of the error term in the selection equation and $\sigma_{\varepsilon u}$ the covariance between both error terms. Since γ can be estimated only up to a scale factor, it is assumed that $\sigma_u^2 = 1$ hence $\sigma_{\varepsilon u} = \rho\sigma_\varepsilon$ where ρ is the coefficient of correlation between ε and u.

Using equation (1), one can show that the expected rating conditional on having requested one is given by:

$$E(Rating_i \mid Solicited_i = 1, X_i, W_i) = X_i\beta + \delta + \rho\sigma_\varepsilon \left[\frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)}\right] \tag{5}$$

where ϕ denotes the normal density function and Φ the normal cumulative function. For banks with an unsolicited rating, the counterpart to (5) is:

$$E(Rating_i \mid Solicited_i = 0, X_i, W_i) = X_i\beta + \rho\sigma_\varepsilon \left[\frac{-\phi(W_i\gamma)}{1 - \Phi(W_i\gamma)} \right] \tag{6}$$

The difference in expected rating between banks which request a rating and those which do not is given by the difference between equations (5) and (6) i.e.

$$E(Rating_i \mid Solicited_i = 1, X_i, W_i) - E(Rating_i \mid Solicited_i = 0, X_i, W_i) =$$

$$\delta + \rho\sigma_\varepsilon \left[\frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)\left[1 - \Phi(W_i\gamma)\right]} \right] \tag{7}$$

where the first term on the right-hand side, δ, measures the treatment effect and the second term in brackets is the hazard rate. If the latter term is omitted from equation (1), the above difference is what is estimated by the least squares coefficient of the dummy variable $Solicited_i$. For instance, in the presence of positive self-selection ($\rho > 0$), the second term in (7) is positive hence the least squares estimator of δ overestimates the treatment effect.

The model described by equations (1) to (3) can be consistently estimated by either maximum likelihood or a two-step method. The latter method consists in estimating a probit equation for the probability of soliciting a rating, before estimating equation (1) augmented with the hazard rate obtained from the probit equation (the standard errors of the least squares estimates must be corrected). A test for $\rho\sigma_\varepsilon = 0$ is a test of selection based on unobservable rating determinants. If $\rho\sigma_\varepsilon$ is not significantly different from zero, one may reasonably decide that selectivity is not a problem and proceed to use ordinary least squares instead of a treatment effect model (Davidson and MacKinnon, 1993).

4.3 Endogenous switching regression model

All methods examined so far are based on the outcome equation (1), which assumes that soliciting a rating has only an intercept effect on individual ratings. However, soliciting a rating may also have a slope effect, i.e. the coefficients of the *X*s may differ according to the solicited status. In addition, the above models assume that the variance of the unobserved component of individual ratings, which includes private information, is the same for banks with a solicited rating and for banks with an unsolicited rating. A more general version of the outcome equation, which allows for treatment heterogeneity and for error terms with different variances, is given by:

$$Rating_{1i} = X_i\beta_1 + \varepsilon_{1i} \quad \text{if } Solicited_i = 0 \tag{8}$$

$$Rating_{2i} = X_i\beta_2 + \varepsilon_{2i} \quad \text{if } Solicited_i = 1 \tag{9}$$

where it is assumed that X is exogenous and that ε_1, ε_2 and u follow a trivariate normal distribution with mean vector zero and covariance matrix $\mathbf{\Omega}$ equal to:

$$\Omega = \begin{bmatrix} \sigma_1^2 & . & \sigma_{1u} \\ . & \sigma_2^2 & \sigma_{2u} \\ . & . & \sigma_u^2 \end{bmatrix} \tag{10}$$

where σ_1^2 and σ_2^2 are the variances of the error terms in the outcome equations, σ_u^2 the variance of the error term in the selection equation and σ_{1u} and σ_{2u} the covariances between ε_1 and u and ε_2 and u, respectively (the covariance between the error terms in the outcome equations is not defined since $Rating_{1i}$ and $Rating_{2i}$ are never observed simultaneously). Since γ can be estimated only up to a scale factor, it is assumed that $\sigma_u^2 = 1$ hence $\sigma_{1u} = \rho_{1u}\sigma_1$ and $\sigma_{2u} = \rho_{2u}\sigma_2$ where ρ_{1u} and ρ_{2u} are the coefficients of correlation between ε_1 and u and ε_2 and u, respectively.

Let the decision to request a rating be generated from the same model described by equations (2) and (3). One can show that the expected rating conditional on having requested one is given by:

$$E(Rating_{2i} \mid Solicited_i = 1, X_i, W_i) = X_i\beta_2 + \rho_{2u}\sigma_2 \left[\frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)}\right] \tag{11}$$

For banks with an unsolicited rating, the counterpart to (11) is:

$$E(Rating_{1i} \mid Solicited_i = 0, X_i, W_i) = X_i\beta_1 + \rho_{1u}\sigma_1 \left[\frac{-\phi(W_i\gamma)}{1 - \Phi(W_i\gamma)}\right] \tag{12}$$

The difference in expected rating between banks which request a rating and those which do not is given by the difference between equations (11) and (12) i.e.

$$\begin{aligned} &E(Rating_{2i} \mid Solicited_i = 1, X_i, W_i) - E(Rating_{1i} \mid Solicited_i = 0, X_i, W_i) = \\ &X_i(\beta_2 - \beta_1) + \rho_{2u}\sigma_2 \left[\frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)}\right] - \rho_{1u}\sigma_1 \left[\frac{-\phi(W_i\gamma)}{1 - \Phi(W_i\gamma)}\right] \end{aligned} \tag{13}$$

where the first term on the right-hand side, $X_i(\beta_2 - \beta_1)$, is the "average treatment effect" (ATE) which measures the average gain or loss from soliciting a rating *for a randomly chosen bank* (this quantity was denoted by δ in the models of subsections 4.1

and 4.2). Wooldridge (2002) shows that, under fairly weak assumptions, a consistent estimator of the average treatment effect is given by:

$$\hat{\text{ATE}} = \bar{X}(\hat{\beta}_2 - \hat{\beta}_1) \tag{14}$$

where ¯ is used to denote average and ˆ parameter estimates obtained by estimating the system formed by equations (2)-(3) and (8)-(9).

Another quantity of interest in this model is the "average treatment effect on the treated" (ATT), which measures the average gain or loss from soliciting a rating *for those banks which have requested a rating.* Formally, the average treatment effect on the treated is defined as:

$$\begin{aligned}
&\text{ATT} \equiv E(Rating_{2i} - Rating_{1i} \mid Solicited_i = 1, X_i, W_i) = \\
&E(Rating_{2i} \mid Solicited_i = 1, X_i, W_i) - E(Rating_{1i} \mid Solicited_i = 1, X_i, W_i) = \\
&X_{2i}(\beta_2 - \beta_1) + (\rho_{2u}\sigma_2 - \rho_{1u}\sigma_1)\left[\frac{\phi(W_i\gamma)}{\Phi(W_i\gamma)}\right]
\end{aligned} \tag{15}$$

where X_{2i} denotes X_i in the group of banks with a solicited rating. A consistent estimator of the average treatment effect on the treated is given by:

$$\hat{\text{ATT}} = \bar{X}_2(\hat{\beta}_2 - \hat{\beta}_1) + (\hat{\rho}_{2u}\hat{\sigma}_2 - \hat{\rho}_{1u}\hat{\sigma}_1)\left[\overline{\frac{\phi(W_i\hat{\gamma})}{\Phi(W_i\hat{\gamma})}}\right] \tag{16}$$

A test for $\rho_{2u}\sigma_2 = \rho_{1u}\sigma_1 = 0$ is a test of selection based on unobservable rating determinants. If the test fails to reject that both parameters are jointly equal to zero, we cannot reject the null hypothesis of no selectivity bias in the solicited and unsolicited groups and we have no argument against using ordinary least squares. A Chow test can also be used to test whether the βs are identical in the solicited and unsolicited groups. If they are, the treatment effect model of the previous subsection is more efficient than the model described by equations (2)-(3) and (8)-(9).

The endogenous switching regression model is estimated by maximum likelihood using the procedure outlined in Greene (1995).

5 Results

Two basic specifications of equation (1) are reported in Table 4. The first specification includes five financial variables and three non-financial variables in addition to a *Solicited individual rating dummy.* These variables cover the different areas of

Fitch's bank rating methodology: risk management (*Loan loss provisions/Net interest revenue*), liquidity (*Net loans/Total assets*), capitalisation (*Equity/Total assets*), earnings and performance (*Cost to income ratio*), market environment (*Consolidated statement dummy*), diversification/franchise (*Log of total deposits*), corporate governance (*Bank ownership dummy* – one if the bank is majority-owned by another bank and zero otherwise) and public disclosure (*Disclosure index*). The second specification adds two variables that control for additional aspects of market environment (*Unqualified statement dummy*) and corporate governance (*State ownership dummy* – one if the bank is majority-owned by the State and zero otherwise). Finally, the *Solicited individual rating dummy* is interacted with an *Other individual rating dummy* (one if the bank had an individual rating from Moody's or Capital Intelligence before it obtained an individual rating from Fitch and zero otherwise). The resulting variable captures whether there is a difference in rating between banks which request an individual rating without being rated by a competitor of Fitch and banks which request an individual rating while being rated by a competitor of Fitch. Such a difference may exist if banks which are rated by a competitor agency engage in "rating shopping" and only request an individual rating from Fitch when they are a confident that it will be higher than their existing individual rating.[13] The two specifications are estimated by ordinary least squares (OLS) and by instrumental variables (IV) to account for the potential endogeneity of the *Equity/Total assets* and *Disclosure index* variables. The instruments for both variables consist of the exogenous variables in both specifications and country dummies that reflect the average level of the intrumented variables in each country. A Durbin-Wu-Hausman test of the null hypothesis that OLS delivers consistent estimates was carried out. The value of the Durbin-Wu-Hausman statistic in specifications (1) and (2) is 2.28 and 3.32, respectively, with associated probabilities of 0.32 and 0.19. This means that one cannot reject the null hypothesis that any endogeneity of *Equity/Total assets* and *Disclosure index* does not have deleterious effects on OLS estimates in both specifications. The discussion of Table 4 will therefore be based on the OLS results.

The coefficient of the *Solicited individual rating dummy* in specifications (1) and (2) is equal to 0.829 and 1.208, respectively, and is highly significant. This means that there is an important premium for banks which request an individual rating once controlling

[13] Note that no bank with an unsolicited rating from Fitch is rated by Moody's or Capital Intelligence, which prevents analysing whether there is a difference in the way Fitch treats banks not soliciting a rating but having a rating from a competitor agency versus banks that have no other rating.

for other rating determinants. For other variables, the results appear to be standard. For example, *Loan loss provisions/Net interest revenue* and *Cost to income ratio* negatively impact individual ratings, while *Equity/Total assets*, *Consolidated statement dummy*, *Bank ownership dummy* and *Disclosure index* are positively associated with Fitch's assessments of banks' financial strength. Interestingly, the coefficient of the *Disclosure index* is equal to 0.14 in both specifications, meaning that banks which increase by 7% the number of items that they report in *Bankscope*'s global detailed format raise their individual rating by one notch on average. Other variables common to both specifications as well as the variables added in the second specification are not significant. In particular, the marginal effect that the *Other individual rating dummy* has on how *Rating* is affected by the *Solicited individual rating dummy* is zero. The statistics at the bottom of the table also indicate that the two specifications have similar prediction rates and classify about one-third of banks in the correct rating category and about one-half in the rating category immediately above or below the actual rating. Since the variables added in specification (2) are not significant, I will work with specification (1) from now on.

Table 5 further investigates the impact of soliciting a rating by interacting the rating determinants with the *Solicited individual rating dummy* and adding the resulting variables to specification (1).[14] The model is estimated by ordinary least squares and by instrumental variables. As in Table 4, a Durbin-Wu-Hausman test does not reject the null hypothesis that OLS delivers consistent parameter estimates (the test statistic is 1.43 with an associated probability of 0.23). The results in Table 5 show that the marginal effect that soliciting a rating has on how individual ratings are affected by bank fundamentals is zero for each variable except for *Net loans/Total assets*. An F-test further fails to reject the null hypothesis that the coefficients of the rating determinants are the same in the solicited and unsolicited groups (the test statistic is 1.25 with an associated probability of 0.27). Together with the results of specification (1), this indicates that the *Solicited individual rating dummy* has an intercept effect but no slope effect on individual ratings. Thus, specification (1) of Table 4 appears to be appropriate to study the determinants of individual ratings.

The coefficient of the *Solicited individual rating dummy* in specification (1) suggests that there is an important difference in treatment between banks that ask for a rating and those which do not. However, ordinary least squares may overestimate the impact of

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[14] For comparison purposes, specification (1) of Table 4 is also reported in Table 5.

the treatment if banks that request a rating are positively self-selected. For this reason, I proceed to use the methods described in section 4 to correct for the potential sample selection bias.

Table 6 presents the estimates of the treatment effect model. The first two columns report the results of a two-step method which treats *Equity/Total assets* and *Disclosure index* as exogenous, while the last two columns report the results of a three-step method which consists in instrumenting both variables before applying the two-step method.[15] For each method (two-step and three-step), the table reports the results of the selection and of the outcome equation.

For identification purposes, the selection equation must include at least one variable that affects the decision to ask for a rating but not the rating itself. The variable which enters the selection equation but not the outcome equation is *Solicited long-term debt rating dummy* (one if the bank had a solicited long-term debt rating from Fitch before it obtained an individual rating and zero otherwise).[16] This variable is used as an exclusion restriction because Fitch started to issue long-term debt ratings in the 1980s, long before individual ratings. Therefore, banks which initially requested a long-term debt rating from Fitch should be more likely to have subsequently asked for an individual rating. At the same time, it is unlikely that paying for a long-term debt rating influenced the individual rating. Since I view the decision to request an individual rating as a sequential process (i.e. banks' decision to buy an individual rating was influenced by their decision for the long-term debt rating), I treat the *Solicited long-term debt rating dummy* as a lagged endogenous variable which does not have to be instrumented.

The results of the two- and three-step methods in Table 6 are relatively similar. I will therefore focus on the two-step results. Looking at the selection equation, the signs of the estimates suggest that smaller banks with a consolidated statement, a high level of public disclosure and a solicited long-term debt rating from Fitch are more likely to request an individual rating. Interestingly, banks with a better financial profile (as measured by *Loan loss provisions/Net interest revenue*, *Net loans/Total assets*, *Equity/Total assets* and *Cost to income ratio*) are not more likely to be rated on a

[15] As in Tables 4 and 5, the instruments for *Equity/Total assets* and *Disclosure index* consist of the exogenous variables in specification (1) and country dummies. The t-statistics of the parameter estimates in the three-step method are computed by bootstrapping.

[16] For the minority of banks which obtained both types of ratings at the same time, the *Solicited long-term debt rating dummy* is thus equal to zero. Setting the *Solicited long-term debt rating dummy* to one if the bank had a solicited long-term debt rating before or at the same time it obtained an individual rating and zero otherwise does not affect the results.

solicited basis. The statistics at the bottom of the selection equation also indicate that the model correctly predicts the decision to request an individual rating for roughly two-third of banks. Looking at the outcome equation, the estimates and their significance are in line with those reported in Table 4 except for the *Solicited individual rating dummy*, which is now insignificant. However, the coefficient of the hazard rate is insignificant so there is no evidence that there is a selectivity problem in the outcome equation. The statistics at the bottom of the outcome equation also show that the classification accuracy of the treatment effect model is comparable to that of ordinary least squares.

The results so far could be due to the fact that the above models are misspecified or too restrictive. For this reason, I consider a more general framework which allows the parameters of the outcome equation to differ according to whether or not banks have solicited a rating, while simultaneously controlling for sample selection. The results of the endogenous switching regression model are reported in Table 7 (the results of the selection equation are omitted). The first two outcome equations treat *Equity/Total assets* and *Disclosure index* as exogenous while the last two outcome equations adopt an instrumental variable approach which consists in instrumenting both variables before performing the maximum likelihood estimation.[17]

Looking at Table 7, three variables (*Loan loss provisions/Net interest revenue, Cost to income ratio* and *Disclosure index*) are jointly significant in the unsolicited and solicited groups in the first two outcome equations and only one (*Cost to income ratio*) in the last two outcome equations. The coefficients of these variables have the expected sign, i.e. *Loan loss provisions/Net interest revenue* and *Cost to income ratio* negatively impact individual ratings, while *Disclosure index* is positively related to Fitch's assessment of banks' financial strength. The statistics at the bottom of the table indicate that the classification accuracy of the model is slightly better in the unsolicited than in the solicited group. For clarity reasons, I will focus on the first two outcome equations to further discuss the results of the endogenous switching regression model (the last two outcome equations offer similar results).

First, a Chow test of the null hypothesis that the coefficients of individual rating determinants are the same in the solicited and unsolicited groups was carried out. The value of the test statistic is 0.78 with an associated probability of 0.63, meaning that one

[17] The set of instruments for *Equity/Total assets* and *Disclosure index* are the same as in Tables 4 to 6. The t-statistics of the parameter estimates in the last two outcome equations are computed by bootstrapping.

cannot reject the null hypothesis that the coefficients of individual rating determinants are identical in both groups. This result is consistent with the findings in Table 5 but contrasts with Butler and Rodgers (2003) who find that soliciting a rating induces Moody's and S&P to place less weight on rating determinants reflecting public information. My result also contradicts the findings of Poon and Firth (2004) who conclude that Fitch does not use the same model in assigning solicited and unsolicited bank ratings and that the rating standards applied to solicited ratings are more lenient than those applied to unsolicited ratings. However, it important to stress that Poon and Firth's results are based on a different sample of bank ratings and on a neural network model which reduces individual ratings to a dichotomous variable (1 if investment grade, 0 otherwise), hence these results are not necessarily comparable with mine.

Second, an F-test of the null hypothesis that the correlation coefficients between the error term in the selection equation and the error terms in the outcome equations are jointly insignificant was performed. The value of the test statistic is 0.13 with an associated probability of 0.88, meaning that one cannot reject the null hypothesis that ρ_{1u} and ρ_{2u} are both equal to zero and that there is no selection bias in individual ratings. Thus, the results in Tables 7 (like the results in Table 6) do not support the self-selection hypothesis and contrast with Poon (2003a), Poon (2003b) and Poon and Firth (2004) who find evidence of either positive or negative sample selection in S&P's and Fitch's ratings. As mentioned earlier, these papers use a standard model of sample selection, which is less appropriate than a treatment effect model or an endogenous switching regression model to study program effectiveness while simultaneously controlling for sample selection.

Third, the average treatment effect and the average treatment effect on the treated, which measure respectively the average gain from soliciting a rating for a randomly chosen bank and the average gain from soliciting a rating for those banks which have requested one, are obtained by estimating equations (14) and (16). The average treatment effect (ATE) is equal to 0.669 while the average treatment effect on the treated (ATT) is equal to 0.440. However, biased corrected confidence intervals based on 1,000 bootstrap replications indicate that both effects are not significantly different from zero (the confidence intervals are [-0.533 ; 1.846] for ATE and [-0.612 ; 1.572] for ATT).

Thus, the difference in treatment between solicited and unsolicited ratings is positive and significant when using ordinary least squares (Table 4) but insignificant when using a treatment effect model (Table 6) and an endogenous switching regression model (Table

7). An inevitable question is whether we should rely on ordinary least squares or on treatment effect model results.[18] On the one hand, no sample selection was detected in individual ratings, so one could argue that a treatment effect model is not – from a theoretical point of view – more appropriate than ordinary least squares. On the other hand, the treatment effect model has one considerable virtue: there is no justification for considering that the treatment is exogenous, as is assumed in ordinary least squares. Ordinary least squares estimates, therefore, may suffer from the inconsistency due to omitted variables. Fortunately, we can distinguish between the two models by using the specification test devised by Hausman (Greene, 2003). It is based on the idea that under the null hypothesis, both ordinary least squares and treatment effect estimates are consistent, but treatment effect estimates are inefficient, while under the alternative, treatment effect estimates are consistent but ordinary least squares estimates are not. Since the Hausman test statistic is equal to 0.023 with an associated probability of 1.0, one cannot reject the null hypothesis that OLS delivers consistent estimates. Thus, there is no argument against using ordinary least squares to study the determinants of bank individual ratings. I will therefore rely on this estimation technique to test the public disclosure hypothesis.

The public disclosure hypothesis implies that issuers who choose not to request a rating and who disclose little public information will receive a low unsolicited rating, whereas issuers who choose not to request a rating but who provide extensive public information will not receive a low unsolicited rating. This hypothesis is tested using a regression of the form:

$$\begin{aligned} Rating_i &= X_i\beta + \delta_1(Unsolicited_i * High\,disclosure_i) \\ &\quad + \delta_2(Unsolicited_i * (1 - High\,disclosure_i)) + \varepsilon_i \end{aligned} \tag{17}$$

where $Unsolicited_i$ is a dummy variable equal to one if bank i has not requested an individual rating and zero otherwise and $High\ disclosure_i$ is a dummy variable equal to one if bank i is a high disclosure bank and zero otherwise. If the public disclosure hypothesis is true, δ_1 - which represents the difference between the expected rating of a high disclosure bank which does not request a rating and the expected rating of a bank which requests a rating - should be insignificant while δ_2 - which represents the difference between the expected rating of a low disclosure bank which does not request a rating

[18] The endogenous switching regression model is not considered since the Chow test indicates that it is less efficient than the treatment effect model.

and the expected rating of a bank which requests a rating - should be negative and significant.

Measuring the marginal impact that public disclosure has on the relationship between *Unsolicited* and *Rating* by a dummy variable (*High disclosure*) is rather restrictive since it assumes that Fitch behaves differently when banks pass a certain disclosure threshold. However, a continuous change in Fitch's behaviour seems more plausible than a regime shift at a disclosure threshold specified arbitrarily. Therefore, equation (17) is estimated for different definitions of the *High disclosure dummy*: in a first regression, the *High disclosure dummy* is equal to one if the disclosure index of bank i is equal to or higher than the 50th percentile of the sample distribution of disclosure indexes and zero otherwise; in a second regression, the *High disclosure dummy* is equal to one if the disclosure index of bank i is equal to or higher than the 51st percentile of the sample distribution of disclosure indexes and zero otherwise; etc. The advantage of this approach is that it is unnecessary to model explicitly the marginal impact of public disclosure on the relationship between *Unsolicited* and *Rating*. The marginal impact of public disclosure is implicitly reflected in changing coefficient estimates. Figure 2 plots the estimated coefficients of the different explanatory variables of equation (17) along with their confidence interval against the corresponding definition of the *High disclosure dummy*.

The coefficients of the first eight variables (*LLP/Net interest revenue* to *Disclosure index*) are close to those shown in Table 4, which is not surprising given that equations (1) and (17) are very similar. More interesting are the results for the coefficient of *Unsolicited* interacted with *High disclosure* and of *Unsolicited* interacted with (1 - *High disclosure*). I find that the coefficient of the former variable, δ_1, is insignificant when *High disclosure* is equal to one for values of the disclosure index above the 67th percentile of its sample distribution and equal to zero otherwise. I also find that the coefficient of the latter variable, δ_2, is negative and significant irrespective of the definition of the *High disclosure dummy*. This means that the public disclosure hypothesis is validated when high disclosure banks are defined as the 32 percent (or less) of sample banks with the highest disclosure index.[19] In this case, unsolicited ratings of high disclosure banks are not statistically different from solicited ratings whereas unsolicited ratings of low

[19] It is important to mention that the analysis carried out above also holds if the *High disclosure dummy* is defined using the percentiles of the world distribution of bank disclosure indexes instead of their sample distribution. The world distribution of bank disclosure indexes was obtained by calculating the disclosure index of 10,577 banks from *Bankscope*.

disclosure banks are lower than solicited ratings by one notch on average. The threshold above which the public disclosure hypothesis holds corresponds to a disclosure index equal to 47.4, meaning that banks which release at least 70 items (out of a possible 147) in *Bankscope*'s global detailed format do not receive lower unsolicited ratings.

On the basis of Figure 2, I conclude that my results support the public disclosure hypothesis, which states that the difference in treatment between solicited and unsolicited ratings disappears when banks with an unsolicited rating release enough public information to compensate for the absence of private information. This finding is consistent with the fact that public disclosure gives issuers the benefit of the doubt when they choose not to request a rating (Golin, 2001).

6 Conclusion and policy implications

This paper empirically investigates whether there is a difference in treatment between solicited and unsolicited bank ratings and, if so, why. Using individual ratings of Asian banks, I find that Fitch assigns the same weight to rating determinants reflecting public information in the solicited and unsolicited groups. This result gives some credence to Fitch's claim that the methodology for its unsolicited bank ratings is almost the same as for its solicited bank ratings. However, I also find that unsolicited bank ratings tend to be lower than solicited ones after controlling for rating determinants reflecting public information. The difference in treatment between both types of ratings is economically significant as it represents between 0.8 and 1.2 notches on a 1 to 9 rating scale.

The existence of a difference in treatment between solicited and unsolicited ratings has already been documented for other credit rating agencies. Several explanations are consistent with it, including the fact that issuers with more favourable private information may request a rating or the fact that unsolicited ratings do not involve the disclosure of private information and, as a result, may be more conservative than solicited ones. In addition, many issuers also believe that credit rating agencies assign a lower unsolicited rating in order to persuade them to pay for a solicited rating. Improving on previous research which does not adequately or explicitly control for sample selection, this study uses a treatment effect model and an endogenous switching regression model to test whether banks with more favourable private information self-select into the solicited group ("self-selection hypothesis"). To the best of my knowledge, this study is also the first one to test whether the difference in treatment between solicited and unsolicited ratings disappears when banks with an unsolicited rating release enough public information to compensate for the absence of private information ("public disclosure hypothesis"). The results of this paper reject the self-selection hypothesis but support the public disclosure hypothesis.

The above-mentioned findings are interesting for several reasons. First, Fitch recently announced that it was about to assign unsolicited individual ratings to 150-200 German insurance companies "in order to provide more comprehensive coverage in the European insurance sector to meet the growing demand" for its ratings. In contrast to traditional solicited insurance ratings, these ratings would be "generated solely using a statistical model that utilizes financial statement information" (Fitch, 2004c). Fitch's announcement triggered an immediate reaction from the German Insurance Industry Association GDV, which expressed its deepest concerns and urged Fitch to refrain from publishing any unsolicited ratings unless the new rating methodology had been "fully disclosed and widely discussed with the German insurance industry and the general public" (GDV, 2004). GDV also stressed that Fitch's decision constituted a serious offence to several provisions of the new IOSCO code of conduct for credit rating agencies. Fitch replied by clarifying some points underlying its methodology for unsolicited insurance ratings but decided to press ahead with the publication of these ratings (Fitch, 2005). This study indicates that some of the concerns voiced by GDV may be valid, as it shows the existence of a conservative bias in bank ratings which are primarily based on public information.

Second, possible measures concerning credit rating agencies are currently being discussed at the European level. In particular, the European Commission is investigating the potential need to "disclose, or manage, unsolicited ratings" (European Commission, 2004). Although the results of this study find no evidence of wrongdoing by credit rating agencies, they support additional measures designed to clarify the differences between solicited and unsolicited ratings. For instance, the mere addition by Fitch of the letter "s" (shadow) to its unsolicited bank ratings seems insufficient to mark their difference with ratings which are asked and paid for by issuers. It should therefore be required that the specific characteristics and the limitations of unsolicited bank ratings - including the conservative bias documented in this paper - are made completely transparent to the public.

Third, the New Basel Accord, which is due to be implemented by G-10 banks at the end of 2006, aims at increasing public disclosure by banks in order to ensure that market participants can better understand banks' risk profile and the adequacy of their capital position. It is therefore necessary that financial institution managers understand the need for more disclosure and move in this direction on their own. This paper provides an incentive for bank managers to disclose information as it documents the impact of public disclosure on credit ratings, i.e. on the cost of borrowing, and on the relationship between soliciting a rating and the actual rating outcome. I show that public disclosure has not only a positive effect on individual ratings, but that it also eliminates the downward bias of unsolicited individual ratings.

Finally, it is worth stressing that the individual ratings used in this study are assigned to banks located in Asia. To some extent, this limits the relevance of my results in the European context. Given this caveat, the policy recommendations made above should be interpreted with care.

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Table 1: Distribution of bank individual ratings by country (Asia) [a]

Country	Solicited Freq.	Solicited Perc.	Unsolicited Freq.	Unsolicited Perc.	Total Freq.	Total Perc.
Azerbaijan	1		0		1	
Bangladesh	1	(0.6)	5	(3.0)	6	(3.6)
China	1	(0.6)	15	(8.9)	16	(9.5)
Georgia	1		0		1	
Hong Kong	8	(4.7)	10	(5.9)	18	(10.7)
India	4	(2.4)	28	(16.6)	32	(18.9)
Indonesia	10	(5.9)	2	(1.2)	12	(7.1)
Japan	31		0		31	
Kazakhstan	6		0		6	
Macau	2	(1.2)	1	(0.6)	3	(1.8)
Malaysia	7	(4.1)	4	(2.4)	11	(6.5)
Pakistan	0		4		4	
Philippines	11	(6.5)	2	(1.2)	13	(7.7)
Singapore	6		0		6	
South Korea	9	(5.3)	3	(1.8)	12	(7.1)
Sri Lanka	0		5		5	
Taiwan	20	(11.8)	19	(11.2)	39	(23.1)
Thailand	10		0		10	
Vietnam	1	(0.6)	6	(3.6)	7	(4.1)
Total	128		105		233	
Sample countries [b]	74	(43.8)	95	(56.2)	169	(100)

Note: [a] As of January 31, 2004
[b] Countries with both solicited and unsolicited ratings (shown in *italics*)
Source: *Bankscope* (update 162.2) and *Fitch Research*

Table 2: Distribution of bank individual ratings by rating level (sample countries)

Individual rating	Interpretation [a]	Solicited Freq.	Solicited Perc.	Unsolicited Freq.	Unsolicited Perc.	Total Freq.	Total Perc.
A	A very strong bank	-		-		-	
A / B		1	(0.6)	1	(0.6)	2	(1.2)
B	A strong bank	2	(1.2)	0	(0.0)	2	(1.2)
B / C		11	(6.5)	3	(1.8)	14	(8.3)
C	An adequate bank	17	(10.1)	14	(8.3)	31	(18.3)
C / D		14	(8.3)	11	(6.5)	25	(14.8)
D	A bank that has weaknesses	20	(11.8)	20	(11.8)	40	(23.7)
D / E		5	(3.0)	23	(13.6)	28	(16.6)
E	A bank with serious problems	4	(2.4)	23	(13.6)	27	(16.0)
Total		74	(43.8)	95	(56.2)	169	(100)

Note: [a] See the Appendix for a detailed interpretation

Table 3: Comparison of banks characteristics in the solicited and unsolicited groups

Variables	Solicited			Unsolicited			t-value
	Mean	SD	Obs	Mean	SD	Obs	
1. *Risk management*							
Loan loss provisions/Net int. rev.	33.9	69.6	65	36.4	38.3	90	-0.30
Impaired loans/Gross loans	14.9	19.6	64	9.1	7.7	59	2.14*
2. *Funding and liquidity*							
Net loans/Total assets	48.4	20.5	74	52.6	13.5	95	-1.59
Liquid assets/Total deposits	47.7	71.5	70	31.9	15.7	86	1.99*
3. *Capitalisation*							
Total capital ratio	17.3	17.0	65	12.5	4.4	75	2.35*
Equity/Total assets	13.2	17.2	74	6.2	3.9	95	3.81**
4. *Securitisation*							
(none)							
5. *Earnings and performance*							
Return on assets	0.5	2.7	74	0.5	1.0	95	-0.11
Cost to income ratio	49.0	21.6	73	54.5	24.7	95	-1.51
6. *Market environment*							
Consolidated statement	62.2	48.8	74	44.2	49.9	95	2.34*
Unqualified statement	88.3	17.4	74	77.2	29.4	95	2.86**
Commercial bank	77.0	42.4	74	94.7	22.4	95	-3.50**
Non-banking credit institution	13.5	34.4	74	0.0	0.0	95	3.83**
Sovereign rating long-term	12.9	3.7	71	12.8	3.1	89	0.07
7. *Diversification/franchise*							
Total deposits	15.3	27.4	65	26.5	76.3	95	-1.13
Market share (deposits)	5.6	6.5	62	5.4	10.4	94	0.11
Number of branches/Total assets	51.7	96.9	42	70.9	80.1	80	-1.17
Number of banks per 1,000,000 inh.	3.3	5.0	74	2.3	4.6	95	1.37
8. *Management and strategy*							
Number of directors and managers	19.3	10.0	52	21.8	13.0	79	-1.17
9. *Corporate governance*							
Corporate governance index	6.0	1.3	71	6.8	1.4	89	-3.93**
Domestic shareholders	73.5	44.4	68	77.8	41.8	90	-0.62
Percentage of shares owned by:							
Banks	33.8	41.7	73	23.4	38.2	90	1.66
Individuals/Families	4.3	14.3	73	0.4	1.7	90	2.59**
Industrial companies	10.9	24.7	73	10.0	20.1	90	0.26
State/Public authority	9.1	24.3	73	28.3	40.3	90	-3.57**
Number of subsidiaries maj. owned	7.0	7.7	59	3.2	3.9	78	3.77**
10. *Public disclosure*							
Disclosure index	44.3	5.7	74	42.5	5.7	95	1.97*

Note: See Table 1A for variables definition and unit. Statistics in the table include mean (Mean), standard deviation (SD) and number of observations (Obs) of each variable. The t-values in the last column refer to the t-statistics of the means between the solicited rating group and the unsolicited rating group; * significant at 5%; ** significant at 1%.

Table 4: Determinants of individual ratings (1)

Dependent variable: Individual rating coded on a 9 (A) - 1 (E) scale

	Ordinary least squares		Instrumental variables	
Independent variables	(1)	(2)	(1)	(2)
Constant	-0.713	-0.872	-1.733	-1.853
	(0.47)	(0.58)	(0.97)	(1.05)
Loan loss provisions/Net interest revenue	-0.012**	-0.011*	-0.011**	-0.011*
	(2.81)	(2.60)	(2.72)	(2.50)
Net loans/Total assets	0.002	-0.003	0.001	-0.004
	(0.21)	(0.41)	(0.17)	(0.44)
Equity/Total assets	0.042*	0.046*	0.065*	0.069*
	(2.45)	(2.14)	(2.05)	(2.03)
Cost to income ratio	-0.022**	-0.022**	-0.019**	-0.020**
	(3.92)	(4.04)	(3.11)	(3.25)
Consolidated statement dummy	0.613**	0.672**	0.580**	0.658**
	(2.89)	(3.17)	(2.72)	(3.10)
Log (total deposits)	-0.102	-0.059	-0.078	-0.045
	(1.37)	(0.75)	(0.86)	(0.49)
Bank ownership dummy	0.737**	0.650**	0.724**	0.646*
	(3.08)	(2.63)	(2.95)	(2.56)
Disclosure index	0.140**	0.140**	0.148**	0.154**
	(7.26)	(6.71)	(6.60)	(6.42)
Solicited individual rating dummy	0.829**	1.208**	0.784**	1.199**
	(3.83)	(4.13)	(3.49)	(4.09)
Unqualified statement dummy		-0.296		-0.451
		(0.71)		(0.98)
State ownership dummy		-0.202		-0.129
		(0.83)		(0.52)
*Solicited dummy * Other rating dummy*		-0.607		-0.644*
		(1.94)		(2.09)
Observations	148	148	148	148
Adjusted R-squared	0.57	0.58	0.57	0.57
Classification accuracy (%)				
actual minus predicted rating = 0	34.5	27.7	37.8	31.1
actual minus predicted rating = -1 or 1	48.7	57.4	46.0	53.4
actual minus predicted rating ≥ -2 or 2	16.9	14.9	16.2	15.5

Notes: Robust t-statistics in parentheses; * significant at 5%; ** significant at 1%

Table 5: Determinants of individual ratings (2)

Dependent variable: Individual rating coded on a 9 (A) - 1 (E) scale

	Ordinary least squares		Instrumental variables	
Independent variables	(1)	(2)	(1)	(2)
Constant	-0.713	0.382	-1.733	-4.888
	(0.47)	(0.17)	(0.97)	(1.32)
Loan loss provisions/Net interest revenue	-0.012**	-0.014*	-0.011**	-0.014*
	(2.81)	(2.15)	(2.72)	(2.12)
Net loans/Total assets	0.002	-0.011	0.001	-0.007
	(0.21)	(0.97)	(0.17)	(0.51)
Equity/Total assets	0.042*	0.080*	0.065*	0.228*
	(2.45)	(1.99)	(2.05)	(1.99)
Cost to income ratio	-0.022**	-0.020**	-0.019**	-0.006
	(3.92)	(2.95)	(3.11)	(0.53)
Consolidated statement dummy	0.613**	0.586*	0.580**	0.197
	(2.89)	(1.97)	(2.72)	(0.49)
Log (total deposits)	-0.102	-0.092	-0.078	0.079
	(1.37)	(0.79)	(0.86)	(0.46)
Bank ownership dummy	0.737**	0.605	0.724**	0.554
	(3.08)	(1.78)	(2.95)	(1.62)
Disclosure index	0.140**	0.121**	0.148**	0.141**
	(7.26)	(5.17)	(6.60)	(3.61)
Solicited individual rating dummy	0.829**	-1.882	0.784**	7.126
	(3.83)	(0.54)	(3.49)	(1.21)
*Solicited dummy * LLP/Net interest revenue*		0.001		-0.001
		(0.13)		(0.09)
*Solicited dummy * Net loans/Total assets*		0.033*		0.035
		(2.14)		(1.79)
*Solicited dummy * Equity/Total assets*		-0.059		-0.296
		(1.31)		(1.86)
*Solicited dummy * Cost to income ratio*		-0.004		-0.026
		(0.36)		(1.41)
*Solicited dummy * Consolidated dummy*		-0.180		0.062
		(0.34)		(0.11)
*Solicited dummy * Log (total deposits)*		0.044		-0.010
		(0.22)		(0.03)
*Solicited dummy * Bank ownership dummy*		0.089		0.145
		(0.16)		(0.26)
*Solicited dummy * Disclosure index*		0.022		-0.098
		(0.44)		(0.98)
Observations	148	148	148	148
Adjusted R-squared	0.57	0.58	0.57	0.47
Classification accuracy (%)				
actual minus predicted rating = 0	34.5	34.5	37.8	29.7
actual minus predicted rating = -1 or 1	48.7	50.0	46.0	52.0
actual minus predicted rating ≥ -2 or 2	16.9	15.5	16.2	18.3

Notes: Robust t-statistics in parentheses; * significant at 5%; ** significant at 1%

Table 6: Treatment effect model

Dependent variable (selection equation): Solicited individual rating dummy
Dependent variable (outcome equation): Individual rating coded on a 9 (A) - 1 (E) scale

	Two-step		Three-step	
Independent variables	Selection	Outcome	Selection	Outcome
Constant	-0.139	-0.683	-0.970	-1.742
	(0.08)	(0.49)	(0.38)	(0.81)
Loan loss provisions/Net interest revenue	0.007	-0.011**	0.007	-0.011*
	(1.69)	(3.14)	(1.53)	(1.98)
Net loans/Total assets	-0.001	0.002	-0.002	0.002
	(0.12)	(0.23)	(0.14)	(0.16)
Equity/Total assets	0.010	0.043*	0.037	0.071
	(0.40)	(2.03)	(0.77)	(1.64)
Cost to income ratio	0.001	-0.022**	0.004	-0.019*
	(0.10)	(4.63)	(0.40)	(2.13)
Consolidated statement dummy	0.773**	0.645*	0.734**	0.655*
	(2.99)	(2.21)	(2.60)	(1.99)
Log (total deposits)	-0.268*	-0.111	-0.221	-0.094
	(2.54)	(1.15)	(1.68)	(0.85)
Bank ownership dummy	-0.078	0.731**	-0.070	0.711**
	(0.26)	(2.94)	(0.17)	(2.59)
Disclosure index	0.074**	0.142**	0.069*	0.154**
	(2.96)	(5.68)	(2.00)	(4.35)
Solicited long-term debt rating dummy	1.027**		0.965*	
	(2.80)		(1.99)	
Solicited individual rating dummy		0.718		0.509
		(0.94)		(0.49)
Hazard rate		0.071		0.227
		(0.15)		(0.37)
Observations	148	148	148	148
Pseudo R-squared	0.19		0.19	
Classification accuracy (%) - Selection				
correctly classified	68.9		66.2	
Adjusted R-squared		0.57		0.55
Classification accuracy (%) - Outcome				
actual minus predicted rating = 0		34.5		39.9
actual minus predicted rating = -1 or 1		46.6		36.5
actual minus predicted rating ≥ -2 or 2		18.9		23.7

Notes: Robust t-statistics in parentheses for the two-step method; Bootstrapped t-statistics in parentheses for the three-step method; * significant at 5%; ** significant at 1%

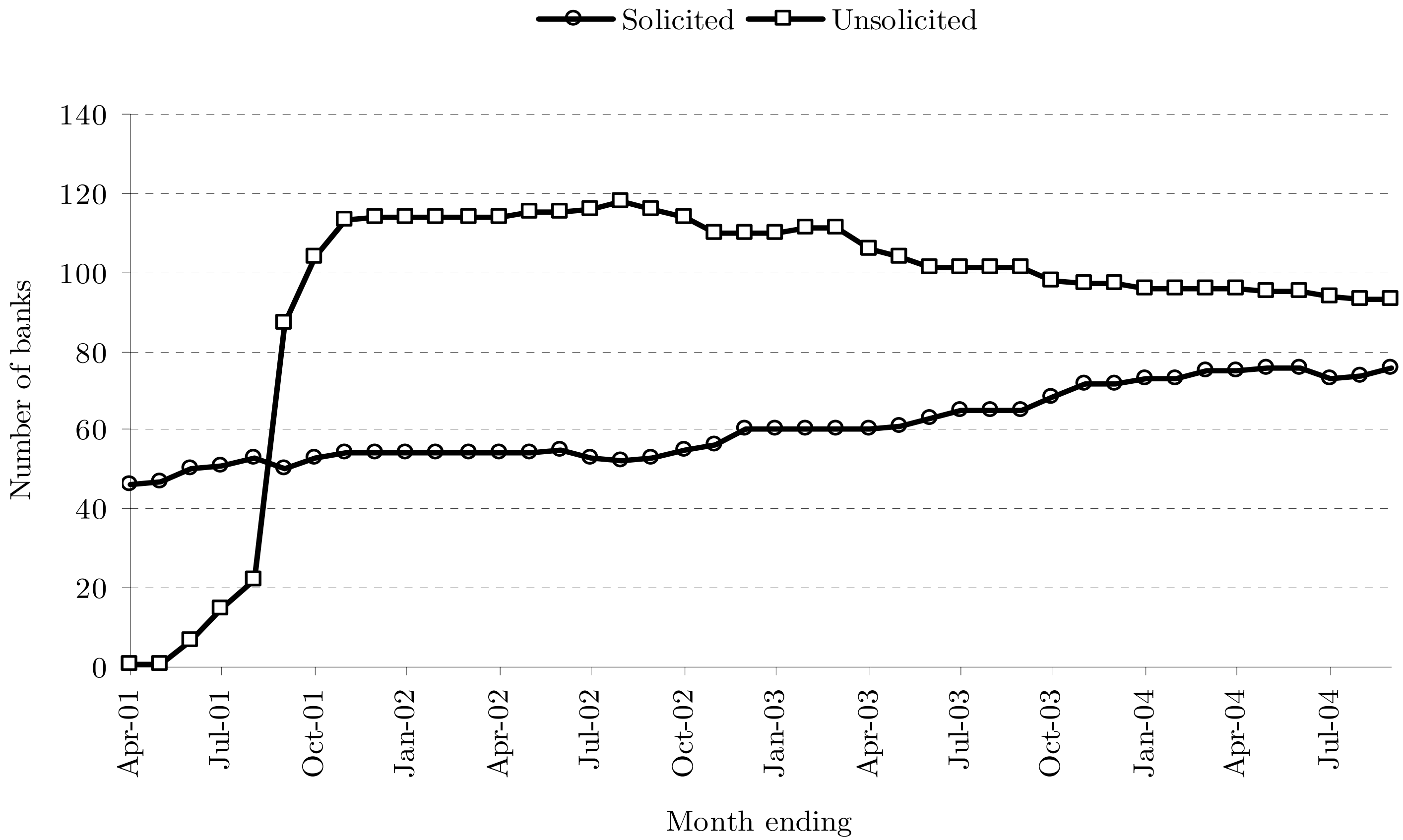
Table 7: Endogenous switching regression model

Dependent variable: Individual rating coded on a 9 (A) - 1 (E) scale

	Max. Likelihood		Max. Likelihood + IV	
Independent variables	Unsolicited	Solicited	Unsolicited	Solicited
Constant	0.403	-1.622	0.418	-2.305
	(0.21)	(0.63)	(0.17)	(0.61)
Loan loss provisions/Net interest revenue	-0.014*	-0.013**	-0.014	-0.014
	(2.04)	(2.70)	(1.54)	(1.83)
Net loans/Total assets	-0.011	0.022	-0.012	0.022
	(1.08)	(1.19)	(1.13)	(1.71)
Equity/Total assets	0.082	0.022	0.056	0.047
	(1.46)	(0.59)	(1.08)	(0.90)
Cost to income ratio	-0.019*	-0.023*	-0.020*	-0.022*
	(2.30)	(2.28)	(2.05)	(2.40)
Consolidated statement dummy	0.654	0.468	0.659*	0.277
	(1.29)	(0.94)	(2.07)	(0.52)
Log (total deposits)	-0.105	-0.077	-0.171	0.181
	(0.81)	(0.30)	(1.40)	(0.81)
Bank ownership dummy	0.604	0.675	0.467	0.737
	(1.75)	(1.38)	(1.49)	(1.37)
Disclosure index	0.126**	0.152**	0.155**	0.082
	(3.63)	(2.59)	(5.30)	(1.02)
Standard deviation $(\varepsilon_1) = \sigma_1$	1.086**		1.162**	
	(6.99)		(7.61)	
Correlation $(\varepsilon_1, u) = \rho_{1u}$	0.122		-0.113	
	(0.21)		(0.25)	
Standard deviation $(\varepsilon_2) = \sigma_2$		0.996**		0.956**
		(8.63)		(8.25)
Correlation $(\varepsilon_2, u) = \rho_{2u}$		-0.150		-0.084
		(0.16)		(0.16)
Observations	85	63	85	63
Adjusted R-squared	0.57	0.37	0.59	0.36
Classification accuracy (%)				
actual minus predicted rating = 0	38.8	31.8	42.4	30.2
actual minus predicted rating = -1 or 1	49.4	47.6	45.9	50.8
actual minus predicted rating ≥ -2 or 2	11.8	20.6	11.8	19.1

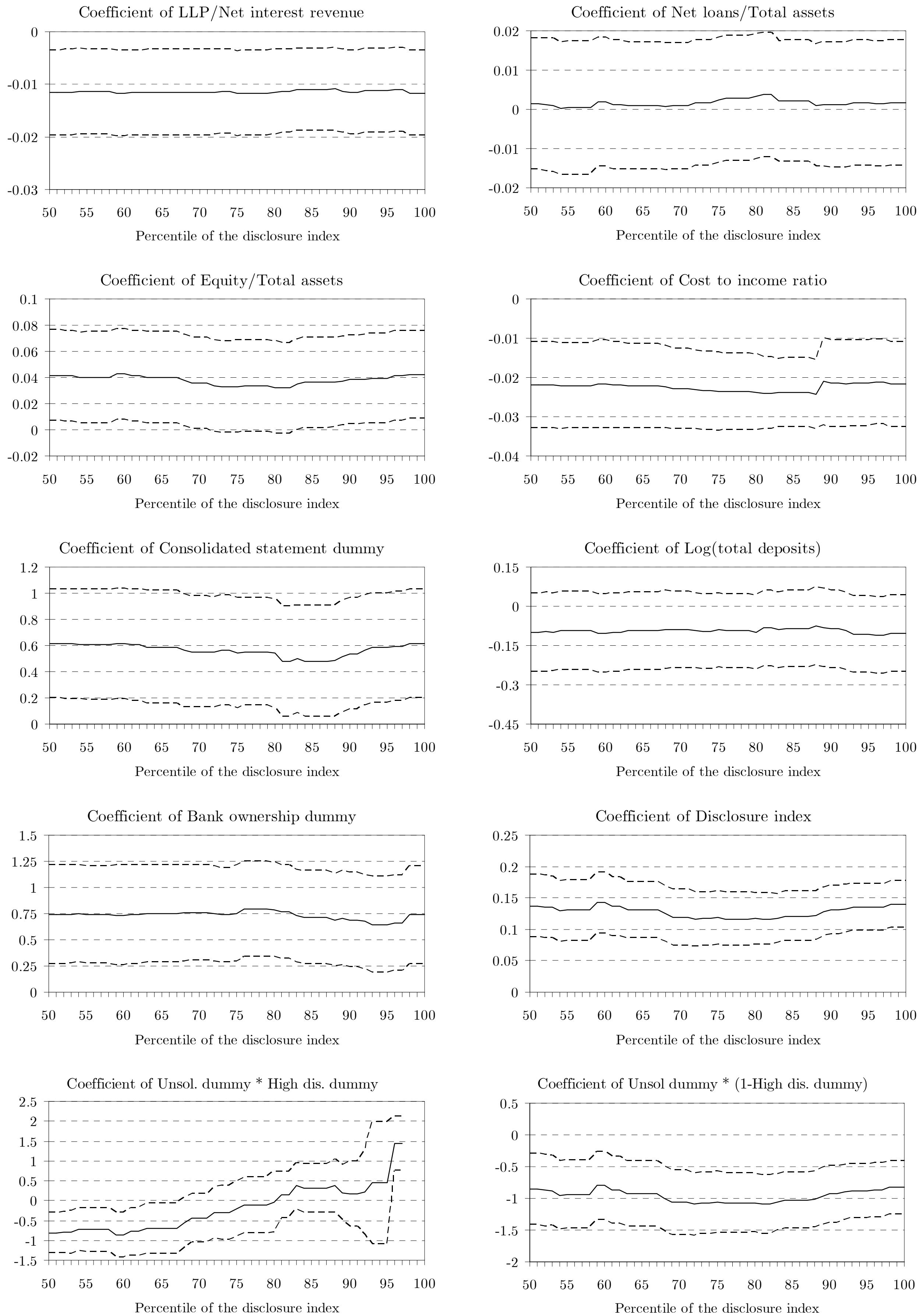
Notes: Results of the selection equation are not reported
Robust t-statistics in parentheses for the Maximum Likelihood estimation; Bootstrapped t-statistics in parentheses for the Maximum Likelihood + IV estimation; * significant at 5%; ** significant at 1%

Figure 1: Number of solicited and unsolicited bank ratings in the sample countries, April 2001 – September 2004



Source: *Bankscope* (updates 129.2 to 170.2) and *Fitch Research*

Figure 2: Estimated coefficients and confidence intervals for the variables included in equation (17)



Appendix

Fitch individual ratings: definition and scale

Definition:

Individual Ratings are assigned only to banks. These ratings, which are internationally comparable, attempt to assess how a bank would be viewed if it were entirely independent and could not rely on external support. These ratings are designed to assess a bank's exposure to, appetite for, and management of risk, and thus represent our view on the likelihood that it would run into significant difficulties such that it would require support. The principal factors we analyze to evaluate the bank and determine these ratings include profitability and balance sheet integrity (including capitalization), franchise, management, operating environment, and prospects. Finally, consistency is an important consideration, as is a bank's size (in terms of equity capital) and diversification (in terms of involvement in a variety of activities in different economic and geographical sectors).

Scale:

A A very strong bank. Characteristics may include outstanding profitability and balance sheet integrity, franchise, management, operating environment or prospects.

B A strong bank. There are no major concerns regarding the bank. Characteristics may include strong profitability and balance sheet integrity, franchise, management, operating environment or prospects.

C An adequate bank, which, however, possesses one or more troublesome aspects. There may be some concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects.

D A bank, which has weaknesses of internal and/or external origin. There are concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects. Banks in emerging markets are necessarily faced with a greater number of potential deficiencies of external origin.

E A bank with very serious problems, which either requires or is likely to require external support.

Note: intermediate categories are also used, i.e. A/B, B/C, C/D, and D/E

Source: http://www.fitchratings.com/

Table 1A: Variables definition and sample descriptive statistics

Variable	Definition	Obs	Mean	SD	Min	Max
1. *Risk management*						
Loan loss provisions/Net int. rev.	100 * (Loan loss provisions/Net interest revenue)	155	35.4	53.5	-75.9	312.9
Impaired loans/Gross loans	100 * (Impaired loans/(Loans + Loan loss reserve))	123	12.1	15.4	0	97.3
2. *Funding and liquidity*						
Net loans/Total assets	100 * (Loans/Total assets)	169	50.7	17.0	-0.1	91.4
Liquid assets/Total deposits	100 * (Liquid assets/Customer and short-term funding)	156	39.0	49.7	0.7	471.3
3. *Capitalisation*						
Total capital ratio	100 * ((Tier 1 + Tier 2 capital)/Risk-weighted assets)	140	14.7	12.2	-12.1	137.8
Equity/Total assets	100 * (Equity/Total assets)	169	9.3	12.2	-20.2	84.0
4. *Securitisation*						
(none)						
5. *Earnings and performance*						
Return on assets	100 * (Net income/Total assets)	169	0.5	2.0	-11.0	7.2
Cost to income ratio	100 * (Overheads/(Net Interest Revenue + Other Operating Income))	168	52.1	23.5	14.5	240.3
6. *Market environment*						
Consolidated statement	100 if the bank's statement is consolidated, 0 otherwise	169	52.1	50.1	0	100
Unqualified statement	100 if the bank's statement has been audited and the accounts have been accepted by the auditors without any remark, 0 otherwise	169	82.1	25.4	0	100
Commercial bank	100 if commercial bank, 0 otherwise	169	87.0	33.7	0	100
Non-banking credit institution	100 if non-banking credit institution, 0 otherwise	169	3.3	1.6	0	100
Sovereign rating long-term [a]	Fitch's sovereign foreign currency long-term rating coded on a 20 (AAA) to 1 (D) scale	160	12.8	3.4	7	17
7. *Diversification/franchise*						
Total deposits	Total deposits (in billion of US $)	160	22.0	61.4	0.0	506.0
Market share (deposits)	100 * (Total deposits at bank j/Total banking deposits in the country of bank j)	156	5.5	9.0	0.1	56.6
Number of branches/Total assets	Number of branches/Total assets (in billion of US $)	122	64.3	86.3	1.4	460.1
Number of banks per 1,000,000 inh.	Number of banks in country j/(Total population in country j/1,000,000)	169	2.7	4.8	0.0	21

Table 1A ctd.

Variable	Definition	Obs	Mean	SD	Min	Max
8. *Management and strategy*						
Number of directors and managers	Number of directors and managers who are members of the supervisory board, the board of managing directors, the executive committee and/or the audit committee	131	20.8	12.0	1	70
9. *Corporate governance*						
Corporate governance index [a]	Country's corporate governance index coded on a 10 (worst) to 0 (best) scale	160	6.4	1.4	4.4	8.3
Domestic shareholders	100 if all bank shareholders are from the bank's country, 0 otherwise	158	75.9	42.9	0	100
Percentage of shares owned by:	Percentage of bank shares owned by:					
Banks	other banks (0 to 100)	163	28.1	40.0	0	100
Individuals/Families	individuals and families (0 to 100)	163	2.1	9.8	0	92
Industrial companies	industrial companies (0 to 100)	163	10.4	22.2	0	100
State/Public authority	State and public authority (0 to 100)	163	19.7	35.3	0	100
Number of subsidiaries maj. owned	Number of bank and non bank subsidiaries majority owned by the bank	137	4.8	6.1	0	42
10. *Public disclosure*						
Disclosure index	$\text{Disclosure index} = \frac{1}{147}\sum_{i=1}^{147}\text{item}_i$ where item_i is equal to 100 if available in the "global detailed" format of *Bankscope*, 0 otherwise. The 147 items in this format include asset items (54), liabilities items (43), income statement items (37) and note items (13)	169	43.3	5.7	28.6	55.8

Notes: [a] These variables are country-specific

Source: All variables are from *Bankscope* except countries' total population and the corporate governance index, which are from *The World Bank* and from *Political and Economic Risk Consultancy, Ltd.*, respectively

Table 2A: Determinants of individual ratings

Dependent variable: Individual rating coded on a 9 (A) - 1 (E) scale

	Ordinary least squares		Ordered probit	
Independent variables	(1)	(2)	(1)	(2)
Constant	-0.713	-0.872	-	-
	(0.47)	(0.58)	-	-
Loan loss provisions/Net interest revenue	-0.012**	-0.011*	-0.012**	-0.012**
	(2.81)	(2.60)	(2.69)	(2.61)
Net loans/Total assets	0.002	-0.003	-0.002	-0.008
	(0.21)	(0.41)	(0.19)	(0.92)
Equity/Total assets	0.042*	0.046*	0.037*	0.039
	(2.45)	(2.14)	(2.38)	(1.93)
Cost to income ratio	-0.022**	-0.022**	-0.024**	-0.024**
	(3.92)	(4.04)	(3.90)	(4.17)
Consolidated statement dummy	0.613**	0.672**	0.591**	0.643**
	(2.89)	(3.17)	(2.88)	(3.10)
Log (total deposits)	-0.102	-0.059	-0.138	-0.078
	(1.37)	(0.75)	(1.76)	(0.91)
Bank ownership dummy	0.737**	0.650**	0.687**	0.579*
	(3.08)	(2.63)	(3.24)	(2.54)
Disclosure index	0.140**	0.140**	0.149**	0.149**
	(7.26)	(6.71)	(6.40)	(6.13)
Solicited individual rating dummy	0.829**	1.208**	0.848**	1.257**
	(3.83)	(4.13)	(4.12)	(4.44)
*Solicited dummy * Other rating dummy*		-0.607		-0.655*
		(1.94)		(2.18)
Unqualified statement dummy		-0.296		-0.106
		(0.71)		(0.23)
State ownership dummy		-0.202		-0.358
		(0.83)		(1.48)
Observations	148	148	148	148
Adjusted R-squared	0.57	0.58		
Pseudo R-squared			0.25	0.26
Classification accuracy (%)				
actual minus predicted rating = 0	34.5	27.7	39.9	38.5
actual minus predicted rating = -1 or 1	48.7	57.4	37.8	38.5
actual minus predicted rating ≥ -2 or 2	16.9	14.9	22.3	23.0

Notes: Cut points of the ordered probit model are not reported
Robust t-statistics in parentheses; * significant at 5%; ** significant at 1%