Economic Effects of Positive Credit Information Sharing: The Case of Korea

Joon-Ho Hahm*, Sangche Lee**

October 2008

Abstract

Currently in Korea, negative credit information, such as loan default and arrears, is collected and shared among all banks via a regulatory agency on a centralized and compulsory basis. However, positive credit information is exchanged among participating banks via private credit bureaus on a voluntary and reciprocal basis. Employing optimal credit decision models of profit maximizing banks, and utilizing a unique dataset of 2 million consumer loan obligors in Korea, we investigate the economic effects of sharing positive credit information in addition to negative credit information already exchanged. We find that the discriminatory power of the credit scoring model improves significantly. We proceed to investigate the economic effects of the information gap in a competitive credit market by assuming two groups of banks that differ only in the level of credit information sharing. Banks that share negative information only suffer from deterioration of the borrower pool and reduced profit, as high credit risk borrowers are more concentrated on this group due to under-pricing of risks. Our finding indicates that banks have incentives to voluntarily participate in the positive information sharing mechanism even in the presence of a public credit registry, since even a small difference in discriminatory power stemming from the information gap may lead to a significant fall in profitability as the distribution of borrower quality changes endogenously due to adverse selection problems.

JEL classification: D82; G21; G28

Keywords: Credit risk; Information sharing; Loan pricing; Adverse selection; Korea

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* Corresponding author, Associate Professor, Graduate School of International Studies, Yonsei University, 134 Shinchon-dong, Seodaemoon-gu, Seoul 120-749, Korea. Tel: 82-2-2123-4210, jhahm@yonsei.ac.kr

** Research Fellow, Korea Institute of Finance, KFB Building, 4-1, 1-ga, Myong-dong, Chung-gu, Seoul 100-021, Korea. Tel: 82-2-3705-6315, sclee@kif.re.kr

1. Introduction

Since the seminal works of Akerlof (1970) and Stiglitz and Weiss (1981), it is now well understood that asymmetric information problems may seriously undermine efficient allocation of credit. One way to overcome this informational rigidity is to share credit information among lenders. Indeed, as surveyed by Miller (2003), we observe various forms of credit information sharing mechanisms around the world. Some countries adopt a formal information sharing mechanism in which public credit registries collect and share data compulsorily reported by lenders. Other countries have developed more voluntary systems in which private credit bureaus act as information brokers.

Regardless of the institutional form of the information sharing mechanism, a large body of theoretical research agrees that there exist positive effects of information sharing on the efficiency of credit allocation. First, the exchange of credit information can improve the screening ability of lenders and thereby reduce adverse selection problems, which lead to better pricing and more credit supply. For instance, Pagano and Jappelli (1993) develop an adverse selection model and show that information sharing on borrower type leads to easing of adverse selection and lower default rates. Padilla and Pagano (1997) also show that information exchange can lead to lower interest rates and increased loan supply.

Second, information sharing can attenuate moral hazard on the part of borrowers by exerting disciplinary effects. Padilla and Pagano (2000) show that lenders' exchange of past default information increases loan repayment probability as default becomes a signal of bad credit quality for outsiders. Hence, borrowers exert more efforts to avoid higher interest rate penalties in the future. However, in contrast to negative information, the exchange of positive information, such as borrower quality and characteristics, may not produce a disciplinary effect, since a high-quality borrower is less concerned about the consequences of default as long as they can remain a high-quality borrower.

Brown and Zehnder (2007a) also study the impact of credit information sharing on the repayment behavior of borrowers. They find that in a market without repeated interaction between lenders and borrowers, the introduction of a credit registry significantly raises repayment rates and loan supply. Note also that another type of moral hazard problem arises when lenders do not know exactly about how much credit the borrower has already obtained. As noted by Jappelli and Pagano (2005), when lenders share information about outstanding loans, the incentive of borrowers to over-borrow from multiple lenders is significantly reduced, and as a result, the repayment probability may increase.

Third, information sharing affects the degree of competition in credit markets and may reduce the informational rents that banks can extract from borrowers. Padilla and Pagano (1997), using a two-period model with a hold-up problem, show that sharing of credit information reduces market power of lenders and leads to more competitive interest rates, which reinforces borrowers' incentives to repay and reduces probability of default. Gehrig and Stenbacka (2005) also considers a similar model, but with a borrower switching cost. They find that, in contrast to Padilla and Pagano (1997), information sharing actually reduces competition in the first period as future informational rents, and thus rewards to competition, are reduced with information sharing.

Note that the ultimate effect of credit information sharing on individual bank performance and profitability is less clear-cut. The improvement in screening ability may lead to reduced default rates and increases in loan amounts. In addition, the disciplinary effect would mitigate moral hazard incentives of borrowers and thereby increase loan repayment rates. Namely, reductions in adverse selection and moral hazard can reinforce bank profitability. However, increased competition and lower informational rents with a weakening information relationship may result in lower interest rates and decreased profits.

Consequently, the threat of increased competition and reduced profits may make banks hesitant to share their credit information with competitors. For instance, Brown and

Zehnder (2007b) examine how asymmetric information and competition in the credit market affect voluntary information sharing among lenders. They find that, while lenders lose market power by sharing information, the incentive for voluntary information exchange increases significantly with more asymmetric information. Bouckaert and Degryse (2006) also find that lenders voluntarily provide information about a portion of their profitable borrowers for strategic reasons in order to reduce competition and scale of entry. Jeong (2006) theoretically explores whether banks have an incentive to share credit information voluntarily in a duopoly model. He finds that two banks have an incentive to share negative information only even though it is socially desirable for two banks to share both positive and negative information.

Relative to the extant volume of theoretical research, there exists limited empirical work in this area. At the macroeconomic level, Jappelli and Pagano (2002) investigate cross-country evidence on the effects of credit information sharing and find that bank lending relative to GDP is higher and credit risk is lower in countries where lenders share credit information. On a similar vein, Love and Mylenko (2003) find that the existence of private credit registries is associated with lower financing constraints and a higher share of bank financing using firm-level data of 51 countries. At the microeconomic decision making level, using the U.S. dataset compiled by a large private information broker, Kallberg and Udell (2003) find that the exchange of private sector business credit information from multiple sources significantly improves predictive power in their failure prediction models.

In the present paper, we also investigate the economic effects of sharing credit information. Our analysis, however, is quite different from the empirical work described above. First of all, we distinguish positive credit information from negative information and investigate the value-added of sharing positive credit information in addition to negative information. Note that the value-added of positive information sharing has crucial implications on the pattern of formal credit information sharing mechanism since

only negative information such as loan default and arrears tends to be exchanged via public credit registries. Hence, our work sheds light on the policy issues such as whether public credit registries can effectively substitute private and voluntary information exchanges.

Korea provides a unique environment in addressing this question. Since the 1997 financial crisis, Korea has developed a dual credit information sharing system. The Korea Federation of Banks (KFB), a self regulatory body, serves as a sort of public credit registry. Participation in this arrangement is compulsory for all banks and imposed by regulation, and the KFB collects and shares mostly negative credit information. It is only recently that private credit bureaus began operating in Korea. In addition to negative information, positive credit information is exchanged via these private credit bureaus on a voluntary and reciprocal basis among participating banks. The positive information includes borrowers' overall loan exposure and guarantees, as well as borrower characteristics such as occupation and income. The membership in private credit bureaus is voluntary, and banks supply credit information to the database of credit bureaus in exchange for access to the information of other participating banks.

Second contribution of our paper is that we explicitly consider optimal credit decision behavior of banks in investigating the economic effects of sharing positive credit information in competitive consumer credit markets. The sharing of positive information in addition to negative information would affect a bank's ability in two attributes: to screen in productive borrowers and to screen out unproductive borrowers. In a competitive credit market environment, while banks are hesitant to share positive information due to concerns about increased competition, there may exist economic factors that lead to voluntary information exchange among banks.

Namely, when some banks begin sharing positive credit information, this may create incentives for other banks to voluntarily participate in this exchange mechanism. This phenomenon arises if the exchange of positive information among a few banks can create

informational advantage with respect to non-participating banks. More accurate screening and pricing on the part of information sharing banks may force low quality borrowers to seek loans from non-participating banks, and the endogenous deterioration of borrower pool due to adverse selection would reinforce incentives for other banks to participate in the information sharing group.

We assume that there are two groups of banks that differ only in the level of credit information sharing, but are otherwise identical. Banks in group 1 utilize only the negative information currently exchanged, while banks in group 2 share additional positive information among themselves. Using the model of Blöchlinger and Leippold (2006), we find that differing level of information sharing lead to economically significant variations in market share, borrower quality, and profit across these two groups. Group 1 with negative information only suffers from reduced profit, as high credit risk borrowers are more concentrated on this group.

The adverse selection problem and deterioration of the borrower pool become even more profound in the pricing regime where Group 1 banks charge insufficient risk premiums and offer relatively lower lending rates to high risk borrowers due to inferior information. The profit gap becomes wider the higher the loss given default, which implies that banks with informational disadvantage may suffer more severely in an economic downturn due to worsening adverse selection problems. Overall our finding indicates that banks have incentives to voluntarily participate in the positive information sharing mechanism even in the presence of a public credit registry, since even a small difference in discriminatory power stemming from the information gap may lead to a significant fall in profitability as the distribution of credit quality changes endogenously due to adverse selection problems.

This paper is organized as follows. Section 2 provides a theoretical framework for optimal credit decision models in bank lending. Section 3 describes data and estimation of underlying credit scoring models with differential information. Section 4 provides

main empirical results on the economic effects of positive credit information sharing. This section analyzes in some depth the relative performance of two bank groups with differing level of information sharing in a competitive credit market. Finally, Section 5 provides a summary and concluding remarks.

2. Optimal Credit Decision Models

Blöchlinger and Leippold (2006) study the economic benefits of using better quality credit scoring models by relating the discriminatory power of a credit scoring model to banks' optimal credit decisions. They find that, even for small quality differences of underlying credit scoring technologies, economic performance of banks may become large and economically significant. Their model framework can be applied to our study. The key difference in our model is that banks are using the same credit scoring technology, but based upon differential set of information. Below, we closely follow Blöchlinger and Leippold (2006) and analyze optimal credit decisions of banks in two alternative regimes: the cutoff regime and the pricing regime.

In the cutoff regime, banks are assumed to maximize profit by identifying and applying the profit maximizing threshold credit score. Banks grant loans for borrowers with credit scores above the cutoff level, and reject loans below the cutoff score. In order to identify the optimal cutoff score, we assume a simplified one period model with exogenously determined loss given default (LGD) and interest rate (R). Given the probability of default for each credit score, the net present value (NPV) per unit of credit for credit score t is written as:

$$NPV(t) = -1 + \left[P\{Y=1|S=t\}(1-LGD) + P\{Y=0|S=t\}(1+R+C) \right] / (1+\delta) \qquad (1)$$

Note that $P\{Y=1|S=t\}$ indicates the conditional probability of default given the credit score t. C indicates a strategic value that can be created by establishing a relationship with the borrower. δ is the risk adjusted discount rate.

We assume that banks do not invest in negative net present value (NPV) project, that is, banks reject all loan applicants that do not satisfy the following condition:

$$R \geq \frac{P\{Y=1|S=t\}}{P\{Y=0|S=t\}} LGD - C + \frac{\delta}{P\{Y=0|S=t\}} \tag{2}$$

From Equation 2, Blöchlinger and Leippold (2006) show that the profit maximizing optimal cutoff score t* satisfies the following condition of zero expected marginal profit:

$$P\{Y=0|S=t^*\}(R+C) = P\{Y=1|S=t^*\}LGD \tag{3}$$

In Equation 3, the left-hand side indicates the probability weighted marginal benefit of making a correct decision when loans are granted to a marginal borrower, namely, the conditional expected revenue when granting the loan to a good borrower. The right-hand side denotes the probability weighted marginal cost of making a mistake, namely, the conditional expected loss when granting the loan to a bad borrower. Hence, banks grant loans as long as their expected revenue is greater than expected loss and their credit score is above the cutoff score, but stop lending at the optimal cutoff score, at which the expected marginal profit becomes zero.

Alternatively, we can assume a pricing regime, in which banks set the minimum loan price for each credit score and accept all loan applicants as long as they are willing to pay this price. Hence, for all loan applicants with respective credit scores, different

minimum prices dependent upon their credit scores are charged. For instance, assuming a zero discount rate δ and required minimum spread k, the minimum interest rate for a borrower with credit score t can be derived from the Equation 2 above as follows:

$$R \geq \frac{P\{Y=1|S=t\}}{P\{Y=0|S=t\}} LGD - C + k \tag{4}$$

3. Data and Credit Scoring Models with Differential Information

3.1. Data and Estimation of Credit Scoring Models

Note that to analyze economic impacts of expanding the scope of information sharing among banks that behave according to the optimal credit decision rules above, we need underlying credit scoring models to compute the credit score and conditional probability of default for each obligor under alternative information assumption. In the following, we assume that the credit scoring model A utilizes the basic and negative information compulsorily shared via the KFB. This KFB information includes basic credit information, such as credit opening date and total amounts of loans and guarantees, and negative information, such as credit and payment guarantee delinquencies and long-term arrears. It also includes the number of credit inspection inquiries and 5 to 90 day short-term arrear information. Credit scoring model B utilizes broader information including both the basic and negative information utilized in model A, as well as positive information exchanged via private credit bureaus. Positive information of private credit bureaus includes various credit transaction information collected from both banking and credit card accounts, which covers total number and amounts of credit obtained, as well as utilization rates of bank and card loan commitments.

To build our credit scoring models with differential information, we selected a

random sample of 2 million consumer loan obligors who, as of December 2006, had at least a credit account in any Korean bank. Hence, the observation period is December 2006. The performance period is the one-year period covering January to December 2007. The default event was defined as delaying debt services more than 90 days during the performance period. Out of the 2 million random sample obligors, we excluded obligors with insufficient data and who had been already in arrears by more than 60 days. The final random sample master data included a total of 1,762,646 obligors. Among the final sample obligors, the number of "bad" obligors who turned out to have defaulted during the performance period was 48,501, which is 2.75% of the final sample obligors. Hence, the number of "good" borrowers in our sample is 1,714,145 (97.25%).

In order to build our credit scoring models, in addition to the 48,501 "bad" borrowers, we randomly selected additional 48,501 "good" obligors from the non-defaulter sample. Hence, the data of 97,002 obligors were utilized to select input variables in our credit scoring models. In using the 97,002 model building samples, the ratio of test data relative to validation data was set to 7:3. We estimated stepwise maximum likelihood logistic regressions to optimize credit scoring models under alternative information set. For model A with negative information only, we considered 198 candidate variables for 6 category profiles, and for model B with both negative and positive information, we considered 340 candidate variables for 10 category profiles. The input variables finally chosen for respective credit scoring models are summarized in Table 1. Note that many of the KFB basic information variables selected in model A such as duration of credit account and total amount of bank loans are no more selected in model B with additional positive information variables.

[Table 1]

3.2. Discriminatory Power of Credit Scoring Models

Using the credit scoring models developed above, we computed credit scores for each of 1,762,646 total master sample obligors. The estimation results for models A and B are summarized in Tables 2 and 3 respectively. The distributions of good and bad borrowers under model A and B in terms of credit scores are also shown in Figure 1.

[Table 2]

[Table 3]

[Figure 1]

In order to compare the discriminatory powers of model A and B, we use two statistical measures – the Kolmogorov-Smirnov (K-S) statistic and the Area Under Receiver Operating Characteristic Curve (AUROC). The Kolmogorov-Smirnov statistic is a widely used nonparametric method for comparing two samples and measured as the supremum of the differences in the empirical cumulative distribution functions. Note that good credit scoring models would have a higher value for the K-S statistic as computed as the vertical distance between bad cumulative and good cumulative distribution functions. Namely, as the credit score rises, the cumulative distribution function for defaulters must increase faster than the cumulative distribution function for non-defaulters. Note that the K-S statistic is 58.2% in model B while it is 55.4% in model A, which indicates that model B that utilizes both negative and positive information has a superior discriminatory power. The K-S statistics are shown in Figure 2.

Another measure of discriminatory power of credit scoring models is AUROC. Note that any credit scoring model can make two mistakes, namely, the type-one error (α-error) and the type-two error (β-error). The type-one error is the error of assigning a high credit score to bad obligors, and the type-two error is the error of assigning a low credit

score to good obligors. The Receiver Operating Characteristic (ROC) curve is constructed using the α-errors and the β-errors for every possible cutoff score. More specifically, we can obtain the ROC curve by plotting the hit rate (one minus the α-error) on the y-axis and the β-error on the x-axis as cutoff score increases. Note that the ROC curve of a powerful scoring model is relatively steep at the left and flat near the upper left corner that represents a perfect model. Note also that the ROC curve for a random forecast model is a diagonal line. Hence, the discriminatory power of a scoring model can be measured by the area under the ROC curve (AUROC), and the larger the AUROC, the better the underlying scoring model.

Figure 3 shows the ROC curves of our credit scoring models. Note that the ROC curve for model B is located closer to the upper left corner. The AUROC for model B is 0.869 while the AUROC for model A is 0.841, which indicates that model B is a superior credit scoring model. Both the K-S and AUROC analyses in this section indicate that utilizing positive information in addition to negative information significantly improves discriminatory power of the underlying credit scoring model. The difference in discriminatory power may in turn cause a large variation in economic performance across banks that utilize different set of information.

[Figure 2]

[Figure 3]

4. Economic Effects of Positive Information Sharing

This section analyzes the economic effects of sharing positive information in addition to negative information by letting two different groups of banks that use heterogeneous information compete in consumer credit markets. There are two groups of banks that differ only in the level of credit information and are otherwise identical. Banks in Group 1

utilize only negative information currently exchanged, while banks in Group 2 share positive information in addition to negative information. Since banks are assumed to be identical except for the scope of credit information utilized, we can assume that two representative banks – Bank 1 and Bank 2 are competing in the credit market. In analyzing the economic outcome of bank competition, we explicitly consider the optimal credit decision rules described in Section 2 assuming two alternative regimes; the cutoff regime and pricing regime.

4.1. Cutoff Regime

We first analyze the cutoff regime in which banks apply their own optimal cutoff credit scores to maximize expected profits, given the credit information of individual obligors. Bank 1 with negative information only and Bank 2 with both negative and positive information use their own credit scoring models developed in Section 2, and compute their respective optimal cutoff scores given exogenously determined loss given default (LGD) and interest rate (R). To simplify analysis, we also assume that banks do not discriminate against obligors in terms of prices, and hence, an identical interest rate is applied to all borrowers under the cutoff regime.

For various combinations of LGD and R, and assuming $C=\delta=0$, we apply Equation 3 to find optimal cutoff scores for Bank 1 and Bank 2. The results are summarized in Table 4, which shows several interesting observations. First, if the LGD remains the same, the optimal cutoff score and the loan rejection rate tend to fall as the loan interest rate rises. This phenomenon is more profound for Bank 1. Second, if the interest rate remains the same, the optimal cutoff score and the loan rejection rate tend to increase as the LGD rises. Third, Bank 2 with both negative and positive information tends to show higher cutoff scores and rejection rates than Bank 1 when LGDs are either relatively high or low. Namely, if LGD is relatively high (e.g. LGD = 60%), Bank 2 with superior information tends to apply a more conservative cutoff score to minimize its expected loss. However,

when LGD is relatively low (e.g. LGD = 30%), Bank 1 with inferior information tends to expand its customer base more aggressively as their optimal cutoff scores are relatively low.

Finally, for a more normal and reasonable LGD level (e.g. LGD = 45%), Bank 2, with superior information, tends to approve more loans, which indicates that the sharing of positive information in addition to negative information may result in the expansion of credits for marginal borrowers in normal economic situation. However, this increased loan supply under the regime of wider information sharing is not observed for lower and higher LGDs.

[Table 4]

Given the profit maximizing optimal cutoff scores, we proceed to analyze the outcome of bank competition in a hypothetical consumer credit market. We assume that each loan applicant obtains one unit of credit from a bank if the loan is approved, and both banks charge an identical interest rate for all obligors regardless of their credit risks. Under these simplifying assumptions, we conduct the following simulation exercise utilizing the master sample data of 1,762,646 consumer borrowers in Korea. First, each loan applicant is randomly assigned to a bank, and the bank computes the credit score of the assigned applicant using its own credit scoring model. If the credit score is above the optimal cutoff score of the bank, then a loan is granted to the applicant. If the loan is rejected, then the applicant is assigned to the other bank. The second bank computes the applicant's credit score and compares it with its own optimal cutoff. If accepted, the second bank grants a loan. If rejected again from the second bank, then the applicant drops out of the borrower pool. By repeating this exercise for all 1,762,646 obligors, we obtain the borrower pool, market share, revenue, loss and profit of respective banks.

The simulation results under three alternative scenarios of LGD and R are summarized in Table 5. Note that, first, the percentage of bad obligors out of approved customers is lower for Bank 2 that utilizes both negative and positive information, which confirms the superior discriminatory power of credit scoring Model B above. The ratio falls to 1.19% when LGD and R are high in Scenario 3. Second, while the market share of Bank 1 that uses negative information only tends to remain stable as LGD and R rise, the market share of Bank 2, with both negative and positive information, decreases significantly. Note that this reduction in the market share of Bank 2 is mainly from its reduction in bad borrowers as LGD and R rise. For instance, the market share of Bank 2 in bad borrowers falls to 19.5% in Scenario 3. Third, consequently, the profit gap between Bank 1 and Bank 2 becomes wider as LGD and R rise. Note that the increasing profit gap results from the fast increasing loss of bank 1 that uses inferior credit information. Namely, as LGD rises, high risk borrowers are increasingly more rejected from Bank 2, and some of those bad borrowers now obtain loans from Bank 1. While Bank 1 also receives more good borrowers, this is not sufficient to compensate for the increased loss from having more bad borrowers.

Note that the difference in the discriminatory power that results from the informational gap leads to non-trivial variations in economic performance across banks, as the borrower quality is endogenously determined by the competition in credit markets. Note also that we assume a uniform loan demand and identical interest rates across all borrowers. The variations in economic performance could be magnified if we consider sufficient heterogeneity in loan demand and risk premium across borrowers with differing credit risks. We consider the case of heterogeneous risk premiums in the next section.

[Table 5]

4.2. Pricing Regime

Next, we analyze the pricing regime in which banks charge risk premiums commensurate with respective credit risks of obligors. We assume a competitive credit market in which the equality in Equation 4 above is binding. In actual simulations, we also assume that the strategic value of relationship banking (C) is zero and the minimum required spread (k) is 75 basis points (0.75%).[1] In principle, unlike the cutoff regime, no loan applicants are being rejected in the pricing regime as long as they are willing to pay the interest rate charged by the lender. However, to avoid unrealistically high interest rates, we introduce an interest rate cap of 49%, which is the maximum possible interest rate that can be charged under the current regulation in Korea.

To simulate the economic effects of bank competition, we first compute minimum interest rates of Bank 1 and Bank 2 for each of the 1,762,646 obligors using their respective bank's own credit scoring model. Then, each obligor is assigned to a bank that offers a lower interest rate. If the same interest rates are offered from the two banks, then a bank is randomly assigned to the obligor. In this process, if the interest rates charged from both banks are above the interest rate cap (49%), then the obligor drops out of the borrower pool. The borrower pool, market share, revenue, loss and profit of respective banks computed under the pricing regime are summarized in Table 6.

[Table 6]

Note that, compared to the cutoff regime, the difference in the scope of information utilized in credit scoring now leads to much more profound variations in economic performance across the two bank groups. First, relative to Bank 1, the market share of Bank 2, which uses both negative and positive information, is much higher in

[1] Note that changes in the values of *C* and *K* only cause a parallel shift in the interest rate. Hence, the qualitative results of our simulation analyses are not sensitive to these values.

good borrowers, and significantly lower in bad borrowers under all three LGD scenarios. This result is driven by the fact that the informational advantage of Bank 2 enables it to offer more attractive prices for good borrowers and higher prices for bad borrowers. Note that this adverse selection problem is more profound in the pricing regime since, in the cutoff regime, high credit risk borrowers whose credit scores are above the optimal cutoff score cannot obtain loans at all. The adverse selection problems and endogenous determination of borrower qualities in turn cause a large profit gap between those two bank groups.

Second, as LGD rises, the profit gap becomes even wider, and Bank 1 with negative information only suffers a great deal from the large loss under high LGDs. Hence, our result implies that banks with informational disadvantage may suffer more in an economic downturn due to worsening adverse selection problems. Our results also indicate that banks have a strong incentive to voluntarily share positive information and participate in the information sharing scheme in order to avoid deterioration in borrower quality and negative economic consequences that they would suffer, should they not participate.

5. Summary and Concluding Remarks

With the outbreak of the 1997 financial crisis, the credit information sharing system has received wide attention as an important financial infrastructure in Korea. While negative credit information is collected and shared via a regulatory agency on a centralized and compulsory basis, it is only a recent development that positive credit information began being exchanged via private credit bureaus on a voluntary and reciprocal basis. Convincing others of the success of the voluntary information sharing scheme is still difficult and at a premature stage, as the threat of increased competition and reduced profit make banks hesitant to share their positive credit information with potential competitors.

Employing optimal credit decision models of profit maximizing banks, and utilizing a unique dataset of 2 million consumer loan obligors in Korea, this paper investigated the economic effects of sharing positive credit information in addition to negative credit information currently exchanged. We found several interesting empirical results. First, the discriminatory power of credit scoring models improves significantly when banks utilize additional positive credit information.

Second, when banks compete in consumer credit markets, differing level of credit information sharing leads to economically significant variations in market share, borrower quality, and profit across banks. Banks with negative information only suffer from reduced profit as high credit risk borrowers are more concentrated on this group. The adverse selection problem and the endogenous deterioration of the borrower pool become even more profound in the pricing regime in which banks with inferior information charge insufficient risk premiums and offer relatively lower lending rates to high risk borrowers due to the information gap.

Third, the higher the loss given default, the wider the profit gap becomes; this implies that banks with informational disadvantage may suffer more severely in an economic downturn due to worsening adverse selection problems. Overall our finding suggests that banks have strong incentives to voluntarily participate in the positive information sharing mechanism even in the presence of a public credit registry, since even a small difference in discriminatory power stemming from the information gap may lead to a significant fall in profitability as the distribution of borrower quality changes endogenously due to adverse selection problems.

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Table 1. Input Variables Selected for Credit Scoring Models

No	Input Variable	Model A	Model B
1	Duration since the first opening of a credit account	O	X
2	Duration since the most recent opening of a credit account	O	X
3	Total amount of bank loans	O	X
4	No. of banks borrowed from (recent two years, less than 10 mil KRW)	O	X
5	No. of non-banks borrowed from	O	O
6	No. of credit guarantees	O	O
7	No. of arrears and delinquencies	O	X
8	Duration since the most recent arrear	X	O
9	No. of days in the longest arrear	O	X
10	Highest mount in current arrears	O	X
11	No. of days in the longest arrear within recent two years	X	O
12	No. of current loan arrears	X	O
13	No. of credit inquiries	O	O
14	No. of loans	_	O
15	No. of days since credit card opening	_	O
16	Utilization rate in bank loan commitment	_	O
17	Amount of the largest loan	_	O
18	Utilization rate in card loan commitment (recent 12 months)	–	O
19	Utilization rate in credit card cash advance (recent 6 months)	–	O
Total number of variables selected		10	12

Table 2. Estimation of Credit Scoring Model A
(Negative Information Only)

SCORE	Interval						Cumulative			K-S	AUROC
	Total	Bad	Good	Total	Bad	Good	Total	Bad	Good		
250	196	160	36	0.0%	0.3%	0.0%	0.0%	0.3%	0.0%	0.3%	
300	812	601	211	0.0%	1.2%	0.0%	0.1%	1.6%	0.0%	1.6%	0.0%
350	2,646	1,594	1,052	0.2%	3.3%	0.1%	0.2%	4.9%	0.1%	4.8%	0.0%
400	5,634	2,350	3,284	0.3%	4.8%	0.2%	0.5%	9.7%	0.3%	9.4%	0.0%
450	11,719	3,945	7,774	0.7%	8.1%	0.5%	1.2%	17.8%	0.7%	17.1%	0.1%
500	17,500	5,452	12,048	1.0%	11.2%	0.7%	2.2%	29.1%	1.4%	27.7%	0.2%
550	34,567	5,992	28,575	2.0%	12.4%	1.7%	4.1%	41.4%	3.1%	38.3%	0.6%
600	81,093	7,853	73,240	4.6%	16.2%	4.3%	8.0%	57.6%	7.4%	50.3%	2.1%
650	109,791	5,450	104,341	6.2%	11.2%	6.1%	15.0%	68.9%	13.5%	55.4%	3.8%
700	215,648	4,915	210,733	12.2%	10.1%	12.3%	27.2%	79.0%	25.7%	53.2%	9.1%
750	677,805	7,526	670,279	38.5%	15.5%	39.1%	65.7%	94.5%	64.8%	29.7%	33.9%
800	464,639	2,314	462,325	26.4%	4.8%	27.0%	92.0%	99.3%	91.8%	7.5%	26.1%
850	135,735	341	135,394	7.7%	0.7%	7.9%	99.7%	100.0%	99.7%	0.3%	7.9%
900	4,861	8	4,853	0.3%	0.0%	0.3%	100.0%	100.0%	100.0%	0.0%	0.3%
Total	1,762,646	48,501	1,714,145	100.0%	100.0%	100.0%				55.4%	84.1%

Notes: K-S denotes the Kolmogorov-Smirnov Statistic. AUROC is the area under receiver operating characteristic (ROC) curve, which plots the hit rate (one minus the α-error) on the y-axis and the β-error on the x-axis as cutoff score increases.

Table 3. Estimation of Credit Scoring Model B
(Both Negative and Positive Information)

SCORE	Interval						Cumulative			K-S	AUROC
	Total	Bad	Good	Total	Bad	Good	Total	Bad	Good		
200	3	3	0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
250	63	54	9	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%
300	478	366	112	0.0%	0.8%	0.0%	0.0%	0.9%	0.0%	0.9%	0.0%
350	2,005	1,341	664	0.1%	2.8%	0.0%	0.1%	3.6%	0.0%	3.6%	0.0%
400	5,492	2,697	2,795	0.3%	5.6%	0.2%	0.5%	9.2%	0.2%	9.0%	0.0%
450	12,062	4,476	7,586	0.7%	9.2%	0.4%	1.1%	18.4%	0.7%	17.8%	0.1%
500	21,074	5,849	15,225	1.2%	12.1%	0.9%	2.3%	30.5%	1.5%	28.9%	0.2%
550	39,792	6,444	33,348	2.3%	13.3%	1.9%	4.6%	43.8%	3.5%	40.3%	0.7%
600	72,599	7,101	65,498	4.1%	14.6%	3.8%	8.7%	58.4%	7.3%	51.1%	2.0%
650	118,231	6,592	111,639	6.7%	13.6%	6.5%	15.4%	72.0%	13.8%	58.2%	4.2%
700	229,105	6,073	223,032	13.0%	12.5%	13.0%	28.4%	84.5%	26.8%	57.7%	10.2%
750	450,701	4,950	445,751	25.6%	10.2%	26.0%	54.0%	94.7%	52.8%	41.9%	23.3%
800	356,294	1,739	354,555	20.2%	3.6%	20.7%	74.2%	98.3%	73.5%	24.8%	20.0%
850	374,930	731	374,199	21.3%	1.5%	21.8%	95.5%	99.8%	95.3%	4.5%	21.6%
900	73,907	80	73,827	4.2%	0.2%	4.3%	99.7%	100.0%	99.7%	0.3%	4.3%
950	5,910	5	5,905	0.3%	0.0%	0.3%	100.0%	100.0%	100.0%	0.0%	0.3%
Total	1,762,646	48,501	1,714,145	100.0%	100.0%	100.0%				58.2%	86.9%

Notes: K-S denotes the Kolmogorov-Smirnov Statistic. AUROC is the area under receiver operating characteristic (ROC) curve, which plots the hit rate (one minus the α-error) on the y-axis and the β-error on the x-axis as cutoff score increases.

Table 4. Optimal Cutoff Scores and Loan Rejection Rates

LGD (%)	R (%)	Bank 1 (Model A)		Bank 2 (Model B)	
		Cutoff Score	Rejection Rate (%)	Cutoff Score	Rejection Rate (%)
30	2.75	650	16.2	650	16.4
30	3.00	640	13.7	650	16.4
30	3.25	610	7.1	650	16.4
45	2.75	660	18.7	650	16.4
45	3.00	660	18.7	650	16.4
45	3.25	660	18.7	650	16.4
60	2.75	670	21.2	680	24.0
60	3.00	660	18.7	670	21.0
60	3.25	660	18.7	670	21.0

Table 5. Economic Effects of Bank Competition under Cutoff Regime

[Scenario 1] LGD = 30%, R = 2.75%

Assign	Good		Bad		Total		% of Bad out of Approved
	No	(%)	No	(%)	No	(%)	
Bank 1	816,082	(47.6)	12,288	(25.3)	828,370	(47.0)	1.51%
Bank 2	818,231	(47.7)	11,944	(24.6)	830,175	(47.1)	1.46%
All Rejected	79,832	(4.7)	24,269	(50.0)	104,101	(5.9)	
Total	1,714,145	(100.0)	48,501	(100.0)	1,762,646	(100.0)	

	Market Share	Revenue	Loss	Profit
Bank 1	47.0%	22,442	3,686	18,756
Bank 2	47.1%	22,501	3,583	18,918
All Rejected	5.9%	-	-	-

[Scenario 2] LGD = 45%, R = 3.0%

Assign	Good		Bad		Total		% of Bad out of Approved
	No	(%)	No	(%)	No	(%)	
Bank 1	807,216	(47.1)	11,719	(24.2)	818,935	(46.5)	1.45%
Bank 2	822,138	(48.0)	11,956	(24.7)	834,094	(47.3)	1.45%
All Rejected	84,791	(4.9)	24,826	(51.2)	109,617	(6.2)	
Total	1,714,145	(100.0)	48,501	(100.0)	1,762,646	(100.0)	

Assign	Market Share	Revenue	Loss	Profit
Bank 1	46.5%	24,216	5,274	18,943
Bank 2	47.3%	24,664	5,380	19,284
All Rejected	6.2%	-	-	-

[Scenario 3] LGD = 60%, R = 3.25%

Assign	Good		Bad		Total		% of Bad out of Approved
	No	(%)	No	(%)	No	(%)	
Bank 1	819,122	(47.8)	12,347	(25.5)	831,469	(47.2)	1.51%
Bank 2	792,993	(46.3)	9,450	(19.5)	802,443	(45.5)	1.19%
All Rejected	102,030	(6.0)	26,704	(55.1)	128,734	(7.3)	
Total	1,714,145	(100.0)	48,501	(100.0)	1,762,646	(100.0)	

Assign	Market Share	Revenue	Loss	Profit
Bank 1	47.2%	26,621	7,408	19,213
Bank 2	45.5%	25,772	5,670	20,102
All Rejected	7.3%	-	-	-

Table 6. Economic Effects of Bank Competition under Pricing Regime

[Scenario 1] LGD = 30%, R Cap = 49%

Assign	Good		Bad		Total	
	No	(%)	No	(%)	No	(%)
Bank 1	603,918	(35.2)	26,822	(55.3)	630,740	(35.8)
Bank 2	1,110,041	(64.8)	20,806	(42.9)	1,130,847	(64.2)
All Rejected	186	(0.0)	873	(1.8)	1,059	(0.0)
Total	1,714,145	(100.0)	48,501	(100.0)	1,762,646	(100.0)

Assign	Revenue	Loss	Profit
Bank 1	9,707	8,047	1,660
Bank 2	13,195	6,242	6,953

[Scenario 2] LGD = 45%, R Cap = 49%

Assign	Good		Bad		Total	
	No	(%)	No	(%)	No	(%)
Bank 1	603,694	(35.2)	26,337	(54.3)	630,031	(35.7)
Bank 2	1,109,816	(64.8)	20,419	(42.1)	1,130,235	(64.1)
All Rejected	635	(0.0)	1,745	(3.6)	2,380	(0.1)
Total	1,714,145	(100.0)	48,501	(100.0)	1,762,646	(100.0)

Assign	Revenue	Loss	Profit
Bank 1	12,151	11,852	299
Bank 2	15,514	9,189	6,326

[Scenario 3] LGD = 60%, R Cap = 49%

Assign	Good		Bad		Total	
	No	(%)	No	(%)	No	(%)
Bank 1	603,387	(35.2)	25,954	(53.5)	629,341	(35.7)
Bank 2	1,109,413	(64.7)	19,900	(41.0)	1,129,313	(64.1)
All Rejected	1,345	(0.1)	2,647	(5.5)	3,992	(0.2)
Total	1,714,145	(100.0)	48,501	(100.0)	1,762,646	(100.0)

Assign	Revenue	Loss	Profit
Bank 1	14,525	15,572	-1,047
Bank 2	17,683	11,940	5,743

Figure 1. Distributions of Good and Bad Borrowers

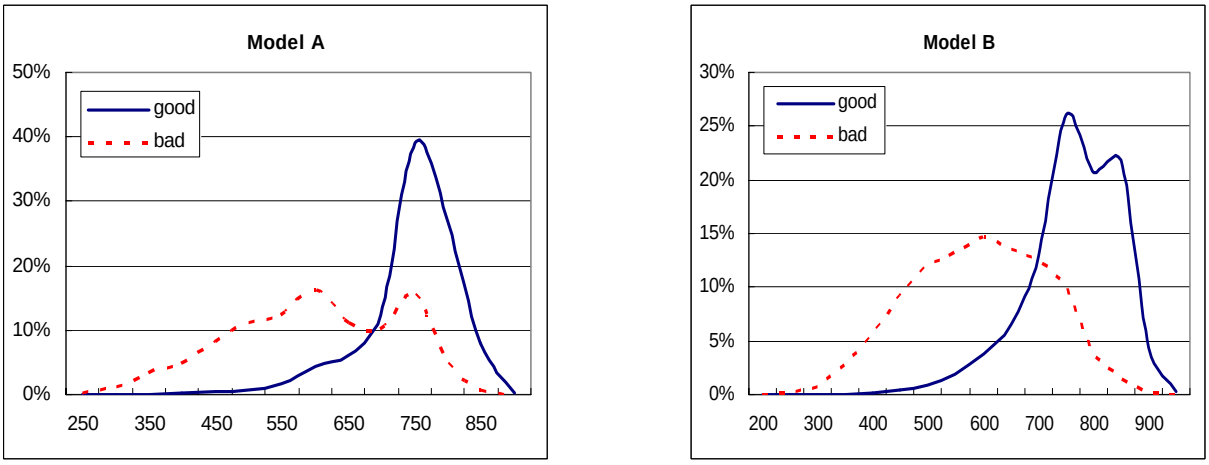

Figure 2. Kolmogorov-Smirnov Statistics

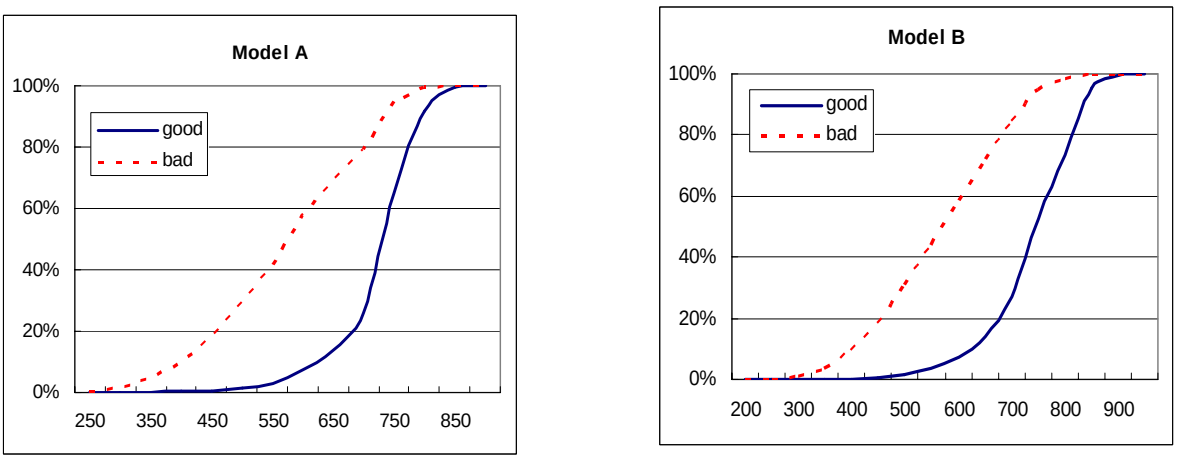

Figure 3. ROC curves