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MEASURING RISK ON CONSUMER INSTALMENT CREDIT*†

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The advantages of statistical measures for grading credit risks in lending to consumers have been widely recognized but relatively little use has been made of such systems. The paper develops a relatively simple statistical method for measuring risk on individual accounts that can also be used for measuring and controlling portfolio quality and for estimating loss rates. The procedure entails four steps:

1. Comparison of good and bad accounts in the search for characteristics that are associated with bad accounts;
2. Calculation of bad account probabilities for discriminating characteristics;
3. Development of a risk index from bad account probabilities to be used in grading accounts;
4. Evaluation of the risk index.

A test of the method on the accounts of a commercial bank is described and the judgements implied by the risk index are compared to the criteria used by interviewers in rejecting applicants. A great many similarities are found between the results of the two methods but a number of striking dissimilarities are observed.

The last section of the paper illustrates the ways in which the risk index can be used to adjust credit quality to the desired volume and loss experience. It also demonstrates its use in measuring portfolio quality and in estimating loss rates.

Consumer credit institutions lend billions of dollars each year, much of it to people they have never seen before. Yet their losses often seem surprisingly low. It is not clear whether this favorable experience reflects the efficiency of their screening systems or the honesty and dependability of the public. Even assuming that the industry's success is largely due to the honesty of the public, the success of an individual credit operation depends upon the ability of its staff to detect and reject bad credit risks.

Over the years, a system of appraising consumer credit risks has grown up that is often described in picturesque but vague terms as the four C's of credit. The C refers to a number of concepts that begin with the letter C, such as character, capacity, collateral, capital and at times others. These abstract concepts, however, do not provide very specific guidance. More useful guidelines have been developed that relate risk to personal traits, such as age, sex, maturity, income, ownership of home, etc. But even these are inexact and difficult to apply.

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The lack of precise methods for measuring credit risk creates a number of problems for the industry: 1) Experienced personnel are hard to find and the absence of specific methods makes it difficult to train new personnel; 2) The costs of reviewing applications are high; 3) Credit decisions are often far removed from collection problems, whereas the corrective feedback from collections is essential to the development of judgment skills in the people approving loans; and, 4) Decisions to tighten or ease credit standards are risky and are difficult to translate into changes in screening practices.

Although statistical systems offer great promise to the consumer credit industry, they have not been very widely adopted. Perhaps the major deterrent is their complexity. Managers are understandably reluctant to adopt systems that they don't completely understand. Simplicity, therefore, appears to be a necessary condition for the widespread adoption of quantitative methods in the industry. The following discussion introduces a number of modifications in the usual techniques applied to this problem in an effort to develop a system that can be used and understood by people who are familiar with the problems of detecting bad accounts but who are not familiar with statistical methods.

Theoretical Approach

Numerous attempts have been made to quantify risks on individual applications and a number of successful systems are now in operation.[1] The usual approach compares samples of good and bad accounts in a search for variations in traits that can be used as a guide in detecting bad accounts [1, 2, 4, 6, 7]. Discriminatory analysis provides the most systematic approach and has apparently been adopted and modified to handle the wide variety of classifications that have been introduced into the problem. Published descriptions of the methods, however, are incomplete.

The proposed method focuses on the problem of estimating the probability that an account with certain traits will go bad. As will be indicated, statistical and logical problems make the direct estimation of the probabilities for any given account impractical. A risk index can be developed, however, to provide a simple and flexible device for grading accounts and converting the grades into estimates of the probability that an account will go bad. One of the advantages of this approach lies in the statement of the problem in terms of probabilities that are familiar to the credit industry as loss ratios.

The proposed method involves four steps:

1) Comparison of good and bad accounts in the search for characteristics that are associated with bad accounts.
2) Calculation of bad account probabilities.
3) Development of a risk index from bad account probabilities that can be used to compare and grade accounts.
4) Calculation of the bad account probabilities associated with risk index values and the evaluation of the risk index.

[1] Spiegels, Inc. and the American Investment Co. of Ill. have pioneered in the development of credit pointing plans and are currently using statistical systems.

1. *Search for discriminating characteristics*

The search for significant characteristics associated with risk is limited by available information and is complicated by the large number of traits and combinations of traits that might be relevant. Earlier studies of risk and practical credit experience serve as a guide in the search. Loan applications have been designed to collection information that is believed to be related to risk and this information provides a starting point in the search.

The procedure used at this stage is similar to that used by David Durand in one of the early studies of risk in consumer lending [1, pp. 22–28]. Comparisons of the distributions of good and bad accounts by characteristics readily reveal important differences. For example, in one case it was found that 46 per cent of the bad accounts, but only 7 per cent of the good accounts, did not have telephones. Such differences can be tested by the Chi square test for significance and ranked in terms of their discriminating ability.

2. *Calculation of bad account probabilities*

The bad account probabilities associated with each borrower trait can be computed from sample data or from the distribution of traits used in testing for discriminatory significance.

The distributions used in the tests for significant differences can be converted into conditional probabilities for the good and bad account classifications by dividing the number of good accounts with each trait by the total number of good accounts and by repeating the same procedure for bad accounts. These conditional probabilities can be used to obtain posterior probabilities by Bayes' theorem by applying the prior probabilities for good and bad accounts obtained from the company's experience. Where B equals the number of bad accounts, G equals the number of good accounts, and A is some discriminatory characteristic with i classifications, the posterior probabilities of a bad account with traits A_i can be obtained by Bayes' theorem as follows:

$$\begin{aligned} P(B \mid A_i) &= P(B)P(A_i \mid B)/[P(B)P(A_i \mid B) + P(G)P(A_i \mid G)] \\ &= P(B, A_i)/P(A_i) \end{aligned} \tag{1}$$

Table 1 illustrates the calculation of these probabilities for the ownership status of the borrower's residence.

The bad account (or posterior) probabilities can also be computed from the sample data by multiplying the sample results by the sample fractions to obtain universe estimates. The bad account probabilities are then obtained by dividing the number of bad accounts with a given trait (A_i) by the total number of accounts with that trait. The probabilities used in the illustration later in the paper were computed from sample data by this method. Some of the computations are shown in Table 2.

3. *Development of a risk index*

As the objective is to obtain an estimate of the probability that any given account will go bad, the probabilities for each characteristic of an account have to be combined into an overall estimate for that account. Theoretically, it would

TABLE 1

Calculation of Posterior Probabilities for Residence Status

Residence Status (A)	Condition prob.		Joint prob.[1]		Marginal prob. $P(A_i)$ Col 3 + Col 4	Posterior prob. P — bad[2] $(B \mid A_i)$ Col 4 ÷ Col 5
	Good (G) $P(A_i \mid G)$ (1)	Bad (B) $P(A_i \mid B)$ (2)	Good $P(G, A_i)$ (3)	Bad $P(B, A_i)$ (4)	(5)	(6)
1. Owns home	.779	.471	.7700	.0054	.7754	.0070
2. Rents-house	.029	.058	.0287	.0007	.0294	.0238
3. Rents-apt.	.094	.277	.0929	.0032	.0961	.0333
4. Rents-room	.013	.088	.0129	.0010	.0139	.0719
5. Lives with someone	.085	.106	.0840	.0012	.0852	.0141
	1.000	1.000	.9885	.0115	1.0000	.0115

[1] Obtained by multiplying the prior probabilities $P(G)$ and $P(B)$ by data in columns 1 and 2 respectively. The prior probabilities are obtained from company records on bad debt experience. In this sample they were: $P(G) = .9885$ and $P(B) = .0115$.

[2] These probabilities differ slightly from those in Table 2 because of difference in rounding involved in the two methods of calculation.

seem best to compute posterior probabilities for all combinations of traits by methods outlined in the preceding section. Two practical difficulties arise, however. First, the calculation of reliable probabilities for the combinations of traits requires larger bad account samples than can be obtained from most credit operations. Second, the grading of individual accounts would be complicated and time consuming and would require elaborate tables of probabilities for all possible combinations of traits. Although these objections might not be critical for a large nation-wide operation if a small number of variables were used and the grading could be done by computer, the limitations of local sample size would make local applications impractical.

The probabilities for separate traits cannot be combined by logical rules because no justifiable assumptions can be made about the interrelationship of various traits. They are clearly not statistically independent. Their effects may be confounded in some cases and additive in others. As a result an intermediate step is proposed that involves the ranking of accounts. If any two accounts have traits that are identical in all but one respect, it seems likely that the account with the highest bad loss probability on that one differing trait will be somewhat riskier than the other. By extension of this argument, it seems plausible that the sum of the probabilities of individual traits for each account would serve as a basis for ranking the accounts according to risk. The resulting sum (multiplied by 1,000) will be used as a risk index which can be expressed as follows:

$$R = (pa_i + pb_i + pc_i + \cdots + pn_i)1{,}000 \tag{2}$$

Here p is the posterior probability for each trait and the small letters indicate different traits with i classifications.

Several tests of the index, one of which is present in a subsequent section, seem to justify its use. The bad account probabilities for successive index values computed from sample data increase nearly monotonically.

If the index can be shown to be effective, it has many advantages that recommend its use. It is relatively easy to construct and can be used to incorporate a wide variety of traits. Any classification that is mutually exclusive and exhaustive can be used. It can be applied to non-ordinal classifications such as postal zones or neighborhoods or to any mixture of classifications. It also provides a very simple method for grading individual accounts. A table of posterior probabilities (multiplied by 1,000) for significant traits can be used to assign values to each trait and the index value for the account can be obtained by simple addition.

4. *Evaluation of risk index*

The effectiveness of the risk index in discriminating between good and bad accounts can be measured by comparing the distribution of all accounts and bad accounts by risk index values and by computing the bad account probabilities for each range of index values (see Table 4).

If the index is used for rejecting applicants, it is important that the proportion of potentially good accounts in relation to bad accounts is as small as possible in the higher ranges of the index. One simple measure is given by the proportion of bad accounts falling into index groups with bad account probabilities above some cut-off point. For purposes of comparing index values an arbitrary cut-off point of groups with a loss probability greater than .25 will be used in this study. This implies that if all accounts in that category were rejected, no more than three good accounts would be lost for every bad account lost. This measure will be referred to as an efficiency ratio (E) which has a maximum value of unity and can be expressed as follows:

$$E = [\text{Number of bad accounts in index groups with } P > .25] / [\text{Total number of bad accounts}] \tag{3}$$

Illustration of the Risk Index Method

Information from a moderately large commercial bank was used to illustrate the development of a sample risk index. No attempt was made to improve the efficiency of the index obtained from the a priori selection of traits. Considerable improvement should be possible but the results of this test suggest that a reasonably effective index can be prepared from known risk relationships. The calculations were limited to direct personal loans including those on automobiles. The information on the personal traits of the borrower and the characteristics of the loan was obtained from loan applications. The study covered loans accepted during a five and a half year period beginning in mid-1952 and extending to the end of 1958 and it included all bad accounts and a sample of one and a half per cent of the 106,000 good loans accepted during the period. The term "bad account" refers to all accounts sent to the collection department. It covers many loans that were ultimately collected, but it excludes loans that were delinquent at one time or another for short periods. In addition information was obtained from a small sample of rejected applications for comparative purposes.

All of the information that was available on the loan applications and could be converted into mutually exclusive and exhaustive classifications was used in the search for differences between good and bad accounts. When the loan was made to both the husband and wife, combined traits were used when relevant, such as combined income; otherwise the loan was classified by the traits of the husband. In addition, a number of ratios, such as the ratios of monthly payments to monthly income, were calculated. Twenty classifications were tested in the initial tabulations:

1. Purpose of loan
2. Number in family
3. Time in last residence
4. Time in residence (Average of last two residences)
5. Occupation
6. Ownership or rental of residence
7. Time on last job
8. Time on last two jobs
9. Monthly income including income of spouse
10. Age
11. Sex and marital status
12. Bank account
13. Monthly payments (including payments on the loan, other instalment payments, and mortgage or rental payments).
14. Monthly payments as a percentage of monthly income.
15. Monthly payments as percentage of monthly income per member of family.
16. Interviewer's appraisal (a numerical scale of three values)
17. Down payment
18. Residential area (postal zone or suburban area)
19. Employment status of wife
20. Telephone

The distributions of good and bad accounts for these classifications were compared. Variations between the distributions of good and bad accounts were tested by the Chi-square test for significance. The P value was less than .01 in sixteen of the classifications. Only one classification had a high P value (about .50) and that was #16, the interviewer's appraisal.

The traits were then ranked according to their ability to discriminate between good and bad accounts as indicated by an adjusted Chi-square value.[2] Since there were two indexes for both time in residence and time on the job, only the higher ranking one was used. In both cases, the time on last job and time in last residence proved to be a more significant test than the average of the time in the last two jobs or residences.

Thirteen classifications were used in the preparation of the risk index. The

[2] The ratio of the calculated Chi-square value to the Chi-square value associated with a P value of .01 for the appropriate degrees of freedom was used as an index in ranking traits.

classifications used are listed in order in Table 2. In addition, two separate indexes were prepared for the five highest ranking classifications and the ten highest ranking classifications to see if a smaller number of highly discriminating traits would be as effective as the larger number of traits. As these two indexes proved to be less effective than the one using all 13 classifications, they are not presented in this paper.

Surprisingly, traits designed to measure the financial ability of the borrower to carry monthly payments were the least effective in discriminating between good and bad accounts. As a result none of the classifications involving size of the monthly payments or ratios of monthly payments to income were included. The reasons for the relatively poor performance of these measures are not clear.

Bad account probabilities were calculated for each subdivision of each trait (column 3, Table 2), multiplied by 1,000 and used to calculate the risk index values for each account by formula (2). The maximum possible index value for the sample was 517.5 and the minimum was 79.1. The largest actual index value was 431 and the smallest was 110.

If, as originally assumed, the index assigns higher values to high risk accounts than to low risk ones, bad accounts should be more frequent in the high index values. This proved to be the case. A third of the bad accounts had index values above 250 while only 3 % of the good accounts fell within this range (see Table 3). Twelve per cent of the bad accounts had values above 300 but only .2 of 1 % of the good accounts were in that group. At the other extreme 1,754 good accounts had index values between 110 and 119 but only two bad accounts fell in that range.

The bad account probabilities ranged from .001 at the lowest end of the index scale to .423 at the top (Table 4). A more detailed breakdown of values at the top of the range would have indicated a number of groups with even higher bad account probabilities; but as the number of accounts was small these figures are not shown separately.

The efficiency ratio of the index, computed by formula (3), was .194. This indicates that nearly 20 % of the bad accounts fell within a range of the index that would have permitted the use of index values to reject applicants with a loss of less than three good accounts for each bad account. As will be pointed out later, most lending institutions would consider this a highly satisfactory trade.

The risk index method performed surprisingly well by comparison to published results from studies based on a variety of more elaborate methods using discriminant and regression analysis [4, 8]. The efficiency ratio of this test was higher than all but one of the other eleven sets of results. The highest ratio (.23) was obtained by a modified system of discriminant analysis. There is every reason to think that with greater attention to the selection of traits the risk index method could match the best results of the more elaborate systems currently available.

Sample Bias

A serious question of bias arises when the risk index is based on loans that have already been screened. A few studies have been conducted on unselected

TABLE 2

Bad Account Probability by Traits and Subclassifications

(Listed in order by ability of trait to discriminate between good and bad accounts[1])

	Total number of accounts[2]	Number of bad accounts	Bad account probability
Total	107,460	1,234	.0115
Telephone status			
Telephone	99,397	669	.0067
No telephone	8,053	565	.0701
Residence			
Owns home	81,985	564	.0069
Rents			
house	3,153	70	.0222
apartment	10,141	331	.0326
room	1,436	105	.0731
Lives with someone	8,956	127	.0142
Bank account			
None	21,157	556	.0263
Regular checking account only	16,230	184	.0113
Special checking account only	24,682	228	.0092
Savings account only	18,958	109	.0058
More than one type of account	20,685	85	.0041
Purpose of loan			
Purchase automobile	14,269	115	.0081
Purchase household goods	25,378	153	.0060
Consolidate debt	23,698	435	.0184
Medical	6,682	165	.0247
Purchasing clothing	1,713	31	.0181
Taxes and insurance	4,444	30	.0068
Travel	1,917	25	.0130
Loans to relatives	1,209	18	.0149
Other	27,855	247	.0089
Time in last residence			
6 months or less	5,350	165	.0308
7 to 12 months	7,348	131	.0178
13 to 24 months	10,641	131	.0123
25 to 36 months	10,086	136	.0135
37 to 48 months	7,883	105	.0133
49 to 60 months	6,803	76	.0112
61 to 120 months	23,524	191	.0081
121 to 180 months	12,704	91	.0072
181 or more months	17,796	138	.0078
Time on last job			
6 months or less	3,402	109	.0320
7 to 12 months	5,054	79	.0156
13 to 24 months	9,121	152	.0167
25 to 36 months	7,745	107	.0138
37 to 48 months	4,489	75	.0167
49 to 60 months	6,600	83	.0126
61 to 120 months	20,534	214	.0104
121 to 180 months	16,548	151	.0091
181 or more months	27,159	182	.0067

TABLE 2 (*Cont.*)

	Total number of accounts[4]	Number of bad accounts	Bad account probability
Sex and marital status			
Single			
male	8,795	176	.0200
female	4,377	33	.0075
Married			
male	87,243	917	.0105
female	3,734	21	.0056
Divorced[3]	2,598	75	.0289
Neighborhood			
Postal zones and suburban areas—range	107,460	1,234	.1139 to .0014
Maturity of loan			
12 mos. or less	29,263	464	.0159
13 to 18 months	44,853	499	.0111
19 to 24 months	19,417	148	.0076
25 months or more	13,927	123	.0088
Occupation—Range	105,181	1,198	.0345 to .0043
Monthly income			
$200 or less	2,151	49	.0228
201 to 300	11,651	230	.0197
301 to 400	26,650	304	.0114
401 to 500	23,164	249	.0108
501 to 700	23,128	215	.0093
701 to 1000	11,951	110	.0092
1001 to 1500	5,008	33	.0066
1501 and over	1,342	11	.0082
Age			
25 or under	5,049	74	.0147
26–30	11,064	203	.0184
31–35	15,286	221	.0145
36–40	18,126	188	.0104
41–45	14,594	160	.0110
46–55	25,387	232	.0091
56–65	12,147	94	.0077
66 and over	3,246	23	.0071
Number in family			
1	16,875	268	.0159
2	33,864	300	.0089
3	17,307	210	.0121
4	20,754	224	.0108
5	10,423	123	.0118
6	4,047	53	.0131
7	1,983	21	.0106
8 or more	575	15	.0261

[1] Order of listing of traits is based on Chi-square values adjusted for differences in the number of degrees of freedom. The number of accounts given for various classifications do not necessarily add to the totals because of the exclusion of accounts that could not be properly classified.

[2] Estimates for the 106,226 good accounts accepted during the sample period were based on a sample of 1,516 good accounts.

[3] The coded information did not permit the distinction between male and female. The significance of this distinction in the other marital status groups suggested that it might have added to the discriminatory value of the classification.

TABLE 3

Cumulative Distributions of Good, Bad and Rejected Accounts, by Risk Index Values

Risk Index	Good Accounts	Bad Accounts	Rejected Accounts
110–149	100.0	100.0	100.0
150–199	51.9	85.1	76.3
200–249	11.6	57.2	31.2
250–259	3.1	33.8	11.2
260–269	1.8	29.3	10.7
270–279	1.1	25.4	5.6
280–299	0.4	20.1	5.1
300 and over	0.2	12.5	3.6

TABLE 4

Bad Account Probabilities by Risk Index Values

Risk Index	Total number of accounts[1]	Bad Accounts	Bad Account Probabilities
110–119	1,754	2	.0011
120–129	10,053	33	.0033
130–139	18,703	64	.0034
140–149	20,896	85	.0041
150–159	14,852	67	.0045
160–169	10,529	89	.0085
170–179	8,901	72	.0081
180–189	4,411	67	.0152
190–199	4,464	50	.0112
200–209	2,360	48	.0203
210–219	2,154	53	.0246
220–229	2,091	59	.0282
230–239	1,187	66	.0556
240–249	1,465	63	.0430
250–259	1,457	55	.0377
260–269	749	48	.0641
270–279	766	65	.0849
280–299	304	94	.3092
300 and over	364	154	.4231
Total................	107,460	1,234	.0115

[1] Estimates for the 106,226 good accounts accepted during the sample period were based on a sample of 1,516 good accounts.

accounts but comparisons of results of selected and unselected samples have not been published [7]. Since, however, the same type of information on the traits of rejected applications can be obtained, the comparison of these traits with those of accounts in the selected sample makes possible some judgment about the possible bias.

The covariance of the distributions of rejected accounts and bad accounts compared with the distribution of good accounts was positive in all but one case and a relatively high correlation was indicated for most traits. The relationship was negative in only one case, on the maturity of the loan. This suggests that the risk index might be more or less effective in detecting bad accounts than trained personnel but that the traits of the rejected accounts would be similar in either case.

A comparison of the traits of the rejected accounts with those of good accounts gives some indication of the importance of various criteria used in the decision to reject the applicant. Such a comparison cannot, of course, account for decisions based on information not covered by the listed traits—such as adverse credit information or obvious evidence of alcoholism. Table 5 shows seventeen traits listed by discriminatory significance as measured by the adjusted Chi-square values based on the comparison of distributions of good and bad accounts and the positions of those traits as indicated by a similar comparison of the distributions of good and rejected accounts. Just as these variations in distributions were considered as a basis for detecting potential risk, they indicate the traits that the interviewers most frequently used (implicitly or explicitly)

TABLE 5

Comparison of Criteria Used in Measuring Credit Risk[1]

	Risk Index	Rejected accounts
Telephone in residence	1	16
Ownership or rental of residence	2	1
Bank account	3	10
Purpose of loan	4	11
Time in last residence	5	14
Time in last job	6	7
Sex and marital status	7	9
Neighborhood	8	4
Time in last 2 jobs	9	6
Maturity of loan	10	3
Time in last two residences	11	13
Occupation	12	12
Monthly income	13	17
Age	14	8
Number in family	15	15
Monthly payment as % of income	16	5
Interviewer's appraisal	17	2

[1] Numbered according to size of variations from the distribution of good accounts as measured by Chi-square values (adjusted for differences in degrees of freedom).

in rejecting accounts. As previously indicated there is a high correlation between many of the traits but that was to be expected as the study concentrated on factors believed to be important by experienced interviewers. The differences are therefore more interesting than the similarities and as indicated by Table 5, there is a slight negative rank correlation between the two lists of criteria. The trait with the highest rank in the risk index, telephone status, ranked sixteenth in the rejected list. Bank account status ranked third on the risk index list and tenth on the rejected list. The length of time in the last residence ranked fifth in the risk index list and fourteenth on the rejected list although this factor usually has a high rank in the industry discussions of important factors.

The interviewer's appraisal was second on the rejected list although, as was pointed out earlier, it was of questionable significance in identifying the bad accounts in the sample. The third ranking item in the rejected list was the maturity of the loan. This item ranked tenth in the risk index list and it was the only one for which a negative covariance was obtained between the distributions of bad and rejected loans as compared to the distribution for good loans. Loan appraisers tended to reject a higher proportion of applications for long-term loans whereas the bad debt experience was worse on the short-term loans.

Using a Risk Index

Risk index values for new loan application can be found by assigning the appropriate bad account probabilities (times 1,000) in Table 2 to the new loan applicant and by adding them together as indicated by formula (2). If it proves desirable, the risk index values can be converted into a probability estimate for the account by the values in Table 4. For most purposes, however, the risk index values can be used without the conversion.

Few if any lenders would be willing to accept or reject applicants on a basis of a single number. Some check against the possibility of misrepresentation or fraud is needed. After such checks, however, the index values can be used as a guide in accepting and rejecting accounts. Either an absolute cut-off point can be used to reject applications or the index can be used as a signal to indicate accounts for which further investigation is required.

The index itself provides a relatively easy method for finding the best cut-off point. If the expected losses on bad accounts exceed the expected return on good accounts the business is obviously unprofitable. The expected loss can be estimated by multiplying the average loss on bad accounts (L) by the bad account probability (p). The expected return on good accounts can be estimated by multiplying average return on good accounts (R) by the probability that an account will be good (g). The cut-off point occurs when the expected losses on bad loans (pL) equals the expected return on good loans (gR). As g equals $(1 - p)$, the cut-off point can be stated in terms of bad account probabilities as follows:

$$\begin{aligned} pL &= (1 - p)R \\ p &= R/(L + R). \end{aligned} \tag{4}$$

If the return on an average account (after all costs including the cost of money) is $20.00 and the average loss on bad accounts (including collection costs) is $400, the break-even point would occur when $p = 0.0476$. Any account with bad loan probabilities in excess of that figure would be unprofitable and all accounts with lower probability values would be profitable. In terms of the risk index it would pay to reject all accounts with an index value of 260 or more (see Table 4). This example is based on commercial bank data and implies that the lender is willing to lose 20 good accounts for every bad one. If the return on loans is higher, larger losses could be absorbed and the cut-off point would be higher.

The risk index can also be used merely as a guide in efforts to lower the cost of investigation. Less time and effort would be spent on applicants with low index values while those with high index values would be investigated thoroughly. Even when a cut-off point is used, some further attempt might be made to salvage the good loans from high index values or to identify the bad loans in the low index ranges. Whenever further investigation can narrow the risk, such measure would be worthwhile.

The risk index can also serve to measure and control credit quality. A running check on the quality of new business can be prepared by tabulating risk index values. These tabulations can be used to forecast probable losses. Table 6 indicates the type of analysis that can be developed from risk index values. Cut-off points can be raised or lowered to adjust the quality of the business accepted and to control expected loss rates. Changes in credit standards can be accomplished with far more precision by making changes in the acceptable index values than by making changes in subjective screening practices.

TABLE 6

Quality of New Loan Volume

Risk Index	p	Number of loans			Percentage Distribution		
Values		Jan.	Feb.	Mar.	Jan.	Feb.	Mar.
1. 100–149.....	.0036	1,202	988	1,318	48.1	43.9	39.9
2. 150–199.....	.0078	1,000	968	1,455	40.1	43.0	44.1
3. 200–249.....	.0312	212	214	393	8.5	9.5	11.9
4. 250–299.....	.0800	83	76	129	3.3	3.4	3.9
5. 300 and over	.4231	3	4	5	.1	.2	.2
6. Total................		2,500	2,250	3,300	100.0	100.0	100.0
7. Total index value for all new loans......		396,750	362,450	543,900	—	—	—
8. Average index value (7 ÷ 6)............		159	161	165	—	—	—
9. Expected loss rate (in per cent) (p × # loans in each index group) × 100 ÷ line 6.............		1.07	1.14	1.24	—	—	—

The accuracy of risk index estimates cannot of course be taken for granted. It depends upon many things, among them the quality of the index, the sampling error, and changing business conditions. The influence of changing business conditions on the index can be mitigated to some extent by careful construction of the index. Sample information should be drawn over a period that includes recessions as well as booms. A continuing review of the index should make it possible to develop a relationship between economic indicators and index values. A carefully constructed index that is designed for a specific type of business should prove to be a valuable management tool.

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