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II

The Major Determinants of Differential Mortgage Quality

In order to assess the influence of various combinations of loan, borrower and property characteristics on mortgage quality, we found it desirable to break down the data in a number of ways. The first division was made according to loan status—loans being classified as current (no payment arrearages or arrearages of less than ninety days), delinquent (ninety days or more), and in foreclosure. Using loan status as the dependent variable, we then ran regressions for current vs. noncurrent (delinquents and loans in foreclosure), delinquent vs. loans in foreclosure, and, for the USSLL data, current vs. loans in foreclosure.[1] Second, we ran separate sets of regressions for each subsample, USSLL, MBA, and NAMSB. The purpose here was twofold. Given the large number of observations and variables, it was more convenient computationally to work on the subsamples separately. In addition, there were important differences among the subsamples which would have been "washed out" had they been combined. A further division of the regressions was made according to the number and definition of variables in each of the subsamples. In the so-called individual versions of the equations we made maximum use of the information available to us. In the "pooled" versions, however, we included only variables on which we had data in each of the subsamples, and these variables were defined in

[1] It was necessary to restrict our comparisons to paired cases, since the regression framework will not accommodate a dummy dependent variable which assumes more than two values. Multiple discriminant analysis offers a possible alternative, but, given the large number of variables and observations we had to work with, it proved to be much too cumbersome from a computational standpoint.

such a way that we had compatability among the equations. This permitted us to focus attention on similarities and differences among the three subsamples. The end result of all this was a set of thirteen regression equations. Full detail on these equations, along with relevant statistical tests, is provided in Appendix B.[2] The sections which follow, however, are intended to set forth and evaluate the findings without going into unnecessary technical detail.

1. Delinquency Risk

Delinquency risk equations were developed by treating the dependent variable, loan status, as a dummy. Thus the variable was assigned a value of zero if the loan was not currently in difficulty (current) and a value of one if it was either ninety or more days delinquent or in foreclosure (noncurrent). While we refer to such functions as risk index equations, they have often been referred to in econometric studies as linear probability functions. Ostensibly the function is linear because it employs the technique of multiple linear regression. It is considered a probability function because it is estimated by using a dependent variable which can assume a value of zero or one. Thus the output of the estimated equation, when particular values are assigned to the dependent variables, should be a number between zero and one. The closer the value falls to one (noncurrent in our classification scheme), the greater the *probability* that the loan will be delinquent. The closer the value falls to zero, the less the probability of delinquency. Unfortunately, there is no way of guaranteeing that a particular combination of observed values of the variables will invariably lead to a solution falling between zero and one. In cases where negative values or values greater than one arise, it is not possible to assign a probability interpretation to them. We choose, therefore, to call the regression functions *risk equations* and to call the outputs of these equations *risk indexes*. It is clear that if the equations have good discriminating power, lower values for the out-

[2] The general form of the regression equations is:

$$r_d = a_1 + a_2RLS + a_3T + a_4RPI + O_i + DN_i + SM_i + AB_i + P_i + FJ + TLD_i + TLN_i + R_i$$

The subscripted variables are used to show the presence of two or more dummy classes, and the variable names (mnemonic symbols) are as defined in the text. In the case of dummy variables it is not necessary to show both a coefficient and a variable, since whenever the variable falls within a given class it will assume the value of the coefficient and whenever it falls outside it will assume a value of zero.

put indicate low risk and high values indicate high risk, whether or not such values are less than zero or greater than one.

INDIVIDUAL EQUATIONS

As was indicated above, the individual equations for the three sets of data (USSLL, MBA, and NAMSB) use the maximum number of variables and data available in each subsample. This means that because there were differences among the questionnaires and response rates, the coefficients of the three regression equations cannot be directly compared. It has the advantage, however, of making maximum use of the information the lender had at his disposal at the time the loan was made. Since we were primarily interested in discovering the relationship between loan quality and variables which might enter into the lending decision, we did not explicitly consider such variables as the age of the loan when the sample was drawn, stated reasons for delinquency, or borrowers' status at the time of delinquency (or drawing of the sample). Variables which were included in one or more of the regressions are loan-to-value ratio (*RLS*), term to maturity (*T*), monthly payment-to-income ratio (*RPI*), borrower occupation (*O*), number of dependents (*DN*), marital status (*SM*), borrower age (*AB*), loan purpose (*P*), junior financing (*FJ*), type of lender (*TLD*), type of loan (*TLN*), and region (*R*). While data were available on age and location of property, preliminary analysis did not lead us to believe such variables would be important. The same may be said for property value and borrower income. Simple cross tabulations relating these variables to loan status failed to reveal any relationship. It was expected that two of the variables listed above, loan-to-value ratio and payment-to-income ratio, would capture the important value and income relationships since they link them to the pertinent loan characteristics, the former giving a measure of the borrower's vested interest and the latter his financial burden. Given the large number of variables we had to work with some economizing was essential for computation purposes.

The discriminating power of the equations themselves was tested in three ways—through over-all *F* ratios, analysis of coefficients of determination (R^2's), and Lorenz tests. The *F* ratios are used to determine whether the regressions are or are not significant. They are computed by forming the ratio "regression variance/residual variance." Since the numerator of the ratio measures how much variance is explained by the fitted regression function and residual variance measures how much is left unexplained, it follows that large ratios are indicative of good discriminating power and that small ratios raise doubts about the estimated relations. Any given ratio may, however, be due solely to chance, so it becomes necessary to determine how large a ratio pure chance might lead us to expect. *F* tables exist for this purpose. Thus by comparing our results with those found in an *F* table, we can determine whether our ratios are likely to be due to chance or whether the regressions upon which they are based are, in fact, significant.

The second statistic which was employed, the coefficient of determination, is useful for two reasons. First, it expresses the ratio of the sum of the squared deviations "captured" by the regression plane to the sum of the squared deviations around the mean of the dependent variable. Thus it shows the proportion of deviations explained by (or attributable to) the regression. A second interpretation of the statistic relates it to the coefficient of multiple correlation. More specifically, it can be shown that R^2, the coefficient of determination, can be obtained by squaring the coefficient of multiple correlation, R. These two interpretations, taken together, underscore the usefulness of the statistic. It will readily be seen that its value will range between zero and one and that the closer it lies to one, the greater is the discriminating power of the regression.

Lorenz tests, which are not part of the standard statistical repertoire, were developed to show graphically how well the regressions distinguished between "good" and "bad" loans.[3] The basic idea was to use the regression equations to calculate a risk index for each loan in the sample and to array the loans according to the size of the index, beginning with the smallest values and proceeding through the largest. At each value of the index two ratios were calculated, one showing the percentage of all loans in the sample having an index value equal to or less than the one indicated, and another showing the percentage of "bad" loans thus classified. These ratios were then plotted on graphs, such as Chart 9, below. It should be immediately apparent that a function which has low discriminating power will result in a series of plots near the reference line, a 45 degree diagonal from the origin. Conversely, high discrimination would yield plots near the horizontal and vertical axes. Thus the closer the Lorenz curve lies to the axes (the more bow it has), the greater the degree of discrimination.

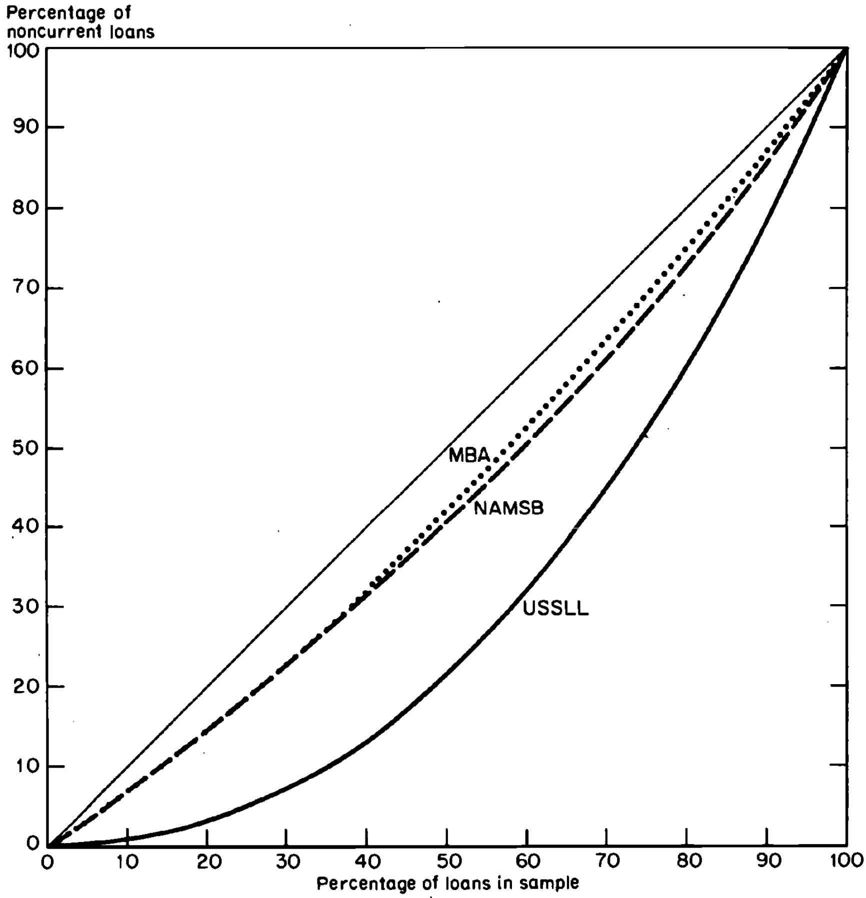
[3] The authors wish to acknowledge the considerable help of Donald Steward in developing these tests. Mr. Steward, a member of the Social Science Research Institute computational staff, took some rather vague ideas, expressed them in more rigorous form, and worked out the computer programs necessary to develop the tests.

The individual versions of the equations for all three subsamples yielded F ratios which were significant at the 1 per cent level, thereby indicating that at least some discrimination was achieved.[4] The ratio was highest for the USSLL equation and lowest for the MBA. Similar patterns emerged for the coefficients of determination and the Lorenz tests. The USSLL equation produced the highest coefficient of determination (about 11.5 per cent), followed by the NAMSB version (just under 5 per cent) and the MBA (under 4 per cent). These values are quite low by any standards, but they are not totally meaningless. If it were possible to predict quality absolutely on the basis of the few variables and simple functional forms we have included, mortgage underwriters would long ago have developed rating schemes to reflect this fact. The truth is many variables interact, and in ways not yet imagined. That does not mean that studies of this type are fruitless, for in spite of what remains unexplained, valuable insights emerge. A second point to bear in mind is that cross-section microeconomic data such as we used typically yield much lower R^2's, than the time series data to which so many of us have become accustomed. This is true largely because these observations can be explained by circumstances that are idiosyncratic to individual households and have no particular relevance or interest from the point of view of economic analysis. Finally, the use of a dummy dependent variable and the large number of observations almost certainly reduced the R^2's below what they otherwise would have been. Consider the influence of dummies. If the sample on which the regression is being run is roughly 50 per cent current and 50 per cent noncurrent (as ours were), the expected value of the dependent variable over the whole sample must be one-half (.5). Theoretically, its value for any particular set of observations on the independent variables will fall somewhere between zero and one, with a probability of zero of its being either zero or one exactly. Yet when this calculated value is compared to the observed value (which *must* be either zero or one by definition) any deviation will lower the value of the R^2, sometimes by a substantial amount. In spite of these anomalies, the *relative* sizes of the coefficients are probably indicative of the differences

[4] The statement "significant at the 1 per cent level" means simply that when we assert some statement is true (for example, that the equations *do* discriminate between good and bad loans), we can expect to be wrong no more than one out of a hundred times. Similarly, if we were to say "significant at the 5 per cent level," we could expect to be wrong one out of every twenty times. We follow standard usage of these terms in subsequent sections by referring to 1 per cent significance as "highly significant" and 5 per cent significance as "significant." Those interested in seeing the statistics upon which our statements are based can find them in Appendix B.

CHART 9

Lorenz Curves, Current vs. Noncurrent, Individual



SOURCE: Appendix Tables B14–B16.

in the discriminating power among the equations, and for this reason, together with its familiarity, we will continue to use the statistic.

The Lorenz curves in Chart 9 confirm the findings of the R^2 tests as to the relative discriminating power of the three equations.[5] It is obvi-

[5] The curves referred to do not, strictly speaking, fall under the usual definition of a Lorenz curve. The manner in which an ordinary Lorenz curve is constructed insures that it will increase at a constant or increasing rate throughout its length. The method we used for plotting values provided no such assurance. Nevertheless a freehand fitting of curves to the plotted values yielded, perhaps

ous from this chart, however, that the equations do a better job of discriminating between good and bad loans than the low value of the R^2's might suggest. Indeed, the rather pronounced bow in the USSLL curve indicates that that equation does a fairly decent job of quality rating. This is not to suggest that the equation could not be improved upon or that misassignments occur only occasionally, but at least it indicates a step in the right direction.

With regard to the independent variables used in the regressions, a number of noteworthy points emerged.[6] We discuss these in the variables' order of appearance in the equations. Loan-to-value ratio bore a strong positive relation to delinquency risk in all three equations. In fact, it turned out to be the most important variable in both the MBA and NAMSB equations. In the USSLL equation it trailed only loan purpose and junior financing in order of importance.[7] Neither of the latter two variables appeared in the MBA and NAMSB versions. It should also be noted that the coefficient for this variable was significant at the 1 per cent level in all three equations.

The behavior of the term to maturity variable was most surprising. It differed significantly from zero only in the NAMSB equation, but it carried a negative sign in all three versions. This would seem to indicate that longer maturities are associated with a lower rather than a higher risk of delinquency. In view of the fact that most lenders (and we ourselves) regard a liberalization of terms, *ceteris paribus,* as adding to risk, how can such a phenomenon be explained? First of all, the reader must bear in mind that we are speaking only of risks of delinquency—not foreclosure or potential loss on the loan. Secondly, the negative sign might well be no more than a statistical aberration which stems from the form of the equations we employed. Of the three equations we estimated, the NAMSB version (the one in which the negative sign was significant) contained the fewest number of variables. It is worth noting in this connection that the coefficient was smallest

accidentally, curves with Lorenz characteristics. A more important reason for adopting the terminology, however, is that the curves we have constructed and Lorenz curves are designed for the same purpose—to graphically portray inequality in one distribution with reference to another.

[6] Simple correlations between the independent variables suggest that multicollinearity was not a serious problem. In all cases but one (loan-to-value ratio vs. term to maturity) the correlations were well below .2. Even in the exceptional case, the coefficient typically was below .5.

[7] Importance was measured in two ways, through partial correlation coefficients and beta coefficients. The former are self-explanatory; the latter are used to determine how many standard deviations of change occur in the dependent variable for each standard deviation change in the independent.

in the USSLL version and this is the only one in which we were able to include loan purpose and junior financing. It would appear then, that the dropping of variables, particularly loan purpose and junior financing, biases the coefficient in the negative direction. Why might this be? If, as is likely to be the case, loans for refinancing or repair or which have junior financing associated with them have shorter maturities, the latter variable could be acting as a proxy for the other two. That such a possibility is indeed likely will be seen when the pooled versions of the equations are examined. When loan purpose and junior financing were dropped from the USSLL equation, the negative coefficient grew in size and its "*t*" value became significant at the 1 per cent level. Furthermore, examination of scaled down (intermediate) versions of all three equations reveals that as more variables are dropped, the negative value of the coefficient increases, as does its "*t*" value.

Even in the most complete version of the equation (USSLL) we may not have been able to include all the relevant variables. For example, we were unable to include either wealth or liquid assets, both measures of financial strength and borrowers' ability to pay. It stands to reason that loans with shorter maturities will carry higher monthly payments. If, therefore, no explicit account is taken of financial strength and if shorter maturities are associated with weaker borrowers, results similar to ours could be expected. Shorter maturities might well be associated with weaker borrowers if lenders, in perceiving the greater (but still acceptable) risks, require a more rapid repayment of the loan to ensure a quicker buildup of equity.

In sum, it would appear that the negative signs we observed are not likely to be indicative of the "true" relationship between risk and term to maturity. Rather, it would appear that the most likely association is one of no net influence when the equation is properly specified. Even this conclusion must be interpreted with caution, however, for it applies only to what one is likely to observe in practice. If lenders were to throw all caution to the winds and require little or no buildup of equity on a property which is declining in value, defaults would almost certainly ensue.

The behavior of the monthly payment-to-income variable was hardly less surprising than that of term to maturity. It too carried a negative sign, even though it failed the significance test at the 1 per cent level. In one case, however (the MBA version), it turned out to be significant at the 5 per cent level. We had anticipated that this ratio would serve as a good measure of financial burden and would thus vary directly with delinquency risk. That it did not might be evidence that lenders have been successful in controlling this aspect of risk. Since our sample included only those loans which passed the lenders' (and in the case of FHA and VA, the underwriters') screening process, loans with dangerously high ratios may have already been filtered out. If that is the case, we may have observed only random variability in the ratio rather than variability which would be indicative of risk. This possibility seems to be borne out by some cross tabulations which we ran on the data. In the USSLL and MBA subsamples, for example, more than 96 per cent of the loans had payment-to-income ratios under 25 per cent.[8] In the NAMSB sample, 92 per cent of the loans were so classified. These figures would indicate that, for the most part, lenders imposed a fairly strict upper limit of about 25 per cent on the ratio. It could be that such a limit is well within the "safe" range and the observed delinquencies must, therefore, be attributed to other causes.

Occupation provided a good example of the need for common definitions among the samples. There is little doubt that the variable is important, but differences in occupational groupings made comparison extremely difficult. Nevertheless, a few clear-cut patterns did emerge. Salesmen showed high risk coefficients in all three equations, even though in one case (MBA) the difference between this coefficient and that of the reference group (skilled laborers) was not significant. Self-employed persons were also high risk in the one sample in which they appeared (USSLL). At the other end of the spectrum, professionals (not significant in NAMSB) and managers, executives, and proprietors (not significant in NAMSB) yielded the lowest risk coefficients.[9] The remaining occupational groups, including skilled and unskilled labor, service workers, clerical or civil service employees, and craftsmen or foremen were pretty well clustered together between the low and the high risk extremes. The one exception to this was in the USSLL sample, where white-collar workers were at the low risk end of the spectrum.

Number of dependents bore a direct relationship to risk in the USSLL version, with risk coefficients increasing steadily from the second

[8] It is perhaps worth noting that variability below the 25 per cent level was much greater for the USSLL than for the other two groups. For example, only 7 per cent of the MBA loans had ratios under 10 per cent, while 33 per cent of the USSLL loans were under this figure.

[9] The practice which both the MBA and NAMSB adopted of lumping proprietors in with managers almost certainly gave a coefficient closer to zero than would have otherwise been the case. It is clear from examining the USSLL data that self-employed persons (which includes proprietors) are high risk, while executives or managers are low.

through the eighth dependent. In the MBA and NAMSB samples, however, the variable did not turn out to be significant. Some tendency toward a direct relationship was evident, but it was far from clear-cut. In view of the fact that the USSLL equation showed the greatest discriminating power, we are inclined to accept the evidence that a direct relationship between number of dependents and risk does exist. There is also a fairly strong a priori basis for this conclusion, since larger families mean higher expenses in expenditure areas where we lacked data.

Marital status did not appear to be a significant factor in any of the equations, though the risk coefficients were uniformly lower for married than for single borrowers. In the USSLL sample, where a finer breakdown was provided, the ranking in terms of the size of the coefficients was widowed, divorced, single, and married, in that order. Borrower age was a significant factor in both the USSLL and MBA equations, but the pattern was so mixed that any conclusion must be highly tentative. Granting the exceptions, it appeared that younger borrowers (those under 40) might offer greater risks than those 40 and above. We hasten to add, however, that the evidence is far from conclusive on this point.

Loan purpose, which was included in only the USSLL sample, proved to be an extremely important determinant of risk. As one might expect, loans extended for house purchase showed the best performance, and by a considerable margin. Construction loans came next in order of risk, followed by loans for repair and, finally, refinancing. The degree of risk associated with refinancing is underscored by the fact that it carried a larger coefficient (and higher "*t*" value) than any other dummy variable in the equation. Junior financing, which also was excluded from the MBA and NAMSB samples, was virtually on a par with loan purpose in order of importance. Loans for which some form of secondary financing was present carried much higher risk coefficients than those without.

Region was included in the equations only to isolate the effects of geographical influence and, as one might expect, risk bore a direct relationship to regional delinquency patterns. The fact that there were significant differences among the regions indicates that failure to include the variable would have seriously biased the results. This applies particularly to the USSLL equation, where the greatest differences emerged.

None of the coefficients for lender type was significant, even though some weak patterns were in evidence.[10] Perhaps not surprisingly, loans from commercial banks and trusteed funds appeared to be somewhat less risky than loans held by mortgage bankers for their own account or for individuals. The differences were not sharp, but they may indicate that some loans in the mortgage bankers' portfolios are there because they were not salable to other institutions. Another possibility is that they reflect loans transferred back to the mortgage banker for foreclosure.

Loan type (FHA, VA, or conventional) entered into both the NAMSB and MBA equations, but since the USSLL sample included only conventional loans, the variable does not appear in that version. Surprisingly, FHA and VA loans showed significantly lower risk coefficients than conventionals. These differences were significant at the 1 per cent level for the MBA sample and at the 5 per cent level for the NAMSB. It is possible that this finding reflects only differences in underwriting and appraisal practices—factors which we could not measure. It most certainly does *not* indicate that conventionals are more risky, per se. Indeed, when the *combined* influence of this variable and the others is considered, it is likely that FHA's and VA's are more, not less, risky than conventionals. We have already noted, for example, that high loan-to-value ratios are associated with high delinquency risk. Since FHA and VA loans are likely to involve lower downpayments than conventional loans, this factor could dominate.

POOLED EQUATIONS

The pooled versions, as was noted above, were arrived at by dropping variables for which data were not available in all three subsamples and by redefining others so as to make them compatible. We had initially intended actually to pool all of the observations and compute one equation which we could compare with similar equations for each of the subsamples. This would have enabled us to determine whether differences among the subsamples were *statistically* significant. We can make judgments about these differences, however, by merely comparing equations for each subsample. In view of the additional programming and computer time involved in developing the statistical tests associated with the initial plan, it was decided to abandon it in favor of the less sophisticated "judgment" approach.

The over-all discriminating power of the pooled equations was, as

[10] Lender type applied only to the MBA equation since loans in the USSLL and NAMSB samples were, by definition, held by savings and loan associations and mutual savings banks.

we anticipated, somewhat less than for the individual versions. All the equations, however, continued to be significant at the 1 per cent level, as measured by their F ratios.[11] R^2's (coefficients of determination) were somewhat lower for all equations, but especially for the USSLL version, where a drop from 11.5 to 8 per cent was recorded. Even so, the relative rankings were maintained, with the USSLL showing the best discriminating power, followed by NAMSB and MBA, in that order. Similar patterns were observed in the Lorenz tests (Chart 10), although the apparent loss in discriminating power there was not as great as shown the R^2's. For example, while the R^2 value in the USSLL equation declined by nearly one-third, it does not appear that the area between the reference line and the USSLL Lorenz curve diminished by more than about 20 per cent. Shifts in the MBA and NAMSB curves were negligible.

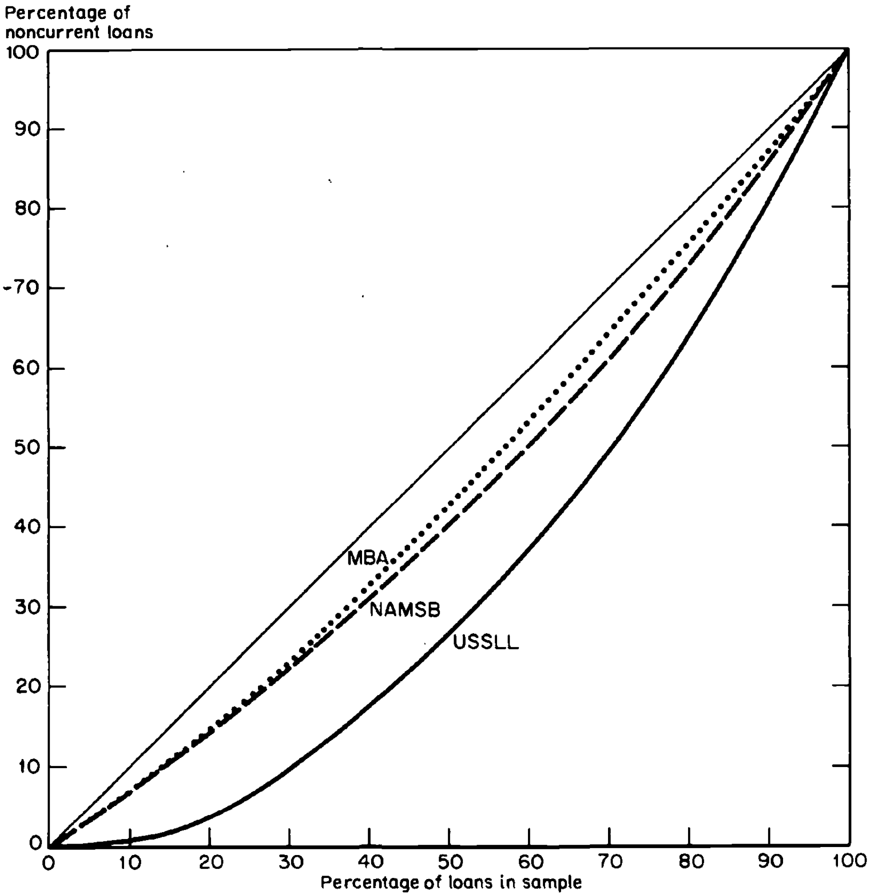
Loan-to-value ratio continued to show a strong positive relationship to risk, yielding highly significant positive coefficients in all three equations. Negative signs were again indicated for the term-to-maturity coefficients and these were significant at the 1 per cent level in both the USSLL and MBA versions, and at the 5 per cent level in the NAMSB. This tends to confirm the point made earlier, that this variable is probably serving as a proxy for some which we omitted. It will be recalled that in the individual versions only one coefficient (NAMSB) was significant. Dropping variables, as we did in the pooled versions, however, has the effect of generating larger coefficients, pushing "t" values over the critical level. Payment-to-income ratio once again failed to satisfy the significance tests at either the 1 per cent or 5 per cent level.

Among the occupational groupings salesmen had high risk coefficients in all three cases, although the MBA coefficient did not quite satisfy the criterion for significance. Proprietors and self-employed were among the high risks in the USSLL and NAMSB samples, but not in the MBA—possibly, as was indicated earlier, because managers were included in this group. Unskilled laborers were fairly high risk in all three cases, even though the coefficients were just at the margin of significance for the MBA and NAMSB. Service and miscellaneous workers and skilled labor were near the center of the risk spectrum, followed by clerical workers. It should be noted, however, that in the NAMSB sample, the risk coefficient was greater for clerical workers

[11] Actually, the F ratios for the pooled versions of the MBA and NAMSB equations were slightly higher than they were for the individual versions. This can be attributed to the fact that some variables which were not significant in the individual versions were dropped from the pooled versions.

CHART 10

Lorenz Curves, Current vs. Noncurrent, Pooled



SOURCE: Appendix Tables B17–B19.

than for either skilled labor or miscellaneous. Professional and technical personnel had the lowest risk coefficient in every case, except for the USSLL, where white-collar workers (classified clerical) had the best performance. Considering the definitional problems raised by differences in the questionnaires, it was encouraging from an analytical standpoint to be able to establish the importance of occupation. One can only conclude that the nature of a borrower's employment has an important bearing on default risk, and the evidence is quite strong that there is an inverse relation between job skill and risk. The self-employed or proprietor category provides a notable, but not surprising, exception to this pattern. The fact that the risk coefficient is high for this group may be indicative of the inseparability of one's personal and business affairs. Typically, when a proprietor is facing financial problems in his business, he must resort to using his personal resources to attempt to remedy the situation.

Number of dependents proved to be significant (at the 1 per cent level) in only one equation (USSLL). Nevertheless, the same general pattern was observed here as in the individual equations. The degree of risk increased steadily with increasing numbers of dependents, except at the extremes (zero or seven or more dependents), where the results were mixed. Marital status was significant in the USSLL version, but once again failed the test in the other two. That the one coefficient which was significant showed married people to be better risks tends to confirm the earlier findings concerning this variable.

Borrower age, as in the individual versions, presented a very irregular pattern. By the greatest stretch of one's imagination, a general downward trend in risk with increasing age can be detected. Exceptions, however, occur in every sample. For the USSLL the pattern is broken by the coefficients for the 30–34 age bracket (too low) and the 50–59 bracket (too high). For the MBA the 30–34 coefficient is too high, the 35–39 too low, and the 50–59 too low. For the NAMSB the 30–34 bracket is too low and the 40–44 bracket is much too high. Considering all the exceptions, the safest course would probably be to conclude that age has no apparent systematic effect on risk.

Regional coefficients, as well as loan type and lender type, generally followed the patterns observed in the individual versions. One exception to this was under loan type in the MBA sample. In the earlier version, FHA 203 loans and other FHA's were treated separately. Lumping them together for the pooled version apparently reduced the value of the coefficient to the point where it was no longer significant.

2. *Foreclosure Risk*

Up to now our analysis has been concerned with only one aspect of quality—delinquency risk. We now turn our attention to a second, namely, foreclosure risk. Foreclosure risk was measured in two ways for this study: first, as a conditional probability showing risk of foreclosure, given that a loan was already in default; second, as an unconditional probability showing the risk that a current loan will end up in foreclosure. The first measure was calculated in the same way as delinquency risk, only in this case we worked exclusively with the noncurrent part of the sample, comparing loans in foreclosure with loans which were delinquent but not in foreclosure. This was done for all three subsamples and for both individual and pooled versions. The second measure was developed by comparing current loans with loans in foreclosure. Because the USSLL sample seemed to provide the best data, this second measure of foreclosure risk was developed only for that group and only in the form which made maximum use of the data available (individual).

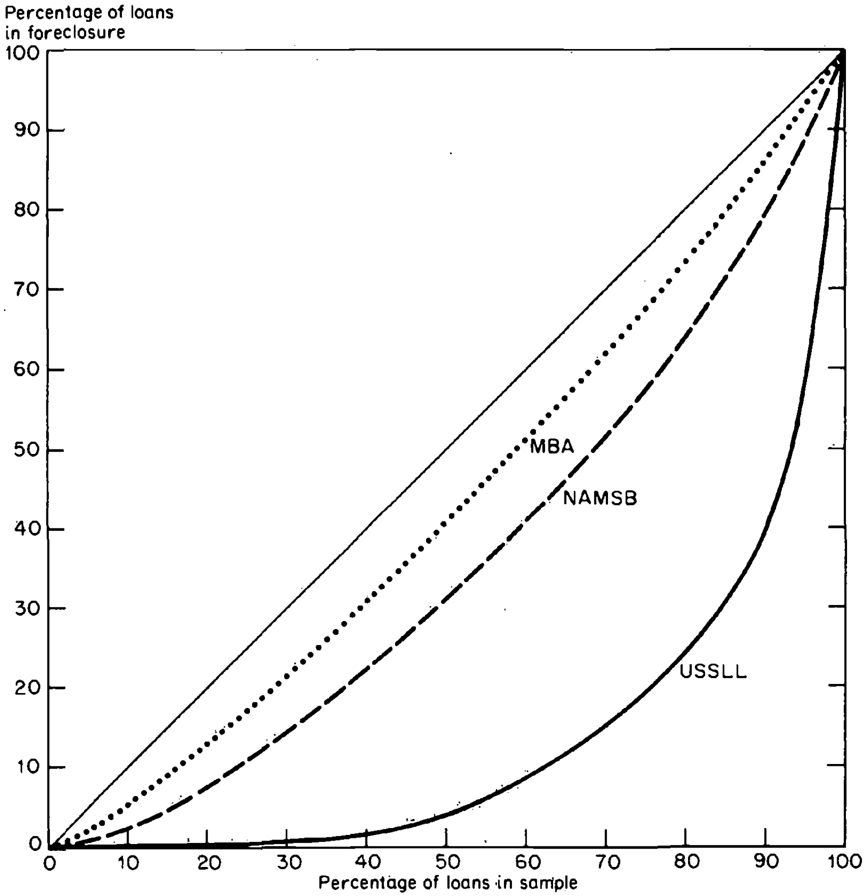
INDIVIDUAL EQUATIONS

The discriminating power of the foreclosure risk equations proved to be somewhat better than for the delinquency risk set. As before, F ratios were all significant at the 1 per cent level, but there was noticeable improvement in both the coefficients of determination and in the Lorenz curves. "Explained" variation (R^2) rose to about 13 per cent for the USSLL equation, to nearly 7 per cent for the MBA, and to just over 10 per cent for the NAMSB. The more dramatic improvement, however, was in the Lorenz curves. In the USSLL version, for example, the lowest quartile of loans as ranked by the risk index contained only about 1 per cent of the loans in foreclosure, and the lowest half only about 2 per cent (Chart 11). In fact, the index had to rise to the point where 90 per cent of all loans were included before the proportion of foreclosures reached the 50 per cent mark. This kind of performance certainly could not have been inferred from the R^2 which we calculated for this equation, and is perhaps indicative of the pitfalls associated with that statistic. Our regression equations do not fit perfectly into the classical least-squares framework because of our use of dummy variables. Nevertheless, approaches such as ours have been standard in the literature for several years. We merely point out that the Lorenz tests indicate that when the usual assumptions do not hold, rather important discrepancies may arise.

While the same independent variables were used in the foreclosure risk equations as in the delinquency risk set, we had no reason to believe that they would behave in the same way. There is no a priori basis for regarding loans in foreclosure merely as delinquents viewed at a later point in time. In fact, most loans which become seriously delinquent subsequently are restored to current status. It seems likely, therefore, that there are important differences between delinquents, per se, and loans which ultimately result in foreclosure. This point is

CHART 11

Lorenz Curves, Delinquent vs. Foreclosures, Individual



SOURCE: Appendix Tables B20–B22.

underscored above by our findings concerning the discriminating power of the equations. The improved estimates of the foreclosure risk equations is clear evidence that at least some of the variables we used are better predictors of foreclosure (given that delinquency has occurred) than of delinquency.

Loan-to-value ratio, as in the case of the delinquency equations, was directly related to risk. The coefficient was positive in all three equations and, except in the USSLL version, was significantly greater than zero. Term to maturity also yielded positive coefficients, but only one of these (USSLL) was significant at the 5 per cent level. In the NAMSB and MBA cases, t values were just short of the critical levels. The fact that both of these variables yielded positive signs emphasizes the inherent risks in low-equity loans. Small initial equities coupled with slower buildups (through stretched-out maturities) almost certainly pose substantial foreclosure hazards once a default has taken place.

The coefficients for payment-to-income ratio did not differ significantly from zero, except in the USSLL version, where it carried a positive sign. It would seem, however, that the fact that all the coefficients were algebraically larger than they were in the delinquency risk equations is not without significance. A priori, one would expect this kind of pattern if the variable serves at all to measure financial burden. Once a loan has slipped into the seriously delinquent category (by being three or more payments in arrears), it should be more difficult for the borrower to continue to make regular payments *and* make up the ones he has missed than to merely keep his payments current. If this is the case, one would expect larger risk coefficients for the foreclosure than for the delinquency equations.

Among the occupational groups there was less differentiation than in the delinquency risk equations, and the patterns that did emerge were quite at variance with the earlier results. For example, salesmen, who had been uniformly high risk in the delinquency case, yielded low risk coefficients for foreclosure in both the MBA and NAMSB equations (both were significant). Conversely, executives and managers, who had been among the better risks in the delinquency equations, provided the only significant coefficient in the USSLL foreclosure equation, but at the high-risk end of the spectrum. The other groups were pretty well clustered near the center, with the relative sizes of the coefficients varying from equation to equation. In contrast to the earlier results, therefore, it would be difficult to argue that there is any discernible relationship between occupational skill level and foreclosure risk.

Number of dependents and borrower age appeared to have little systematic effect on foreclosure risk, although some of the coefficients were significant at the 1 per cent level. The pattern appeared to be more or less random, however, with one possible exception. Very large families (eight or more dependents) yielded high risk coefficients in all three samples, and two of these were significantly greater than zero. This suggests that, within the usual family size limits, little distinction arises between delinquent loans and those in foreclosure; but that once the family becomes unusually large, foreclosure risks increase substantially. Marital status did not contribute significantly to the foreclosure risk. Both USSLL and NAMSB versions yielded lower coefficients for married than for unmarried borrowers, but none of these estimates were statistically significant.

Loan purpose (available only in the USSLL sample) again proved to be highly significant, as did junior financing. Loans for refinancing, as before, yielded a large risk coefficient, but the highest risk is associated with construction loans. This tends to confirm a belief long held by lenders that builder loans pose substantially higher than average foreclosure risks. Given the earlier finding that construction loans carry relatively high delinquency risks, the size of the foreclosure risk coefficient indicates that lenders' fears are well founded. What may be surprising, however, is the degree of risk associated with refinancing. This coefficient too was high for both the delinquency and foreclosure categories, suggesting that these loans are perhaps more hazardous than has heretofore been thought. Junior financing likewise appears to forebode ill, since the risk coefficient in the foreclosure equation is, as it was in the earlier version, quite high.

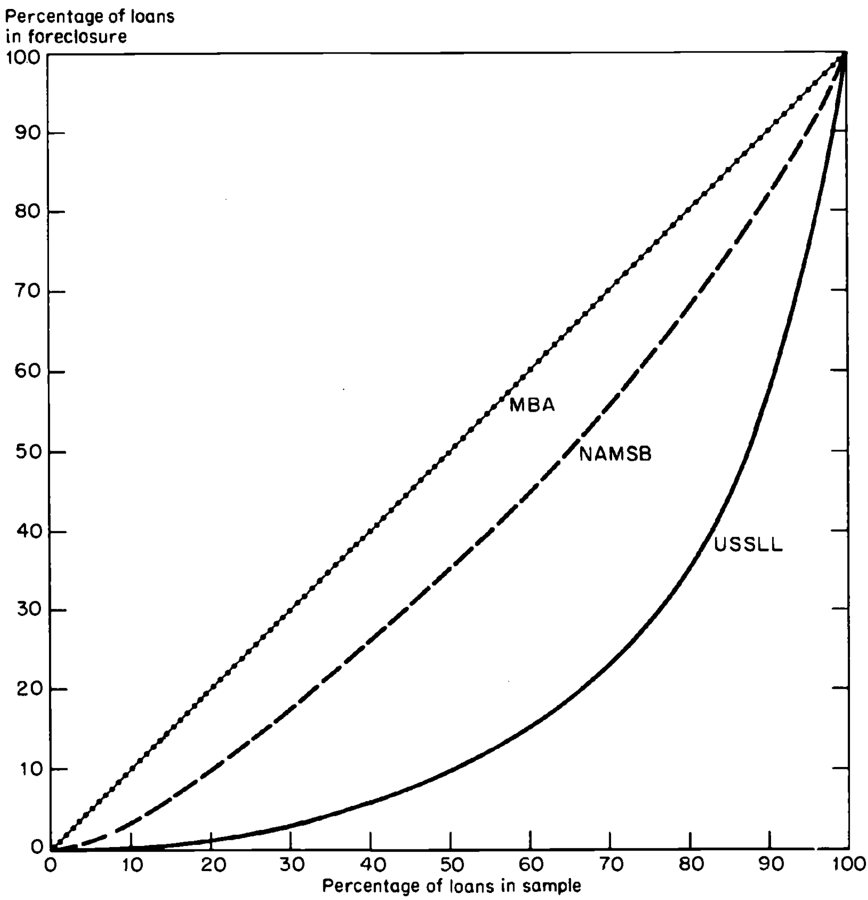
Regional coefficients, as was true in the delinquency equations, were highly significant, but are of little interest in themselves. Lender type, which applied only to the MBA equation, yielded a number of highly significant coefficients. Basically, they show that other things being equal, i.e. the other variables in the equation, the mortgage banker's chances of foreclosure are much less on loans serviced for commercial banks and individuals or on those held in his own account than they are for loans held for other financial intermediaries. Whether this finding reflects differences in foreclosure policies, types of loans for which the banker does servicing, or some other factor, we cannot say. It certainly doesn't imply that the *over-all* risk of foreclosure is higher for lenders other than commercial banks and individuals who leave the servicing to the mortgage banker. The higher risk interpretation once again applies only to the variables whose influence we specifically excluded. Loan type also proved to be a significant factor in the MBA equation, though not in the NAMSB. As was the case with delinquency risk, conventional loans carried the highest risk, followed by FHA's other than 203's, VA's, and FHA 203's. Differences between the latter three categories were not significant, but they all yielded significantly lower coefficients than conventionals.

POOLED EQUATIONS

As was true for the delinquency risk equations, pooling caused some loss in discriminating power. Nevertheless, F ratios for all the equations were well above rejection limits for significance at the 1 per cent level. Coefficients of determination were off somewhat, falling to 11 per cent for the USSLL, 5.5 per cent for the MBA, and 8.2 per cent for the NAMSB equation, but the percentage decline was not as great as in the delinquency equations. There was also a perceptible reduction in the area between the Lorenz curves and the reference line, although the USSLL equation continued to display very good discriminating power (Chart 12).

CHART 12

Lorenz Curves, Delinquent vs. Foreclosures, Pooled



SOURCE: Appendix Tables B23–B25.

Loan-to-value ratio and term to maturity continued to show a positive correlation with risk, but with some loss in significance. The loan-to-value ratio, which had been highly significant in the MBA and NAMSB individual versions, met the 5 per cent criterion in only NAMSB after pooling. The term-to-maturity variable was significant (at the 1 per cent level) only in the USSLL version. While these results do not lend great support to the findings for the individual versions, they certainly do not contradict them.

The payment-to-income ratio coefficient was positive in two of the three equations (USSLL and MBA), but only one of these (USSLL) was significant. The NAMSB coefficient, as in the individual version, was negative but not significant. Again the evidence would seem to support the contention that this variable probably does a better job of measuring financial burden for foreclosure risk than for delinquency.

With but two exceptions, the remaining variables closely followed the patterns already commented upon for the individual versions of the equations. The exceptions, both in the MBA equation, occurred in the marital status and loan-type coefficients. Marital status, in the earlier version, yielded a lower value for single than for married borrowers, but the difference was not significant. This time the order was reversed, even though the coefficient just fell short of the critical level for significance. The result still leaves marital status in the doubtful category as far as significance is concerned, but would indicate that if a relationship does exist, married borrowers are probably less risky than single. As was the case with the delinquency equations, combining FHA 203's and other FHA's appeared to destroy the value of the loan-type variable. None of the coefficients was significant in the pooled version (where they had been in the individual), and the coefficient for conventional loans ranked between FHA's and VA's. These results are parallel to those for the NAMSB (where no breakdown of FHA's was employed).

STRAIGHT FORECLOSURE RISK: CURRENT LOANS VERSUS LOANS IN FORECLOSURE

As was pointed out at the beginning of the foreclosure risk discussion, the previous two sections can be viewed as providing useful measures of the *conditional* probability of foreclosure, given that a loan is already in default. The present section, however, focuses upon the *unconditional* probability of foreclosure, and does so by matching the characteristics of current loans against the characteristics of loans in foreclosure. Since the USSLL data provided uniformly better results in the equations discussed above, it was decided to rely exclusively on that sample for developing the tests in this section. The decision was based in part on consideration of computation expense and in part on a desire to keep the arguments as straightforward as possible. Our previous results lead us to believe that our conclusions would not be substantially altered by the introduction of additional equations.

The discriminating power of estimated relationship was, on the whole, quite good. The *F* ratio was clearly significant at the 1 per cent level, even though it was numerically smaller than some of the others. The coefficient of determination was also lower, accounting for only about 5 per cent of the variation. The Lorenz curve, however, indicates that both of these statistics have a downward bias. The curvature (Chart 13) is only slightly less than it was in the USSLL individual version of the conditional delinquency risk equation, and substantially greater than any of the others. It should be noted, for example, that the lowest quartile of loans, as ranked by risk index value, contained less than 1 per cent of the loans in foreclosure. The lowest half only contained about 11 per cent of the foreclosures, and the lowest three-quarters only about 23 per cent. It would be erroneous, therefore, to place much weight on the low value of the R^2 statistic.

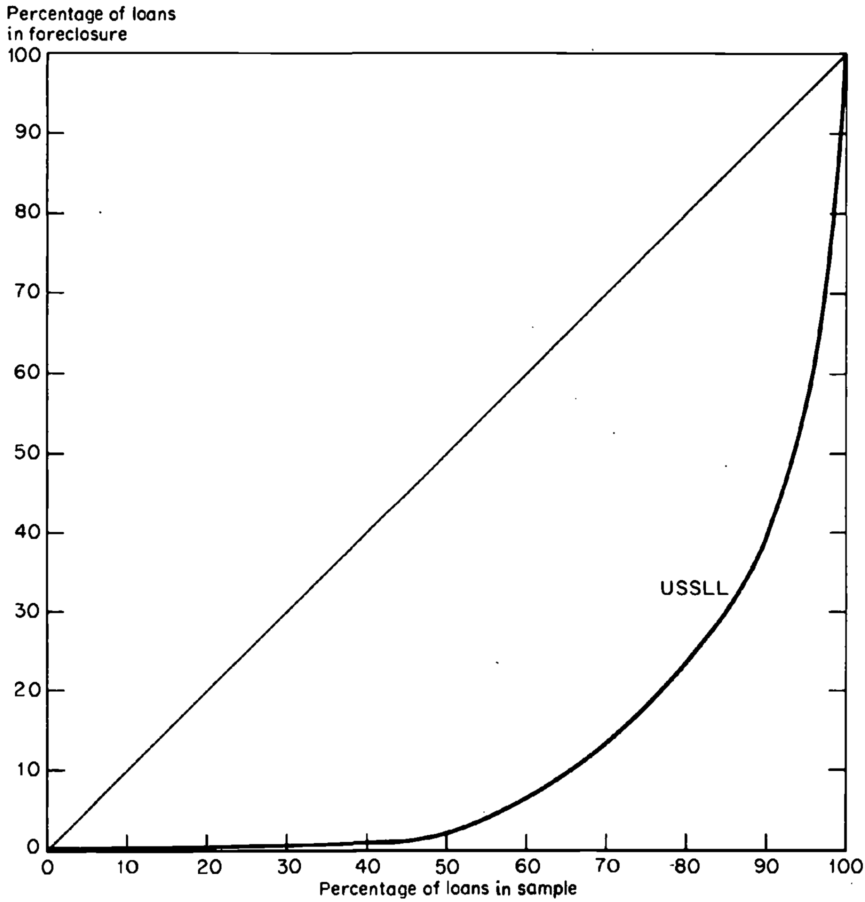
While there were no particular surprises in the signs of the coefficients, some of the variables which we had expected to be significant did not turn out that way. Loan-to-value ratio, payment-to-income ratio, occupation, marital status, and number of dependents all failed the tests, and borrower age yielded only one significant coefficient. It is worth noting that loan-to-value ratio and payment-to-income ratio both yielded positive coefficients, but only the former was anywhere near the required level for significance. Term to maturity, however, yielded a rather large positive coefficient and was significant at the 1 per cent level.

Once again loan purpose and junior financing were the key indicators of risk, the latter provided by far the highest coefficient and correlation with the dependent variable. Construction loans continued to lead loans for all other purposes in terms of contribution to risk, but refinancing and repair were not far behind. Home purchase remained at the low-risk end of the spectrum, and by a significant amount. Regional coefficients also yielded highly significant differences, again emphasizing the need to isolate such influences whenever possible. It is almost certain that some of the other relationships we estimated would have come out differently had this variable not been allowed for.

In general, these results follow the pattern one would expect from examining the coefficients in the current vs. noncurrent and delinquent

CHART 13

Lorenz Curve, Current vs. Foreclosures, USSLL



SOURCE: Appendix Table B26.

vs. foreclosure equations. That is, the coefficients in the present equation tended to fall between the coefficients for the earlier versions. Thus, if the signs on the previous equations differed, the sign for the current vs. foreclosure equation could be either plus or minus, depending on which of the two risks, delinquency or conditional foreclosure, dominated. Where the signs were the same on the earlier versions, the present equation yielded a coefficient whose *sign* confirmed that, but whether or not the coefficient was significant depended on the strength of the earlier relationships. Thus, for example, while loan-to-value ratio was significant in the delinquent vs. in foreclosure equation, it was not in the current vs. noncurrent, and this latter relationship dominated in the current vs. in foreclosure. The usefulness of the latter equation is underscored both by its evident discriminating power and by its ability to draw out such relationships.