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MANAGING STUDENT LOAN DEFAULT RISK: Evidence from a Privately Guaranteed Portfolio

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This research models default development for a large proprietary dataset of private (nonfederally guaranteed) education loans extended to law school students in the early 1990s. Employing the statistical techniques of survival analysis and credit scoring, the study documents a pronounced seasoning effect for such loans and demonstrates the robust predictive power of credit bureau scoring of student borrowers. Other constructs found to be statistically predictive of default include school-of-attendance (or, alternatively, a measure of perceived school reputation), geographic location of attended school, and new attorney unemployment rate within certain regions. Although statistically predictive, these last constructs are of far less substantive importance in assessing credit risk than are the effects of portfolio seasoning and scoring (an ordinal measure of the risk of extending credit to an individual based upon their past credit behavior). The article challenges the prevailing approach to modeling student loan default (one that searches for "institutional" as well as "borrower" explanations) and suggests a return to the older, simpler banking paradigm of borrower willingness and borrower ability to repay.

Student loans, borrowed directly from or guaranteed indirectly by the federal government, have become the lifeblood of American higher education. Few colleges could maintain anywhere near their current levels of expenditures without the liquidity provided their customers through the various loan programs administered primarily by the U.S. Department of Education. It has been estimated, for example, that among 1995–1996 graduates, more than 50% of students earning bachelor's or master's degrees and in excess of 70% of professional degree earners had their education at least partially financed through federal student loans (American Council on Education, 1997).

The most generous loan amounts are those provided for post-baccalaureate studies. By the late 1990s, a professional or graduate school student under his or her signature alone could borrow as much as $18,500 per year in government-insured loans—up to a cumulative total of $138,500. Yet despite this seemingly

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large annual allowance, for certain high-cost graduate professional programs, such as law, business, medicine and dentistry, federally guaranteed loans have proven inadequate to fund a student's tuition and living costs at many private and even some public schools. To overcome these federal limits, a number of *privately* guaranteed loan programs have evolved. One such program is managed by the Access Group, Inc. (formerly Law Access), a nonprofit, membership organization whose board of directors is elected by the deans of the country's American Bar Association-accredited law schools.

Since its separate incorporation in 1993, the Access Group has originated over $1 billion in private loans, primarily its Law Access Loan (LAL) product, a long-term (15 years for the loans analyzed here), unsecured, variable rate consumer installment loan for law students. It is the LAL private loan product that is the focus of this paper. Specifically, we document the early default experience observed among a sample of over 13,000 law school private loan recipients and report on a set of variables found predictive of default. The study, it is believed, provides the first publicly available statistics on default for a privately guaranteed student loan portfolio. Furthermore, it is the first to focus narrowly on default determinants among a set of post-baccalaureate students. Technically, it introduces two statistical approaches, survival analysis and credit bureau scoring, which have not been used together to analyze student loan defaults in any prior published literature. But finally, beyond any narrow contribution this research may make toward understanding loan defaults among lawyers, its broader purpose is to challenge the very framework currently accepted within the higher education community for analysis, in general, of the student loan default problem.

FEDERALLY SPONSORED STUDENT LOANS AND PUBLIC POLICY

Because of their long history, size and importance to higher education, federally sponsored student loan programs have been the subject of virtually all previous academic literature on default. Additionally, because the credit losses inherent in these loan programs are ultimately borne by the American taxpayer, most of the studies on student loan default have addressed public policy issues, that is, How should government manage credit risk while maintaining the policy purpose behind the programs? Many of the studies have taken as a point of departure the most visible mechanism the federal government has employed to manage that credit risk, the refusal to fund students attending institutions where a very high proportion of former students have failed to repay their loans. This policy has been interpreted in casual discussion as "blaming" the institutions for the actions of their students. To borrow from the title of an early student loan study, "Whose fault is default?" (Wilms, Moore, and Bolus, 1987) has been the manner in which the policy question has been posed.

To understand the context in which this question is addressed requires some background on the idiosyncracies (as they would seem to a commercial bank credit officer) of the federally sponsored loan programs. First, the programs, under the mandate for broad access to higher education, require that no student attending an approved institution be denied credit, with the sole exception that an applicant cannot have previously defaulted on a student loan (other indicators of poor credit are generally to be ignored). Second, the loans have a 10-year repayment period, yet no principal or interest payments are required while a student continues in school. Interest does accrue during this in-school period and is capitalized onto the principal when the loan finally enters repayment. Third, the definition of an approved institution of higher (postsecondary) education, one whose students are therefore eligible for federally sponsored loans, is very widely drawn. Ivy League graduate students are lumped together with those attending the Professional Dealers School of America—a school for blackjack dealing—for purposes of determining federal loan eligibility (or at least they were until the latter finally went out of business having reported a default rate of 73% in 1990; Koselka and Oliver, *Forbes*, 1995).

So called proprietary schools, generally for-profit training centers (e.g., hairdressing, truck-driving, commercial art) most of whom are fortunately not as dubious as the Professional Dealers School, nevertheless fall outside of what is normally understood to comprise higher education (which is perhaps why the term "postsecondary education" is a more appropriate one to describe what federal loan programs fund). These proprietary schools are eligible to have their students (who need not have finished high school) receive federally sponsored loans under the same eligibility rules as are applied to Harvard students. With such anecdotal evidence as the Professional Dealers case featured in the popular press, it is easy to form the impression that what was at one point an embarrassingly high overall federal loan default rate (as high as 22.4% in FY90), had been "the fault" of certain schools, in particular a handful of perhaps unscrupulous firms, concentrated among the proprietary class of postsecondary institutions. But as virtually all multivariate statistical studies concur, the data simply do *not* support this view.

PREVIOUS STATISTICAL EVIDENCE ON STUDENT LOAN DEFAULT

The first statistical study of student loan default patterns with wide academic readership was the article whose title, "Whose Fault is Default?" has come to summarize the research agenda for much of the literature in the field (Wilms, Moore, and Bolus, 1987). The study was initiated by the California state legislature which was specifically interested in investigating characteristics and practices of those postsecondary institutions in the state whose default rates were "excessively high" (defined as 15% or greater). This focus effectively narrowed the study to a sample of students who had attended one of 93 California community colleges or 140 accredited proprietary schools. A single academic year's students, 1982–1983, were chosen for analysis; 3,155 individuals with complete data were examined using hierarchical step-wise discriminant analysis. The dependent variable was the dichotomous measure of "default or not" with the independent, predictor variables being of two general classes: (1) characteristics of the borrower, and (2) characteristics and practices of the school of attendance. The hierarchical step-wise approach meant that the independent variables fixed first in time (the borrower characteristics) were entered first into the model, followed by the institutional factors. Using this approach it was found that, after taking into account the characteristics a student brought with him or her to postsecondary study, very little predictiveness was added to the model by also taking into account the characteristics and practices of the school the student attended. With but one exception, adding any of the institutional predictors failed to significantly increase the overall predictiveness of the model. Summarizing their findings, the authors emphasize the "predetermined"/noninstitutional predictors of default: "In short, by knowing a borrower's ethnicity, family income, citizenship, and program—as well as whether the borrower had graduated from high school and completed his or her program—one can accurately predict default in almost two out of three cases" (Wilms, Moore, and Bolus, pp. 48–49). Nevertheless, the article did not report the distribution of defaulters by individual school. School characteristics and practices—not individual school identification—were used to predict default. It would have been interesting to know if particular schools or particular "vocations taught" at a group of schools were related to extraordinary default experience (the Professional Dealers anecdote again comes to mind). This is the question of whether the model was correctly specified; that is, whether institutional factors might, after all, be important predictors of default if one measured them differently.

Obvious caution is advisable in extrapolating the Wilms et al. results to try and explain loan repayment behavior among different student types, as, for example, among graduate law students, the population of concern to this current article. Indeed, it is questionable whether the default determinants found among proprietary and community college students should be expected to bear *any* relationship at all to default predictors for professional school students. In the context of public policy, as Harrison (1995) and Volkwein and Szelest (1995) have stressed, it would seem misguided to design government financial aid programs under the assumption that all borrowers sharing the broad label "postsecondary student" can be classed together. Nevertheless, studies that have followed Wilms et. al. but employed broader samples of student borrowers have generally confirmed their one fundamental finding—that borrower rather than institutional characteristics best predict defaults.

Knapp and Seaks (1992), drawing methodological guidance from earlier work by Greene (1989), studied nearly 2,000 traditional 2- and 4-year college students who had attended one of 26 Pennsylvania institutions, had borrowed federally guaranteed Stafford loans, and had graduated (or dropped below half-time enrollment) during the academic year 1984–1985. Using the maximum-likelihood technique probit (Greene, 1989, had used a related technique, Tobit), the authors found each of the following borrower characteristics to have a statistically significant association with a lower probability of default: (1) parent's income, (2) presence of two parents at home, (3) the student's having graduated (vs. dropping out), and (4) the student's race (whites defaulting less than blacks). The most substantively important variables were found to be graduation and race. For example, a white student with a degree, coming from a two-parent family with a $10,000 family income was reported to have a 2.4% default probability, while the same student, were he/she not to have graduated, was found to be 15.1% default risk. A graduating black student from a two-parent, $10,000 income family, had a 14.2% default risk. That same black student, were he/she not to graduate, carried a 44.1% default risk. Importantly, the authors tested for any school-specific default risk by explicitly entering 25 dummy variables into their models (to account for the 26 different institutions from which data were drawn). They found that the 25 dummies, taken as a group, did *not* significantly improve the predictiveness of their models; nor did any single dummy indicate that any of the schools had a default probability significantly different than all others, after taking into account the individual characteristics of student borrowers. They conclude, emphatically, that "*at least for this sample, there is nothing related to individual collegiate institutions that has any impact upon default rates*" (Knapp and Seaks, p. 407; italicized in original). But, as with the earlier Wilms et al. study, the particular sample of students investigated by Knapp and Seaks, drawn exclusively from among 2- and 4-year colleges in Pennsylvania, potentially limits the generalizability of their findings.

Default analysis on a broad base of student loan borrowers was made possible with the publication of the government-sponsored 1987 National Post-Secondary Student Aid Study (NPSAS). Sampling from among aid recipients who had begun their postsecondary education between 1973 and 1985, the NPSAS documents borrowers' personal, demographic, and family characteristics, academic performance, and financial and occupational circumstances. Several investigators (Dynarski, 1994; Volkwein and Szelest, 1995; Flint, 1997; Volkwein, Szelest, Cabrera, and Napierski-Prancl, 1998) have published statistical analyses of data drawn from the NPSAS. Each of these studies is generally supportive of the notion that predictors of student loan default should be sought at the level of the individual. For example, Flint (1997), using a step-wise technique for entering blocks of possible predictors into his model (similar to the step-wise approach of Wilms et al.) found that "though student background characteristics are strongly related to default, very little additional predictive success is contributed by any blocks of variables entered after student background characteristics” (p. 341). Likewise, Volkwein, Szelest, Cabrera and Napierski-Prancl (1998) found that “default rate differences are based more substantially upon the nature of the borrowers and their achievements than upon the types of institutions the borrowers attended” (p. 224), although it should be noted that the focus of the Volkwein et al. study was on understanding the purported relationship between race and default rather than on the issue of institutional vs. personal variables as predictors of student loan default.

In an earlier analysis of the NPSAS data, however, Volkwein and Szelest (1995) had implicitly accepted as a focus for their investigation the traditional student loan research question, “Whose fault is default?” This Volkwein and Szelest article examined a sample of over 4,000 borrowers drawn from throughout the United States who had graduated or left school by 1994 and for whom relatively complete transcript and survey data were available from the 1987 NPSAS. In the first of the article’s two models, borrower-level characteristics were examined for statistical association with default along with a set of variables used to capture any association of institution-type with default. The test of the latter was a simple one with institution-type captured by categorizing a student’s school of attendance as either a proprietary school, 2-year college, 4-year college, or doctoral university. In one of the article’s principal findings, the authors demonstrate that, when entered into a multivariate logistic regression (a technique akin to both probit and Tobit), the set of dummy variables developed to capture the effect of institution type *failed* to significantly add to the model’s ability to predict default after individual borrower characteristics were taken into account. In contrast, several borrower characteristics—for all types of students—were found significantly predictive of default risk (race, marital status, dependent children, degree completion, college GPA, parental/family support, and current income). In a second model, which because of data limitations excluded proprietary schools, a more exhaustive set of institutional descriptors was tested for association with default risk, and although two were shown to be statistically significant (proportion of minority students, and “auxiliary” expenditures per student), the authors conclude that “(w)e find little evidence that institutional characteristics have an impact on loan default” (p. 59). However, unlike the Knapp and Seaks study, neither of the Volkwein and Szelest models incorporate institution-*specific* dummy variables. This leaves open the possibility that *individual* institutions in their study may have had significantly worse default records than the norm, even after taking into account the characteristics of the student borrowers they attract.

In summary, based on available statistical evidence, there appears to be general consensus among investigators that the determinants of student loan default are primarily borrower-based rather than linked, in any causal manner, to the borrowers’ school-of-attendance. Where there is a relationship detected between a category of school and high default rates, it is not because “offending” schools are causing defaults. High default schools are those who attract students with a high likelihood to default. Default proclivity is a pre-existing condition.

DATA ANALYSIS

All of the literature reviewed above analyzed federally guaranteed student loan portfolios. In contrast, the data analyzed in this study are drawn wholly from a privately guaranteed loan program, one with a tighter credit screen than is employed in federally mandated programs. Furthermore, the data represent loans to a very narrow subset of student borrowers—law school students at American Bar Association-accredited schools. It is not clear that the relationships identified in the previous empirical literature, overwhelmingly associating default risk with borrower characteristics, will necessarily hold, or hold as strongly, among law students borrowing privately guaranteed funds. As part of our statistical analysis, therefore, the issue of borrower proclivity vs, school-of-attendance as predictors of default risk will be re-addressed.

The core dataset analyzed here contains information on more than 60,000 law school students, all borrowers of at least one private Law Access Loan (LAL) and graduating (or otherwise leaving school) in the years 1991–1996. Generally, only information directly pertinent to each borrower’s loan obligations (e.g., number of loans, dollar amount of loans, first disbursement dates, date of student’s graduation, date and amount of any default claims paid) is present in the dataset. The only additional data are borrowers’ date of birth and school-of-attendance (i.e., school of graduation or last school attended). No other demographic data are maintained. Statistical and actuarial results derived from this full initial dataset are those described in the following section, “Survival Analysis.”

A subset of the aforementioned 60,000 record dataset was then formed to investigate in more detail the possible predictors of default. This subset was comprised of all borrowers originating a LAL loan during academic year 1991–1992, which represented a sampling of law student borrowers generally scheduled to graduate in the years 1992, 1993, and 1994. Credit scores for each of these borrowers at the time of loan underwriting were sought from archival sources, and when available, appended to the borrower’s loan repayment record. A dataset was thus formed containing over 13,000 1991–1992 private borrowers with loan performance information coupled to each borrower’s historic credit score. This dataset serves as the basis of the analysis described in the section “Borrower Credit Risk Class as a Default Predictor.”

Finally, school-of-attendance descriptors (e.g., school identity dummies or reputational measures) along with geographic and economic data (e.g., the unemployment rate among new law graduates in the region of each student’s graduation the year they graduated) were added as data elements to the credit scored dataset to investigate various alternative explanatory models of default behavior. These models are examined in the article's third and last data analysis section.

Survival Analysis

As its name implies, survival analysis (Allison, 1995) comprises a set of statistical techniques originally designed to model mortality patterns, death, over time among an organic, often human, population. These techniques are particularly intuitive when the expected time pattern for "events" (death being one type of "event") within a homogeneous population can be expressed as a simple mathematical function. The classic functional form, especially in the natural sciences, is exponential. For example, let S(t) represent the probability of any individual in the population under study surviving beyond time t and specify this "survival function" as $S(t) = e^{-\lambda\tau}$ where t is continuous time and λ is some constant. Associated with each survival function is a "hazard function" which captures the important intuitive notion of risk; that is, associated with S(t) is a hazard function h(t), which may be viewed as giving the instantaneous probability at time t of a non-recurring event taking place (dying, for example). The beauty of the exponential survival function is that its associated hazard function is a constant, $h(t) = \lambda$. If your survival function is exponential, your risk (instantaneous probability) of dying remains constant over time. This does *not* mean, of course, that for a population of individuals with identical survival functions the expected *number* of deaths is constant each period, but only that, of those individuals alive at the beginning of each period (some having died earlier), the same *proportion* is expected to die.

Loan defaults can be thought of as analogous to deaths, "borrower mortality" perhaps. We suspect that the hazard function (default risk as a function of time) for a population of borrowers, initially here all considered identical, can be modeled simply, albeit perhaps not quite as simply as $h(t) = \lambda$. Indeed, actuarial studies assessing the capital adequacy of loan guarantors (insurers against default risk) use such modeling techniques to guide their extrapolation of a portfolio's observed early default experience to estimate an ultimate life-of-the-portfolio default rate. Figure 1 displays data in a format common to actuarial presentations. Displayed are the actual and projected conditional quarterly borrower default rates as of Summer 1996 for all LAL borrowers leaving school in the period 1991–1996. Actual conditional default rates are displayed as black and white bars and projected rates are the gray cross-hatched bars. Over $1 billion dollars in original principal and more than 60,000 borrowers are represented. The x-axis of the graph is the time dimension measured in quarters since borrowers' graduation (or otherwise withdrawal) from law school. Note that the x-axis does not represent fixed calendar dates. Each borrower is examined for

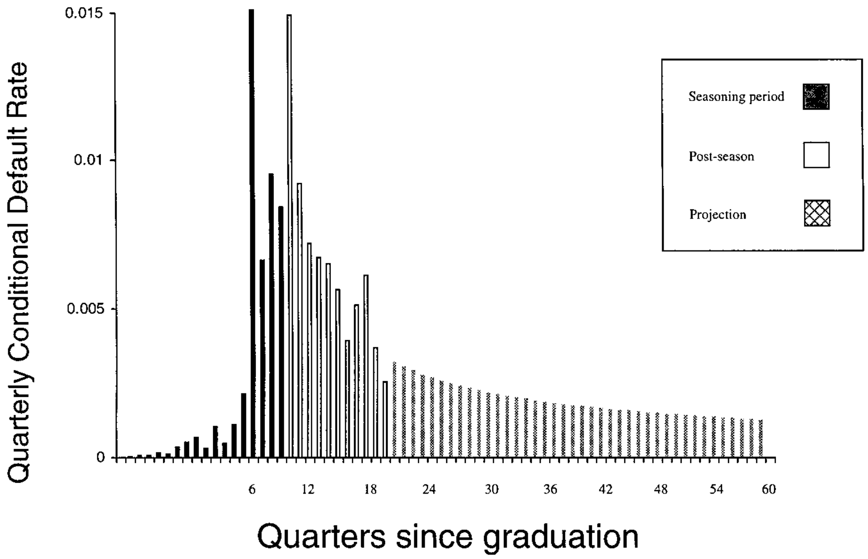

FIG. 1. Quarterly conditional default rates.

his or her own elapsed time since their graduation and categorized together with other borrowers with identical elapsed times, independent of the actual calendar dates of their graduations. These data form a super-set of the 13,000+ borrowers examined in greater detail in the remainder of this article. And, although nothing beyond time trend (survival) analysis was performed on this larger dataset, two fundamental findings about privately guaranteed law student loan default patterns may be derived from the conditional default graph in Figure 1.

First, for largely institutional reasons detailed elsewhere (Monteverde, 1998, Section 2b, Model 1), there appears to be no simple hazard function to describe the default pattern for loans defaulting in or prior to the ninth quarter after graduation. This period, shown in black on Figure 1, we will refer to as the period of loan "seasoning." In subsequent analysis we will capture the effect of this early period (using a dummy variable), but will not attempt to specify any functional form for the default hazard during this period of seasoning. In fact, all periods prior to and including the ninth quarter will be treated as if they were one period.

The second important observation to be made from Figure 1 concerns the conditional default pattern for those periods following loan seasoning. Beginning in Quarter 10, something akin to a mortality curve does appear. Consequently, data from Quarters 10–20, the white bars, may be used to extrapolate future conditional defaults, the gray cross-hatched bars. This is, in essence, the actuarial exercise. This extrapolation is accomplished by specifying a simple function that describes reasonably well the limited default experience of the portfolio to date. The function used to extrapolate the graph of Figure 1, however, is not quite as simple as the exponential survival function (constant hazard function) discussed earlier; that would have led to a projection of flat conditional default rates. Instead, the fitted hazard rate, as graphed here, is of the form $h(t) = \lambda t^{\alpha}$ (a Weibull distribution) with λ some constant, and in this case, $\alpha < 0$; the hazard rate itself declines with the passage of time.

The Weibull hazard function implies a linear relationship between the log of time and log of hazard,

$$\log h(t) = \mu + \alpha \log t, \text{ where } \mu = \log \lambda.$$

Borrower Credit Risk Class as a Default Predictor

Although the time trend provided by this survival analysis is an important prerequisite for modeling default, our real interest is in finding a set of predictor variables that, after taking into account the general default pattern over time, significantly adds incremental explanatory power to the model. We seek predictor variables that differentiate between borrowers. The first such variable to be considered, and the one used here to operationalize the key construct of borrower-based default proclivity, are borrowers' "credit scores" at the time of their loan origination.

Credit Scoring: Background

Generally, two types of credit scoring schemes have evolved in consumer lending. The first type of score, often called a generic (or "bureau") score, is typically available in the U.S. from each of the three major credit bureaus (TransUnion, Experian, and Equifax) who gather and maintain the elementary, detailed information on each individual on which the score itself is based. These elementary data include such things as an individual's number of credit cards, the number of 60-day delinquencies in the last 2 years, the number of derogatory notations, notices of bankruptcy, and so forth. The second type, often labeled proprietary score card development, typically uses credit bureau information *plus* other data about potential borrowers such as their length of residency, length of employment, and income. These items are normally gathered from a loan application. The score card is called "proprietary" because each credit grantor assigns its own "weights," measures of relative importance, to the borrower attributes (whether sourced from a credit bureau or a loan application) that are then used to construct a summary credit score. These weights are determined by previous statistical modeling of that credit grantor's own specific applicant pool. Both types of scores have the same purpose—to provide a single summary measure validated to statistically predict default risk.

The credit scores used in this study are strictly of the first type, generic scores. Accordingly, individual characteristics such as personal or family income, assets owned, race, and marital status are *not* a part of the study because they are not direct credit history elements, and therefore, are not inputs to any generic credit bureau scoring algorithm. The specific credit score series used was TransUnion's, brand named Empirica; this series returns values ranging from 395 to 848, with higher scores indicating better credit risks.

Although a set of credit hurdles had always been employed to qualify the Access Group private borrowers, the generic credit score number itself had not been a part of the underwriting decision process. Nor had past values for borrowers been routinely retained by the Access Group. However, historical credit reports are archived by the credit bureaus themselves. Therefore, with the aid of TransUnion, credit scores were recalculated for Law Access Loan (LAL) borrowers who had taken out this private loan product during academic year 1991–1992. Archived credit reports were rescored for 13,508 unique borrowers; these constitute the database upon which the remainder of this article's models are based. The recalculated credit scores were as of the approximate time that the loans were underwritten for the 1991–1992 academic year (June 1991).

In the analysis that follows, each borrower's individual credit score, derived from their own unique credit history, is used as the single summary measure of their relative creditworthiness. Although use of this borrower-based measure has not been previously reported in the student loan default literature, it is a variable that quite directly captures the borrower-risk proclivity construct that this literature has generally found most predictive of default. But rather than directly using the raw scores themselves (which although quite fine-grained are nevertheless ordinal not interval-level measures), each borrower was instead classified into one of four risk classes based on their score. The categories were determined by first finding ranges that divided the 13,508 borrowers into roughly equal thirds. The two best risk class borrowers were designated "low risk" and "moderate risk," respectively. The bottom third of borrowers, which comprise roughly what the consumer credit industry would normally rate "sub-prime," was then subdivided again into "high risk" and "very high risk" borrowers. The cut-off between these two latter categories was set at the score below which a co-signer was required, in a recent tightening of the Law Access Loan program credit requirements, for the 1997–1998 academic year. For the 1991–1992 retrospective sample, 9% of borrowers had scores that would have placed them in the "very high risk" class.

Credit Class Analysis

To test the predictiveness of credit score classifications, two models were initially built, then combined. First, a test of credit classification as a predictor of default prior to the end of the ninth quarter after graduation, the seasoning period, was performed. Second, a model was constructed of credit class as a default predictor *after* the seasoning period. For both the second preliminary and combined models, the influence of time-since-graduation on default risk was taken into account by imposing a specific functional form for loan mortality (as had been done in graphing Figure 1) onto borrowers surviving into the "post-seasoning" period. The statistical technique employed was logistic regression, the same basic approach used by Volkwein and Szelest (1995).

To be technically precise, logistic regression, when employed in models in which time is a predictor variable, does not model the affect of time on the *probability* of default, the manner in which we have discussed default risk in this article thus far. Instead, logistic regression (the logit model) estimates the risk of default as *odds*. But the relationship between probability and odds is straightforward, probability = odds/(1 = odds), and for small probability values, the two are nearly identical. The logit model typically returns estimates very close to those of models estimating the hazard function directly (the complementary log-log transformation) and has the advantages of readily interpretable coefficients and of being a more familiar technique.

In forming the combined model it was necessary to control for the 9 quarters of initial loan seasoning and to take into account the additional effect of the passage of time on already seasoned loans. Hence, the following adjustments, consistent with survival analysis techniques, were made before the combined logistic regression model was run. First, a pooled borrower cross-section/time series database was created that contained for each borrower surviving into post-seasoning, one observation for each quarter after the ninth up to and including the quarter in which the borrower either defaulted or in which observations on that borrower were "censored" (that is, last observed as a non-defaulter in the last observation period). Second, post-seasoning time periods were re-indexed to the beginning of each borrower's post-season; for example, observations on borrowers made in the tenth quarter after their graduation from law school were re-indexed to time Period 1, the first quarter of their post-season. Third, the database was expanded to include all borrowers (whether or not they survived into the post-season), each borrower coded as having defaulted or not sometime during the multi-quarter seasoning period; for consistency this time period, although longer than subsequent periods, was indexed as Period 0. This third step is the one in which the two preliminary models were effectively combined. The logistic regression on this expanded pooled cross-section/time series database was run with the dummy variable "Seasoned?" which was set to NO if a given observation was for the borrower during the period of seasoning (Period 0) and YES otherwise. In addition, the log time variable was treated analogously to an interactive variable, only entering the model when the dummy "Seasoned?" was YES: that is, only for observations during a borrower's post-seasoning period.

Both preliminary models indicated similarly significant and substantive predictive power for credit score class. In both, the probability of a very high risk (low credit scoring) borrower defaulting was found to be roughly five times the probability of a low risk (high credit scoring) borrower defaulting. A detailed discussion of these preliminary results may be found in Monteverde (1998). Logistic regression results for the combined model, however, are presented in Table 1.

As may be seen in the table, borrower credit class was modeled as a set of 3 dummy predictor variables representing 3 of the 4 levels that credit category can take (the fourth level serving as a reference level). Table 1 displays estimated coefficients for each of three levels of credit risk, their associated standard errors, and chi-squared statistics after controlling for the effect of the simple passage of time. Also shown is the chi-squared statistic for all three levels of credit category taken together. All test statistics show the credit class variables to be significant at a .0001 (very high) level of confidence.

The intercept of the combined model represents the log odds of default for very high risk borrowers (the reference credit class) during the seasoning period (the reference value for "Seasoned?" = NO), where log-of-time-period variable does not come into the model as it does not for borrowers still in their seasoning period. The odds of default for very high risk borrowers during the seasoning period, therefore, is exp(–2.176) = .113, or when converted back to probability, a default probability of about 10%. For low risk borrowers the default odds are calculated by simply aggregating the coefficient associated with the low risk credit class with the intercept before taking the antilog; that is, the default odds are exp(–2.176–1.658) = .022, or a default probability of 2% for low risk bor-

TABLE 1. Combined Model: Predicting Default Odds from Borrower Credit Risk Category

Variable	Coefficient Estimate	Standard Error	Chi-Squared
Intercept	–2.176	.077	795.4****
Credit Class			
Low Risk	–1.658	.108	234.5****
Moderate	–1.100	.094	138.0****
High Risk	–0.502	.089	31.6****
Together			290.4****
Log-of-Time-Period	–0.690	.071	94.8****
Seasoned?	–1.110	.087	164.3****
Log Likelihood	–4725.25		

****Significant at the .0001 confidence level.

rowers during their period of loan seasoning—one-fifth the default likelihood of very high risk borrowers. Notably, this five-fold default likelihood difference between the most and least risky borrowers holds not only in the seasoning period, but also in at least the early post-seasoning periods. This suggests a persistent power for credit score as a predictor of student loan default that is perhaps surprising given the considerable time that elapses between loan origination and any observation of repayment performance. Recall that the LAL product, like the federally guaranteed loan it emulates, capitalizes interest while the student remains in school.

School-of-Attendance, Geographic, and Economic Variables as Default Predictors

Statistical Association of School-of-Attendance with Student Loan Repayment Behavior

All previous literature on student lending has de-emphasized the predictive value of knowing a student's school-of-attendance, after having accounted for individual borrower attributes, when assessing default risk. However, only one of the studies reviewed here, Knapp and Seaks (1992), had explicitly tested for a school effect at the individual institution level. Most studies had instead first grouped schools by type (e.g., proprietary vs. 2-year college vs. 4-year college vs. doctoral university), then sought a relationship between type-of-school and default; or alternatively, the studies sought a statistical relationship between a set of school characteristics (e.g., proportion of minority students, expenditures per student) and the likelihood of borrower default among graduates. We follow Knapp and Seaks here, entering into the combined model described above a set of 126 dummy variables representing the possible schools-of-attendance (i.e., law school graduated or last attended) with which each borrower can be uniquely associated, with a 127th school acting as a reference school. Only data from students attending 127 schools were usable here (vs. data from students at 168 schools used to construct the combined model of Table 1) because some low volume schools had no defaulters (or, as in one case, the single borrower from a school defaulted). The number of usable borrower records was thus reduced from 13,508 to 13,003. Results of the logistic regression incorporating both borrower characteristics (i.e., credit category) and school-of-attendance are given in Table 2. Statistics for only the combined effect of all school-of-attendance dummy variables taken together are shown here. Notably, this variable set *does* significantly add to the predictiveness of the model even after accounting for borrower credit score categories and time elapsed since graduation. Indeed, the set of variables is highly significant, judging from the associated chi-squared statistic. This finding is in stark contrast to the results reported by

TABLE 2. Predicting Default Odds from Borrower Credit Risk Category and Identity of School-of-Attendance

	Coefficient Estimate	Standard Error	Chi-Squared
Intercept	−2.220	.223	98.8****
Credit Class			
Low Risk	−1.630	.110	219.0****
Moderate	−1.080	.096	127.1****
High Risk	−0.507	.091	30.7****
Together			268.0****
Log-of-Time-Period	−0.673	.071	89.2****
Seasoned?	−1.110	.087	161.9****
School Identity			
126 dummies together			236.6****
Log Likelihood	−4553.44		

****Significant at the .0001 confidence level.

Knapp and Seaks whose set of 25 school-specific dummies *failed* to significantly add to the predictiveness of their student default model. In further contrast to Knapp and Seaks, who reported that *none* of their individual school dummies were significant, results here indicate that students attending 11 specific schools had significantly worse (at a .05 confidence level) default odds than students attending the reference school; students at 2 schools had significantly better (at the .05 confidence level) default odds than reference school students, even after accounting for each borrower's individual credit risk and the general pattern of defaults over time.

School Reputation, Economic and Geographic Considerations

Despite the above evidence for an association of school-of-attendance with default likelihood, association does not imply causality. It does not necessarily follow from the results previously discussed that a school's specific administration or faculty, for example, have *any* influence per se, for better or worse, on their graduates' loan repayment behavior. Our findings are completely consistent with the observation made by Knapp and Seaks, based on their own very different results, that any two schools "could exchange the entire staffs of their financial aid offices and continue to observe essentially the same default rates" (p. 411). Although statistically significant even after controlling for borrower-based credit score and elapsed time since graduation, the school-of attendance variable set may still be simply masking more basic underlying influences.

First, it is possible that a school's historic reputation may color employers' views concerning the quality of the school's law graduates and it is through that relative perception that graduates get higher or lower paying jobs (or jobs at all). Employment opportunities, in turn, may be the more *direct* influence on default likelihood. To test for the possible influence of perception of school reputation on default, each borrower record was appended with the value for median 1995 matriculate LSAT score for the borrower's school-of-attendance (U.S. News and World Report, 1996). Any reputational measure will serve our purpose. And, although quite controversial within the legal education community, median LSAT has the advantage of being a standardized measure. Controversial or not, average matriculate LSAT of a graduate's school-of-attendance is a variable we would be negligent *not* to include in a model of loan repayment if potential employers may be suspected of using it to select recruiting venues.

Second, if as suggested above, economic factors are truly those which are most directly influential on loan repayment behavior, then some measure of the economic climate facing each law school student upon graduation might prove quite useful in predicting default likelihood. The National Association for Law Placement (NALP), an association of law school placement officers, publishes a statistical series that traces the percentage of law school students from each graduating class unemployed (and seeking employment) six months after graduation. Furthermore, since at least 1992, NALP has published this series *by region* based on reports received from schools in each of nine geographic divisions of the country concerning the employment success of their graduates (National Association for Law Placement, 1993, 1994, 1995). Nine regional statistics were available, therefore, for each of the three graduating law school classes (1992, 1993, and 1994) investigated in this research. A variable was formed from these NALP data and appended to each borrower record in the dataset reflecting the unemployment rate among all law students graduating in a borrower's same graduation year from schools in the same region as the borrower's school. The measure, therefore, may be thought of as reflecting any supply/demand imbalance for new lawyers graduating from schools in the region of the borrower's own school during the same period the borrower would have been looking for his or her first job as an attorney.

Third, a need to account for specific regional differences is suggested by an examination of the location of the schools categorized as having a "negative" school effect. Ten of the 11 negatively classed schools were located in just 3 of the 9 geographic regions of the country: the Pacific (West Coast states plus Hawaii), the West South Central Region (Texas, Oklahoma, Arkansas, and Louisiana) and the South Atlantic states (the East Coast from Florida up to Delaware, including West Virginia and Washington, D.C.). The eleventh school was located in a state contiguous to the West South Central Region. Accordingly, a new dummy variable (call it, imprecisely, the "Sunbelt" effect variable) was formed and was set to 1 for all borrowers graduating from schools in one of the 3 above-mentioned regions and 0 otherwise.

Employing the three new constructs introduced in this section, (1) perceived school reputation, measured by the median matriculate (1995) *LSAT* score for the borrower's school-of-attendance, (2) regional labor market supply/demand imbalances, measured by the *Regional Law Graduate Unemployment Rate* for the borrower's graduation year, and (3) specific geographic differences, measured by the dummy variable *Sunbelt*, differentiating law school graduates from the Pacific, West South Central, and South Atlantic Regions from law school graduates elsewhere, plus certain interaction effects between these three new constructs, the article's final model may be constructed. This model's statistics are displayed in Table 3. The model's goal was the prediction of default odds using variables that *substitute* for the explicit use of school-identity dummies. Consequently these dummies were removed in this final model, the premise being that the apparent school effect may actually be masking underlying economic determinants of default likelihood.

When only the new main-effect variables, median LSAT, Regional Law Graduate Unemployment Rate, and the Sunbelt dummy, were entered into a preliminary model (not shown here) substantial colinearity between the Sunbelt

TABLE 3. Predicting Default Odds from Borrower Credit Risk Category, School Reputation, Geographic, and Economic Considerations

Variable	Coefficient Estimate	Standard Error	Chi-Squared
Intercept	4.438	1.308	11.5***
Credit Class			
Low Risk	−1.614	.109	219.8****
Moderate	−1.078	.094	130.5****
High Risk	−0.496	.090	30.3****
Together			271.8****
Log-of-Time-Period	−0.684	.071	92.7****
Seasoned?	−1.124	.087	167.4****
Median LSAT	−0.043	.008	25.9****
Sunbelt Region	4.079	1.956	4.3**
Sunbelt × LSAT	−0.029	.013	5.5**
Sunbelt × Unemployed	4.639	1.341	12.0***
Log Likelihood	−4623.6		

****Significant at the .0001 confidence level.
***Significant at the .001 confidence level.
**Significant at the .05 confidence level.

and Unemployment variables resulted, requiring that the latter be dropped as a main-effect predictor in the final model, entering instead as an interactive variable. In fact, two interactive variables were found to incrementally add to the model's predictiveness: (1) Sunbelt crossed (interacting with) with median LSAT, defined as the median matriculate LSAT score of school-of-attendance for Pacific, West South Central, and South Atlantic Region graduates only (otherwise 0), and (2) Sunbelt crossed (interacting with) with Regional Law Graduate Unemployment Rate, defined for Sunbelt graduates only, as the unemployment rate in their region for the year of their graduation (otherwise 0).

Table 4 outlines the *substantive* significance of each of the predictor variables found to be statistically significant in Table 3. Note that the set of Sunbelt variables effectively divide the model in two, one for graduates from the Pacific, West South Central, and South Atlantic regions and the second for graduates from schools in all other regions. The substantive importance of certain of the predictors, therefore, can be most easily illustrated by examining their influence

TABLE 4. Independent Influence of Predictor Variables on Default Odds

1. Credit Class: A borrower whose credit score at loan origination indicated that he or she was a low credit risk has default odds 1/5 those of a very high risk borrower, all other things (e.g., time into repayment and year and region of graduation) being equal. The analogous relative odds figures for moderate and high risk borrowers when compared with very high risk borrowers are 1/3 and 3/5, respectively.

2. Time: Seasoned? The odds of any particular borrower defaulting in the first quarter after their period of loan seasoning (i.e., the tenth quarter after graduation) are about 1/3 whatever that borrower's odds had been during their entire seasoning period.

3. Time: Log-of-Time-Period. For all borrowers who survive beyond the period of loan seasoning, quarterly default odds decrease by 1/3 for every doubling of the time period into that post-season.

For Sunbelt-Regions Graduates:	**For non-Sunbelt-Regions Graduates:**
4. *LSAT:* For each 1 point drop in the median matriculate LSAT score of the borrower's school-of-attendance, default odds increase by 7.5%.	LSAT: For each 1 point drop in the median matriculate LSAT score of the borrower's school-of-attendance, default odds increase by 4.4%.
5. *Regional Law Grad Unemployment Rate:* Each percentage point increase in regional unemployment for new attorneys is associated with a 4.7% increase in default odds.	N/A (not applicable in non-Sunbelt model)

on default odds for each of these two geographically defined student populations considered separately. This approach is taken in the bottom section of Table 4 for predictors 4 and 5. For the set of predictors numbered 1–3 (the original variables of the Combined Model of Table 1), their influence on default odds continues to be modeled as independent of school reputation, employment, and geography; the estimated coefficients for these predictors and therefore their substantive importance are the same for all borrowers in all regions. These predictors, whose influence on default odds remains quite consistent with earlier models, are discussed in the top section of Table 4.

One difference that the interactive model highlights is an apparent geographic difference in the strength of influence that perceived school reputation, as measured by median matriculate LSAT score, apparently has on default risk. Even outside the three Sunbelt regions, a school's median LSAT is a statistically significant predictor of graduates' default risk even after controlling for an individual borrower's credit profile and time-since-graduation. The spread in median 1995 matriculate LSAT score for schools outside the Sunbelt regions was 24 points (from 171 to 147), implying a predicted default rate 2.8 times higher ($=[1.044]^{24}$) for graduates from schools with the lowest reputation vs. graduates from schools with the highest reputations, all other things (e.g., borrower's credit profile) being equal. But in the Pacific, West South Central, and South Atlantic regions, at least during the period investigated here, the effect of school reputation appears to have been even more dramatic. For schools within these Sunbelt regions, the relative default odds between graduates from schools differing in median LSAT scores by a similar 24 points is 5.6–times ($=[\exp(.043 + .029)]^{24}$). This differential holds even after controlling, as before, for individual borrower credit risk, time-since-graduation, and now also for the statistically significant effect of differing levels of new attorney unemployment during the years 1992–1994.

The effect of new attorney unemployment rate on default risk is a particularly intriguing finding, especially as modeled above as one pronounced only in the Sunbelt regions. As background, it should be noted that the association of a borrower's default likelihood with the simple fact of their having graduated from a Sunbelt school (the "main" effect) is statistically significant and generally positive. That is, for example, consider a graduate from a Sunbelt law school with an average matriculate LSAT median (156, the median of medians among all schools in the sample) seeking their first job in a year of average new graduate unemployment in the Sunbelt (13.4%, the median unemployment rate recorded among the three Sunbelt regions over the three years, 1992–1994). That graduate is modeled as having a nearly 20% higher odds-of-default than an otherwise identical graduate from a non-Sunbelt school with the same "average" reputation (as measured by matriculate LSAT median). On top of this is added the variability in default likelihood contributed by swings in Sunbelt new graduate unemployment rates themselves, adding 4.7% to a Sunbelt graduate's odds-of-default for each one-percentage point unemployment rate rise. A borrower from our "average" law school who graduated under the best (albeit not good) of employment conditions existing for Sunbelt graduates (1993 in the West South Central Region with an unemployment rate of 10.3%), nevertheless had default likelihood only 3/5 that of an otherwise identical graduate seeking a job in the worst of recruiting years in the worst of regions (1992 in the Pacific Region with an unemployment rate of 20.7%). In summary, for a law graduate from an average reputation school, Sunbelt regionality is associated with both a higher expected odds-of-default and greater variability in those odds, the latter because of swings in new attorney unemployment rates.

DISCUSSION AND CONCLUSIONS

Perhaps the question that has set the agenda for student loan repayment research, "Whose fault is default?" is simply the wrong question to ask. Instead, as this research suggests, the student loan default problem might more constructively be analyzed not as an issue of morality or blame, but as one of economics. Applying the commercial bankers' old platitude, loan repayment is simply a matter of the borrower's *ability* and *willingness* to repay.

In this research *willingness to repay* may be thought of as having been proxied by an individual's credit bureau score at the point of loan origination. This metric has been long accepted among consumer lenders as a reliable measure of a loan prospect's past credit behavior and as a statistical predictor of such behavior in the future. However, this is the first published research, we believe, demonstrating generic credit score to be a robust predictor of default odds for privately insured student loans. Using a survival analysis approach, it was demonstrated that the predictive power of generic credit scores persists even beyond the period of loan seasoning, a period that stretches more than two years after a student's law school graduation and from 3–5 years after the loan was originated and the credit score calculated.

Not only was a persistent and statistically significant association found between an individual borrower's credit score classification and their default odds, but this relationship was found to have substantive and quite practical implications. Guided (misguided?) in part by the conventional student loan research agenda, this article has devoted considerable space searching for default predictors underlying a statistically significant school-effect uncovered in the data, considerations such as school reputation, geography, and macroeconomic conditions. Although these results are certainly of academic interest and offer some mild credit management direction, they can also become a practical distraction. At the end of the day, the borrower's individual credit profile remains of paramount importance in predicting relative default risk. Consider the predictions of the article's final and most elaborate derivation as detailed in Tables 3 and 4.

In this model Yale University, with its top reputation as measured by its high median LSAT score, is estimated to produce law graduates with the best default profile of all non-Sunbelt schools (and because it is a non-Sunbelt school, its graduates' default odds are unaffected by regional unemployment swings). Nevertheless, a very high risk *individual* borrower graduating from Yale is a *poorer* default risk, according to this model, than a low risk borrower who happens to have graduated from a school with even the very lowest reputation among all schools in the Pacific Region in 1992, the year when graduates from this Sunbelt region's low-reputation schools were most disadvantaged. The borrower-based credit effect simply swamps any school reputation, region, or macroeconomic considerations.

Although discounting its practical importance, as mentioned previously, this research *does* ironically uncover a statistically significant association of school-of-attendance with graduates' default risk. This is a relationship all previous literature had failed to document, generally to the relief of the investigators analyzing the data. Why relief? Within the framework of "Whose fault is default?" evidence of a school effect in predicting graduates' repayment behavior, incremental to the effect of borrower-based predictors, would naturally have led to an uncomfortable discussion of what one school may be doing better than another school. But, again, the discussion is only uncomfortable if blame (or credit) is at issue. Perhaps a school can do *nothing* differently, at least in the short run, to produce any appreciable improvement (or deterioration) in its graduates' loan repayment prospects.

A statistical school effect may simply be one manifestation of graduates' *ability to repay* their student loans. Indeed, our results indicate that it is another set of variables, more economically inspired predictors based upon a school's location, its reputation, and in some regions, the prevailing attorney labor market, that may actually lie behind the apparent school effect. It is tempting to weave new hypotheses concerning the determinants of loan default from the results of our final model. Could it be that certain regions of the country have structural imbalances—too many law schools serving essentially local labor markets? Could this structural imbalance explain why schools in some regions produce graduates whose prospects are more sensitive to school reputation than in other regions?

While interesting, such speculation is of limited practical importance. If it is ability to repay that we are seeing manifested, then *anything* that raises or lowers a student's capacity (a law student's or *any* student's) to service whatever debt they may have incurred should be a predictor of repayment behavior. A student's *individual* success (or failure) in gaining employment and the direct determinants of that success are examples of default predictors that might prove more powerful than such considerations as school-of-attendance, or regionality which, at best, are only indirectly related to employment success. If we wish to move beyond willingness to repay in seeking default predictors (which, as a practical matter, we may not need to do), then we should look to indicators that measure as directly as possible, an individual student's future ability to repay. And the same predictors should work as well for federally guaranteed loans as for privately guaranteed ones. In short, we will search for different predictors of student loan default of all types, perhaps with greater success, to the extent that we jettison the older question of "Whose fault is default?" to place the responsibility squarely on the borrower, and seek to understand what separates borrowers who are both willing and able to meet their student loan obligations from ones who either cannot or will not.

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