Journal of Econometrics 157 (2010) 110–119

Contents lists available at ScienceDirect

Journal of Econometrics

journal homepage: www.elsevier.com/locate/jeconom

The construction of empirical credit scoring rules based on maximization principles☆

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ARTICLE INFO

Article history:
Available online 30 October 2009

JEL classification:
C14
C25
C51
C53

Keywords:
Credit scoring
Binary variables
Profit maximization

ABSTRACT

We examine the econometric implications of the decision problem faced by a profit/utility-maximizing lender operating in a simple "double-binary" environment, where the two actions available are "approve" or "reject", and the two states of the world are "pay back" or "default". In practice, such decisions are often made by applying a fixed cutoff to the maximum likelihood estimate of a parametric model of the default probability. Following (Elliott and Lieli, 2007), we argue that this practice might contradict the lender's economic objective and, using German loan data, we illustrate the use of "context-specific" cutoffs and an estimation method derived directly from the lender's problem. We also provide a brief discussion of how to incorporate legal constraints, such as the prohibition of disparate treatment of potential borrowers, into the lender's problem.

1. Introduction

In this paper we examine some econometric implications of the decision problem faced by a profit- or utility-maximizing lender. We make the simplifying assumption that the lending decision is essentially a binary decision—the terms of the contract are exogenously determined from the decision maker's point of view. The potential profit the lender can make by granting the loan is nevertheless a function of these terms. A similar, and equally important, assumption is that there are essentially two possible consequences of granting the loan. In one state of the world the borrower complies fully with the terms of the contract (i.e. pays the loan back on schedule); in the other the borrower defaults. Again, the loss incurred by the lender in case of default is a function of the terms of the contract.

A lender's ability to generate profits depends fundamentally on how successful they are in predicting default based on observed socio-economic characteristics of the borrower and the terms of the contract. A formal (and widely used) method of relating these variables to the conditional probability of default is known as credit scoring. The method entails assigning a predetermined number of points to the possible values of each covariate. Credit is then granted to applicants with total scores over a fixed cutoff value and denied to those below the cutoff. Such a decision rule is of course intended to ensure that credit is extended to those with a high probability of paying it back. (In fact, credit scores can be regarded as transformed default or compliance probabilities.) For a review of credit scoring methods see, e.g., Hand and Henley (1997) and the references therein.

Hence, there are two aspects to constructing a "good" credit score-based approval rule. First, a "good" estimate of the probability of default must be obtained conditional on the observed covariates. Second, the cutoff must be drawn at an "appropriate" level. But what do "good" and "appropriate" mean? The ultimate goal of the lender is to maximize (expected) profit or utility, and the construction of an optimal approval rule should reflect this goal. We draw on the methodology in Elliott and Lieli (2007) to argue that (1) the optimal (profit- or utility maximizing) cutoff is in general "context-specific", i.e. it varies from contract to contract or borrower to borrower; and (2) the objective (or loss) function used to estimate the conditional probability of compliance should be derived from the lender's economic optimization problem.

In constructing a scoring rule, one must also take into account numerous laws and regulations concerning lending activity. In particular, there is extensive legislation aimed at preventing disparate treatment of certain "protected" or minority groups. The prohibition of disparate treatment has various implications for our framework. Certainly, lenders cannot exhibit or exercise preferences that are disadvantageous for these groups. Moreover, lenders are prohibited from using minority status as a variable

☆ The authors thank Nicholas Kiefer, John Relman and two anonymous referees for their advice. All errors are our responsibility. The paper was part of Robert Lieli's dissertation at the University of California, San Diego.

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doi:10.1016/j.jeconom.2009.10.028

in estimating the conditional probability of default/compliance. Nevertheless, even if a score-based approval rule is carefully designed to avoid *disparate treatment*, it may still have an unintended *disparate impact* on a protected group, and lenders have been held responsible for this effect under the law (see Barefoot, 1997; Cocheco, 1997). We show how our framework can be used to design approval rules that mitigate or eliminate disparate impact.

The plan of the paper is as follows. First (in Sections 2 and 3), we will derive the optimal approval rule under a general formulation of the lender's objective function, where in addition to profits, the lender may care about some characteristics of the borrower and the laws regulating the lending process. We will show that the optimal decision rule is of the form

> "extend the loan if and only if the conditional probability of compliance is greater than a cutoff",

where the cutoff is determined by the lender's objective function and may vary from person to person or with the characteristics of the loan. This is in contrast to existing practice where it is customary to use a uniform cutoff, which is often chosen according to a simple rule of thumb (e.g. one half or some quantile of the estimated default probabilities; see, e.g., Fortowsky and LaCour-Little, 2001).

Second, following Elliott and Lieli (2007), we will argue in Section 4 that the modeling and estimation of the conditional probability of compliance should be based on the lender's economic optimization problem. In particular, we will show that one does not need a fully correctly specified model of this conditional probability in order to consistently estimate the optimal approval rule. Nevertheless, to take advantage of this flexibility, the misspecified model must be estimated by solving the sample analog of the lender's optimization problem, which is not necessarily the same as the maximum likelihood problem. Hence, maximum likelihood-based procedures such as (potentially misspecified) logit or probit regressions may lead to suboptimal decision rules.

Third, in Section 5 we illustrate the proposed methodology by applying it to a data set consisting of records of 1000 customers of a German commercial bank. The results show that the proposed econometric method is indeed capable of producing approval rules in practice that lead to more profitable lending decisions than simple logit regressions. The added gain from the methodology may be enough to compensate for the costlier numerical procedures needed to implement it.

2. A simple view of the lending process

We follow Feelders (2002) in viewing the creditor's problem as consisting of two parts: (i) the selection or decision mechanism; (ii) the outcome mechanism. The former refers to a decision rule by which the lender decides whether to accept or reject a loan application. The focus of the paper is on this binary decision: the terms of the loan contract (the interest rate, the size and duration of the loan, etc.) are assumed to be exogenously given.[1] That is, we view the lender as offering one fixed loan contract or a number of different ones. The prospective borrower then applies for the contract of his choice and the lender merely accepts or rejects the application.

We will assume that each loan contract offered by the lender requires equal monthly installments over the duration of the loan. A loan contract is then completely characterized by the triple $\ddot{X} = (L, D, r)$, where L is the size of the loan, D is the duration of the loan in months and r is the (monthly) interest rate on the loan. The size of the monthly installment I can be determined from the identity

$$L = \sum_{i=1}^{D} \frac{I}{(1+r)^i} = d(r, D)I, \tag{1}$$

where $d(r, D) \equiv \sum_{i=1}^{D}(1+r)^{-i}$.

The outcome mechanism, on the other hand, determines whether a borrower with a vector of observed characteristics $\tilde{X}$ repays the loan in accordance with the terms of the contract. We assume that there are only two possible outcomes in this regard: the borrower either complies fully with the conditions of the contract or the borrower defaults on the loan in which case only a given percentage of the principal can be recovered at the end of the loan's maturity. If Y is the indicator of default (i.e. $Y = -1$ is a "bad loan" and $Y = 1$ is a "good loan") and $X = (\ddot{X}, \tilde{X})$, then the outcome mechanism can be represented as the mapping

$$x \mapsto p(x) = P(Y = 1 \mid X = x).$$

This is the conditional probability of compliance given the observed characteristics of the borrower and the loan contract.

We make a number of additional simplifying assumptions about the lending process. First, even though we allow for loan contracts of varying lengths, time plays a limited role in the setup. The decision problem under examination involves a one-shot static decision—we do not consider the dynamic consequences of the approval decision for the decision environment. Future decisions are not contingent on the decision today. Second, no application is rejected because of the lack of loanable funds. Finally, if an application is rejected, we assume that the lender will instead have the option to invest in a risk-free government bond matching the size and the duration of the loan applied for, but paying a lower interest rate.

While the proposed setup may not be realistic in many aspects, it will enable us to formulate an objective function for the lender, defined over the two-by-two matrix of possible actions (approve/reject) and outcomes (default/compliance). We will show that full knowledge of the outcome mechanism $p(x)$ combined with the given objective function of the lender is sufficient to derive an optimal selection mechanism. Nevertheless, the function $p(x)$ is unknown; one must learn about it from historical loan data using statistical methods. We will argue that, in contrast to standard methods, statistical inference about $p(x)$ (or, more precisely, the optimal decision rule) should be guided by the objective function of the lender.

Finally, we caution that statistical inference about $p(x)$ is complicated by the fact that the data available on credit history is generally contaminated by the selection mechanism used by other lenders. In other words, one can observe the outcome Y only for individuals who were able to pass the selection process of a lender in the past. Therefore, one must either model this selection process or at least recognize that inference will be conditional on being in the formerly selected group.[2] Because the current task at hand is sufficiently challenging without also treating the reject inference problem, we shall abstract from this issue in what follows. Suitable modifications of the approach developed here that accommodate the reject inference problem are the subject of future research.

3. The lender's objective

3.1. Profit-maximizing lender

In this section we consider profit-maximizing lenders, who care only about earning a profit on the loans extended. The profitability

[1] One way to think about this is that the terms of the contract are determined by a competitive market. Another is that the terms of the contract are reviewed at discrete time periods and we focus on optimal decisions in between these periods.

[2] See Feelders (2002) or Crook and Banasik (2004) for a review and evaluation of reject inference methods.