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An Analysis of Fines Default in English Magistrates' Courts.

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Abstract: Data collected by the National Association for the Care and Resettlement of Offenders (NACRO) on fines default in English Magistrates' courts is analysed using a sequential probability model. It is found that an offender's previous history and employment status play a significant role in determining fines default behaviour.

Keywords: fines default; sequential Probit; unemployment; Magistrates' court.

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[1]We are grateful to NACRO for allowing us access to the data. The views expressed in this paper are not necessarily those of NACRO. Thanks also to Rob Brooks for helpful discussions. All remaining errors are our responsibility.

1. Introduction.

Modelling fines default is of importance if policy makers and rehabilitation associations are interested in avoiding any potential problems associated with an individual incurring a subsequent penalty as a result of fine default. By identifying the types of individuals most likely to default, it may be possible to use different penalties (e.g. community service order) to avoid such consequences. For instance, we may find that unemployment of individuals leads to an increase in the probability of defaulting and subsequent imprisonment. In such cases imposing another type of penalty for offenders who were unemployed may avoid the possibility of 'repeat offending' or degeneration of the individual as a result of imprisonment.

In this paper we take a data set on fines default behaviour in English Magistrates' courts[2] and use a sequential discrete choice model, the sequential Probit, to model this behaviour. The aim of our analysis is to determine which factors, if any, influence fines default and to attempt to quantify their impact. Our analysis extends that carried out in previous investigations of this data (see Crow and Simon ((1987a), (1987b)) and Fry and Gill (1988) for details). It is, however, limited in that the data set we have at our disposal is a restricted subset of the data originally collected for the primary study[3] (Crow and Simon (1987a), (1987b)).

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[2]In the Crow and Simon ((1987a), (1987b)) study the pilot work was carried out in a Welsh court. However, the courts selected for the main study were all from England.

[3]To our knowledge the original data file no longer exists. Thus our data set is the only one available on fines default from the NACRO

The plan of the rest of this paper is as follows. Section 2 describes the data for analysis, section 3 summarises previous analyses of this data set and discusses the model we use in our study, the sequential Probit. Our results and a discussion of their implications is included in section 4 and finally section 5 contains our concluding remarks.

2. The Data.

The sample consists of cases taken from six courts in England, chosen from a sampling frame of all Magistrates' courts in England and Wales, excluding courts in London, large cities and small rural towns (see Crow and Simon (1987a), (1987b) for further details of the sample design). The courts were chosen to reflect differences in local unemployment experience. The three types of area chosen were:

(a) relatively low unemployment (South/South East),

(b) very high unemployment (North/North East),

(c) areas that had recently experienced a transition from relatively low to relatively high unemployment during the period of the study (West Midlands).

In each area, two courts were selected on the basis of a comparison of their use of custodial sentences with the regional average. That is, one court traditionally used custodial sentences more than the regional average and the other court used such sentences less than the regional average. Table 1 summarises the structure of the

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study.

sampling scheme in terms of the characteristics of each of the chosen courts.

The data concerns male offenders sentenced between certain dates (ranging from June 1983 to May 1985). From each court, the cases drawn involved males aged 17 or over, whose principal penalty was a fine for offences relating to property crime. Thus we are dealing with a cluster sample based on custodial sentencing traditions and local unemployment experience.

The variables included in our data set are:

Money.

The amount of the financial penalty (fine) is coded 1, ..., 11 with codes between 1 and 10 representing £50 bands beginning at £1 and ending at £500. The code 11 represents a fine between £501 and £2000.

Oscore.

This is the 'offending score' (henceforth Oscore) for the individual, measuring the seriousness of the current offence and the offender's criminal record. The construction of Oscore is described in Table 2. The variable ranged from 3 (least serious) to 19 (most serious). The minimum Oscore for a first offence is 3 and the maximum is 10, while for an offender with a criminal record, the minimum Oscore is 5 and the maximum is 19.

With regard to the variable Oscore our analysis is limited by the fact that this variable has been somewhat arbitrarily constructed by adding a certain number of points for various levels of seriousness of past and present crimes for each offender (see Table 2 for details and Crow and Simon (1987a), (1987b) for further justification for the use of this variable). We should note that given the available data, it is possible for two offenders to get the same Oscore for different things. So, as a total, the Oscore is not very informative.

Employment.

A dummy variable is used to represent the employment status of the individual on the day the fine was imposed. It is coded 0 for unemployed and 1 for employed.

Default.

Records whether or not the individual became at least three weeks behind in the fine payments within six months of its imposition. The variable is coded:

0 - no

1 - yes

13 - no information available.

Warrant.

Records whether, at any time during the study period at the court, a warrant of commitment to prison (suspended or not) in respect of fine default was issued for the defendant. The variable is coded:

0 - no
1 - yes
13 - no information available.

Prison.

Records whether, at any time during the study period at the court, the fine was written off because the defendant had been received into prison. The variable is coded:

0 - no
1 - yes
13 - no information available.

Court dummies.

These dummy variables (C1 → C6), indicating which court the individual is processed at, are incorporated to take account of and quantify the differences, if any, between the courts in terms of sentencing patterns and local unemployment experience.

Initially, the data set contains *804* observations. However, the observations on the (dependent) variables *Default, Warrant* and *Prison* which are coded 13 are excluded as uninformative. This leaves a sample of *740* observations. Within this restricted sample, two observations are found which showed that a warrant was issued, but the offender did not default or go to prison. There are three possible explanations for this result: the codes are mistyped, the warrant was issued for reasons other than fine default, or the warrant was issued for a default that did not occur during the observation period. All three are plausible explanations. However, since they are observationally equivalent, there is no way of telling why we get this result. Thus we exclude these two observations from our analysis which leaves a final sample of *738* observations.

3. The Model.

Previous work with this data on fines default has been carried out by Crow and Simon ((1987a), (1987b)) who fitted linear probability models and Fry and Gill (1988) who fitted a sequential Logit model. We now summarise the salient points of their analyses.

Crow and Simon's study of fines default is only a small part of a larger piece of work concerning the influences, if any, of employment status on sentencing patterns in the courts (see Crichton and Fry (1990), Crow and Simon (1987a), (1987b), and Fry and Gill (1988) for results on this part of the study). The analysis of the fines default data set is primarily concerned with the question of modelling the factors influencing default. After deleting observations for which the Default variable took the value of 13, a separate multiple regression analysis is carried out for each court. That is, Default is regressed upon a constant, Oscore, Employment and Money. It is found that the amount of the fine is not related to the default, but that Oscore is positively and employment negatively related to Default.

Therefore, Crow and Simon fit a 'linear probability' model to the default data. This is unsatisfactory because such models can predict probabilities, in this case of Default, outside of the (0, 1) range and because only fitting one model for Default ignores the possibility of subsequent penalties for individuals who do default. That is, offenders who default on their fine may be subject to further workings of the legal system. These individuals may pay their fines, or they may be subject to a warrant, subsequent to which they either pay their fine or are imprisoned.

To resolve the problem of predictions outside the (0, 1) range a

Logit or Probit model could be estimated (see Maddala (1983)). A solution to the second criticism of failing to take account of the outcome of later workings of the legal system would be to estimate models for the Warrant and Prison variables. In doing this we need to be careful to correctly specify the sample of individuals for analysis. In our data set, only individuals who defaulted are, potentially, the subject of a warrant and only those who both defaulted and had a warrant issued could, potentially, end up in prison. Thus there exists a 'conditioning' in the decision sequence. That is, an individual can only be involved in a warrant or a prison decision if they have already defaulted or defaulted and had a warrant issued.

One approach to dealing with the conditioning is to use a sequential model. Sequential models arise when decision makers face several different decisions which must be taken in a particular time sequence. With regard to modelling fines default, the use of a sequential model may be justified on the grounds that the imposition of a penalty requires a sequence of less serious sanctions, the imposition of each is necessarily separated in time, in that each penalty requires a new step in the decision sequence (e.g. in the case of deciding prison or not, three decisions are required). That is, if we believe that an offender must default before a warrant is issued and default and have a warrant issued before a prison sentence is imposed, then we must use a sequential model to represent this sequence of events. Hence, the unconditional probability of imprisonment must be built up sequentially. This probability is:

$$\Pr(\text{Prison}) = \Pr(P|W \cap D)\Pr(W|D)\Pr(D).$$

Similarly, the unconditional probability of a warrant being issued is:

$$\Pr(\text{Warrant}) = \Pr(W|D)\Pr(D).$$

Thus the probabilities are multiplied out along the branches of a 'decision tree' as illustrated in Figure 1.

This is the modelling strategy adopted by Fry and Gill (1988) who fit a sequential Logit model to this data set, which they describe as "primarily a descriptive exercise" (p.15). They recognise that fitting three separate linear probability models to the whole data set is not adequate, as this would not take account of the conditioning involved. This led them to consider the sequential Logit[4] model in order to derive the conditional probabilities. This decision is deemed to be important, as we expect in general that "the conditional and unconditional probabilities ... differ quite markedly" (p.14).

The explanatory variables included are the same as those used by Crow and Simon, namely Oscore and employment status. Court dummies or interaction terms to account for the differing unemployment experience and custodial sentencing traditions that exist between

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[4]Crow and Simon (1987a) report that using a Logit model confirmed their cross tabulation analysis. Presumably, they are referring to an analysis similar to that of Fry and Gill.

courts are not included. Thus Fry and Gill extend the work of Crow and Simon by recognising and circumventing the problems associated with the linear probability model but do not carry out a full analysis of the available data on fines default.

In this paper we use a sequential model to explain the fines default behaviour. We also make an assumption that any random terms in our model have a normal distribution and thus the model which we use is a sequential Probit model.

There are four possible outcomes to be modelled:

(a) no default,

(b) default, but no warrant,

(c) default, warrant, but no prison,

(d) default, warrant and prison.

However, there are only three decisions to be modelled (see Figure 1), each of which may be represented by a binary choice model *if* we assume that each of the decisions is conditionally independent of the others. The assumption of conditional independence is made to simplify the resulting statistical analysis. It may be a valid assumption to make, as in each decision stage potentially different decision makers are involved. In the first stage, the individual offender decides whether to default or not. Subsequent to the decision to default the magistrates decide whether to issue a warrant or not and if the warrant is issued the (potentially different) magistrates decide whether to imprison the individual or not.

The three binary variables, each corresponding to one of the decisions in the sequence, are:

$$\text{Default} = \begin{cases} 1 \text{ if individual i defaults} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Warrant} = \begin{cases} 1 \text{ if individual i has a warrant issued, conditional on} \\ \quad \text{his having defaulted on the fine.} \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Prison} = \begin{cases} 1 \text{ if individual i goes to prison, given that he has} \\ \quad \text{defaulted on the fine and had a warrant issued.} \\ 0 \text{ otherwise} \end{cases}$$

Using a latent variable model specification for the binary Probit model (see Greene (1990b), Maddala (1983) for details) the selection probabilities of interest are defined as follows:

Probability of Default:

$$\begin{aligned} P_{i1} &= \Pr(\text{Default} = 1) \\ &= \Pr(\mathbf{x}_{i1}'\beta_1 > u_{i1}) \\ &= \Phi(\mathbf{x}_{i1}'\beta_1) \end{aligned}$$

Probability of a warrant being issued, conditional on fine default:

$$\begin{aligned} P_{i2} &= \Pr(\text{Warrant} = 1 \mid \text{Default} = 1) \\ &= \Pr(\mathbf{x}_{i2}'\beta_2 > u_{i2} \mid \mathbf{x}_{i1}'\beta_1 > u_{i1}) \\ &= \Phi(\mathbf{x}_{i2}'\beta_2) \end{aligned}$$

under independence.

Probability of prison, conditional on fine default and a warrant being issued:

$$\begin{aligned} P_{i3} &= \Pr(\text{Prison} = 1 \mid \text{Default} = 1 \cap \text{Warrant} = 1) \\ &= \Pr(\mathbf{x}_{i3}'\beta_3 > u_{i3} \mid \mathbf{x}_{i2}'\beta_{i2} > u_{i2} \cap \mathbf{x}_{i1}'\beta_1 > u_{i1}) \\ &= \Phi(\mathbf{x}_{i3}'\beta_3). \end{aligned}$$

under independence.

Where, in each of the above cases, 'Φ' is the cumulative distribution function of the standard normal distribution evaluated at the given argument and $\mathbf{x}_{ij}$ is the vector of explanatory variables for individual *i* in decision stage *j* (i = 1, ..., 738; j = 1,2,3).

The likelihood function for the entire sequential model is maximised by maximising the likelihood functions of each binary model respectively (see Greene (1990a), (1990b) or Maddala (1983)). Thus the estimation of such a sequential model requires three steps. Firstly, a binary Probit model must be estimated for the decision to default or not, based on the entire sample of observations. Secondly, another binary Probit model must be estimated for whether or not a warrant is issued, given that the individual has defaulted. This involves excluding from the sample those individuals who did not default on the fine. Finally, a third binary Probit model is estimated for whether or not the offenders went to prison, given that they defaulted and had a warrant issued for their arrest. This means reducing the sample yet again by excluding those individuals who did not default, or who defaulted but did not have a warrant issued.

In this model, we may use different exogenous variables at different stages. That is, a variable may be important either throughout the decision-making process or only at certain stages. If we consider the likely direction of the impact of the explanatory variables on the fines default behaviour, *a priori* reasoning suggests that the probability of Default, Warrant or

Prison would increase, *ceteris paribus*, if money or Oscore increase or a person is unemployed as opposed to employed.

Further, the sample design is based upon differing regional employment experience and sentencing traditions. Thus it is important to consider the inclusion of the court dummy variables and their 'interaction' with the other (explanatory) variables: Money, Oscore and Employment as potential explanatory variables in our model to test whether there are indeed differential impacts across the courts.

4. Results.

As explained in section three the estimation of the sequential Probit model is carried out by fitting three binary Probit models to the relevant data. The first model is for the Default decision and is estimated on the whole sample of *738* observations. The second model concerns the Warrant decision and the analysis is carried out conditional upon the individual having defaulted. The resultant sample size is then *421*. The final binary Probit model is for the Prison decision and concerns only those *131* individuals who both defaulted and had a warrant issued.

To obtain our preferred model specification for each step in the sequence we use a series of likelihood ratio tests to test certain simplifications of a 'general model'. The explanatory part ($\mathbf{x}_{ij}$) of this 'general model' is:

$$\beta_1 + \beta_2\text{Oscore} + \beta_3\text{Empt} + \beta_4\text{Money} + \delta_2\text{C2} + \delta_3\text{C3} + \delta_4\text{C4} + \delta_5\text{C5} + \delta_6\text{C6}$$
$$+ \gamma_2\text{C2Oscore} + \gamma_3\text{C3Oscore} + \gamma_4\text{C4Oscore} + \gamma_5\text{C5Oscore} + \gamma_6\text{C6Oscore} +$$
$$\alpha_2\text{C2Empt} + \alpha_3\text{C3Empt} + \alpha_4\text{C4Empt} + \alpha_5\text{C5Empt} + \alpha_6\text{C6Empt} +$$
$$\eta_2\text{C2Money} + \eta_3\text{C3Money} + \eta_4\text{C4Money} + \eta_5\text{C5Money} + \eta_6\text{C6Money}.$$

Model simplification hypotheses are tested within this 'general model'[5] as tests of restricting certain parameters to be zero. The order of testing is such that interaction terms are always tested for significance prior to testing for the main effect. For example, we test for the joint significance of court-Oscore interactions before testing for the overall significance of Oscore.

Both Crow and Simon (1987a), (1987b) and Fry and Gill (1988) find the amount of the fine (Money) to be insignificant in the analysis. Therefore the first set of hypotheses to be tested concern the impact of Money as an explanatory variable. Formally we test the following hypothesis (HA):

H_0: $\eta_2 = \eta_3 = \eta_4 = \eta_5 = \eta_6 = 0$

H_1: at least one non zero η.

If we fail to reject H_0 then we have evidence that there is no differential impact of Money across courts and proceed to test (HB):

H_0: $\beta_4 = 0$

H_1: $\beta_4 \neq 0$.

A priori we might expect Money to, at least, show up as a

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[5]C1 and its interaction terms are excluded to avoid linear dependence in the explanatory part of the model.

significant explanatory variable in the model for the first step (i.e. in the model for Default). However, our results on Money agree with those found in the previous studies using this data set. That is, as Table 3 shows, Money does not turn out to be significant in any of the steps in the sequence.

Our next model simplification hypothesis to be tested is based on a new 'general model' which excluded the variables Money and C2Money, ..., C6Money. The hypothesis we then test is whether there are any interaction effects at all. In other words, we test hypothesis HC:

H_0: $\gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = 0$

H_1: at least one non zero γ or α.

Table 4 shows that in all three models in the sequence HC is not rejected and hence we have evidence that there are no interaction effects of the explanatory variables across courts[6].

Having concluded that there is no evidence of differential impacts of the explanatory variables we proceed to test the significance of the main effects. The first hypothesis of interest here is whether there are any court effects. Thus we test HD:

H_0: $\delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$

H_1: at least one non zero δ.

Table 5 shows that this hypothesis is rejected for both the models for Default and for Warrant (conditional on Default), but that this hypothesis is not rejected for the model for Prison (conditional on

[6]The interaction effects for Oscore and Employment are tested separately with the same results.

Default and Warrant).

The final step in our model selection procedure is to test whether Employment and Oscore are significant explanatory variables in each step. We found that Oscore is significant in all steps, but that Employment is not significant in the model for Prison (t value of -0.09). Hence, our preferred model specification is given in Table 6.

The estimated coefficients are in line with *a priori* expectations namely that Oscore is positively related to the probability of Default, Warrant (conditional on Default) and Prison (conditional on Default and Warrant). Employment is negatively related to the probability of Default and of Warrant (conditional on Default). The court effects in the Default and Warrant (conditional on Default) models serve to move the constant around and are thus difficult to interpret in non-linear models such as these.

Another method of evaluating the effect of explanatory variables is to calculate the point estimates of the effects of these variables on the probabilities of interest. Two sets of probabilities are of interest in this study. Namely, the conditional and unconditional probabilities. The unconditional probabilities refer to the estimated probability of a fined offender, with a given Oscore and employment status in a given court, either defaulting, having a warrant issued or ending up in prison. The conditional probabilities refer to the probability that fined offenders will move a further step in the sequence given that they have reached a certain stage. That is, the probability of a warrant, given that they have defaulted, or the probability of prison, given that they have both defaulted and had a warrant issued.

These probabilities are estimated for all six courts, all Oscore values and both employment states. Figures 2 → 5 show these probabilities for courts one and four[7]. Looking at these figures we can see that the effect of Oscore is positive. That is a higher Oscore value, *ceteris paribus*, raises all of the probabilities of interest. The effect of unemployment, for any given value of Oscore, is to raise the probabilities. That is the curves for the unemployed are "higher" than those for the corresponding employed offender[8]. In other words, an unemployed fined offender is more likely to move further through the sequence (conditional probabilities). He is also more likely to either default, have a warrant issued or end up in prison (unconditional probabilities). This confirms the finding of Crow and Simon's (1987a), (1987b) tabular analysis and of Fry and Gill's (1988) sequential Logit analysis.

5. Conclusions.

In this paper we take an existing data set on fines default in English Magistrates' courts and model it using a sequential Probit model. A sequential probability model is chosen as it best represents the legal process of interest. It also allows us to

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[7]The differences between these two courts are most marked. The other plots tell a similar story and are available on request.

[8]The exception to this is the conditional probability of Prison given both Default and Warrant which is not affected by employment status or court (see Table 6 and its discussion earlier).

produce both conditional and unconditional probabilities.

The original research design is structured to allow for the possibility of differential impacts of the court in which an individual is processed. It is also hypothesised that the offenders previous history, as captured by an index, and his employment status might have an effect on the probabilities of interest.

It is found that there are significant court effects for probabilities of Default, Warrant conditional on Default, but not for Prison conditional on Default and Warrant. The effect of unemployment is to increase the probability of an offender progressing through the process and ending up in prison. Similarly, regardless of employment status, the higher the Oscore (reflecting a more 'serious' offender) the higher these probabilities are. These results confirmed those of earlier, primarily descriptive, studies using this data set (Crow and Simon (1987a), (1987b) and Fry and Gill (1988)).

From a policy viewpoint the result that unemployed fined offenders are more likely to progress through the system must give some cause for concern. This result might prompt consideration of other penalties (e.g. community service order) being used for these offenders in place of a fine.

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Table 1: Characteristics of the courts used in the study.

Use of custodial sentences	Unemployment Low	High	Low → High
Below average	C1	C3	C5
Dates	06/83 → 05/85	07/83 → 12/84	01/84 → 05/84
Above average	C2	C4	C6
Dates	07/83 → 12/84	01/84 → 06/84	01/84 → 09/84

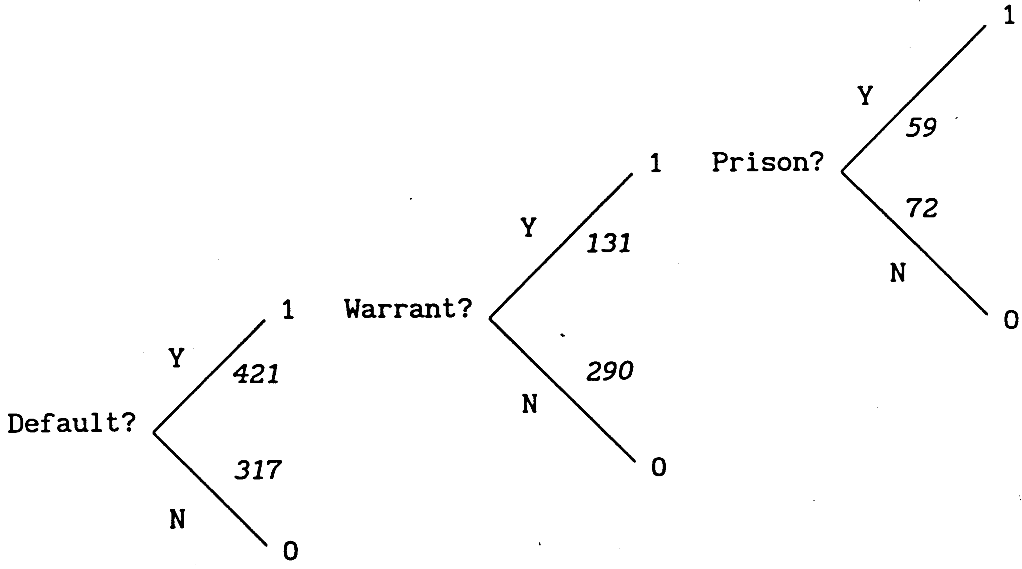
Source: Crow, I. and F. Simon ((1987a), p.8, (1987b), p6).

Table 2: Breakdown of Offending Score.

Item		Add
Current offence:	burglary	4
	theft, fraud, forgery, deception	2
	damage	1
No. of charges:	1	1
	2 or 3	2
	≥ 4	3
Value of property involved:	≤ £20	1
	£20 - £99	2
	≥ £100 or motor vehicles	3
No. of previous convictions:	none	0
	1 or 2	1
	3 or 4	2
	≥ 4	3
Interval:	if current offence was committed less than one year after date of last sentence or release from custody.	1
Similarity:	if any previous offence was of similar type to current one(s).	1
Previous sentences:	for the most severe previous disposal	
	none	0
	discharge, compensation only	1
	fine, probation, supervision, care order	2
	attendance centre, (CSO)	3
	any custodial sentence	4

Source: Crow, I. and F. Simon ((1987b), p.7)

Figure 1: The decision tree for the fines default model.



Figures in italics refer to the numbers of individuals in the sample for each of the outcomes.

Table 3: Test Statistic Values for Money.

	Hypothesis	
Model	HA	HB
Default	6.44	1.82
Warrant	7.82	2.16
Prison	1.81	0.16

Notes: Test of HA has 5 degrees of freedom ($\chi^2_{.05}$ (5) = 11.07) and of HB 1 degree of freedom ($\chi^2_{.05}(1)$ = 3.84).

Table 4: Test Statistic Values for Interaction Effects (HC).

Model	Value
Default	10.98
Warrant	14.70
Prison	17.95

Note: Test of HC has 10 degrees of freedom ($\chi^2_{.05}(10)$ = 18.31).

Table 5: Test Statistic Values for Court Effects (HD).

Model	Value
Default	18.14
Warrant	30.98
Prison	0.77

Note: Test of HD has 5 degrees of freedom ($\chi^2_{.05}(5)$ = 11.07).

Table 6: Estimates for the Sequential Probit Model.

	Default	Warrant	Prison
Constant	-0.5733 (.1581)	-1.6924 (.2990)	-1.2421 (.4211)
Oscore	0.1363 (.0156)	0.1008 (.0220)	0.1013 (.0367)
Employment	-0.5748 (.1049)	-0.6028 (.1565)	
C2	-0.3596 (.1874)	-0.1784 (.3440)	
C3	-0.1948 (.1553)	0.0278 (.2346)	
C4	-0.4323 (.1704)	0.8835 (.2421)	
C5	0.2185 (.1808)	0.4216 (.2376)	
C6	-0.0229 (.1808)	0.7842 (.2443)	
Log-L	-426.65	-220.93	-87.27
L.R.T.	155.08	80.21	7.77
d.f.	7	7	1

Note: standard errors in parentheses.

Figure 2

Court 1: Conditional Probabilities.

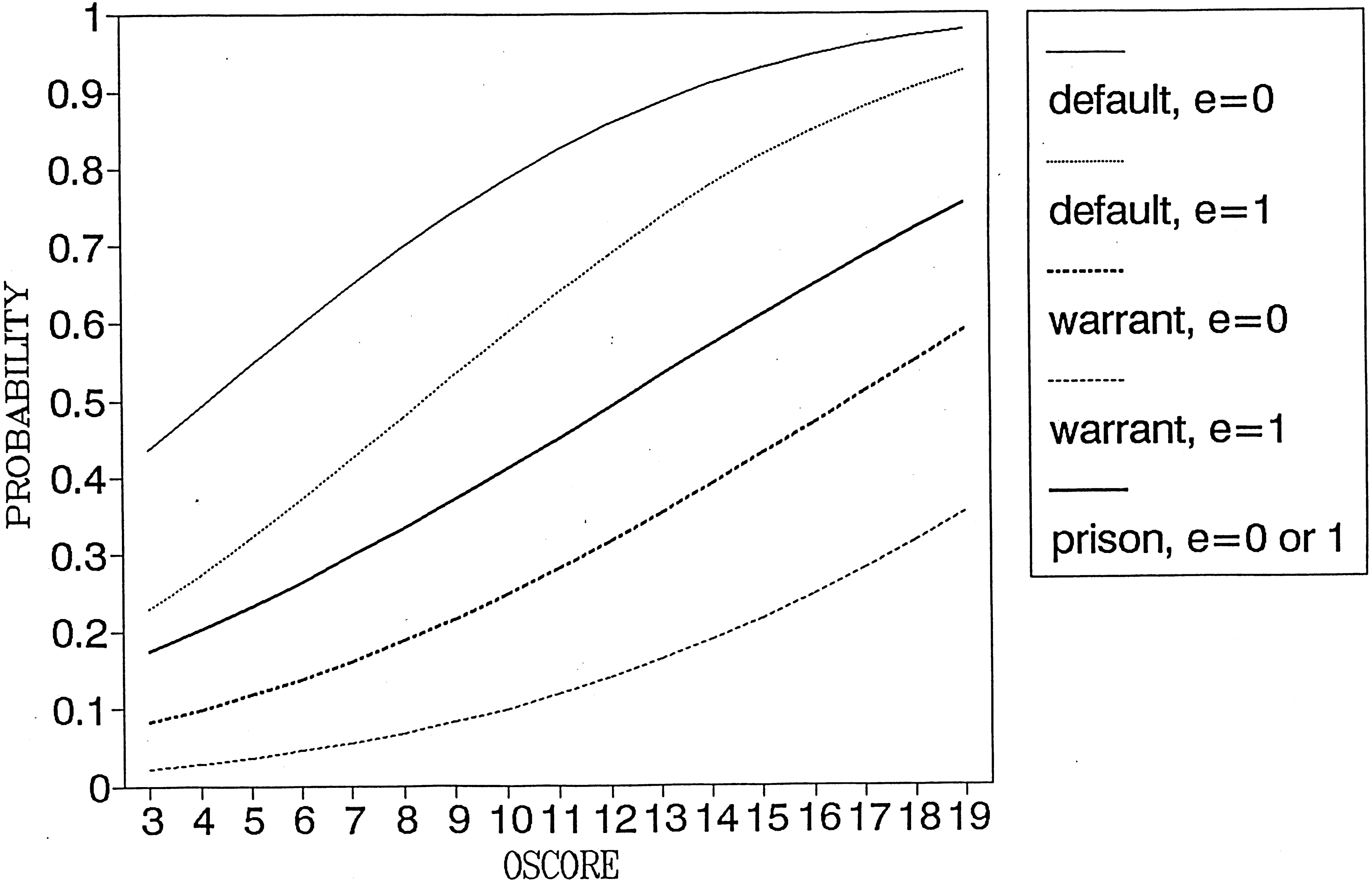
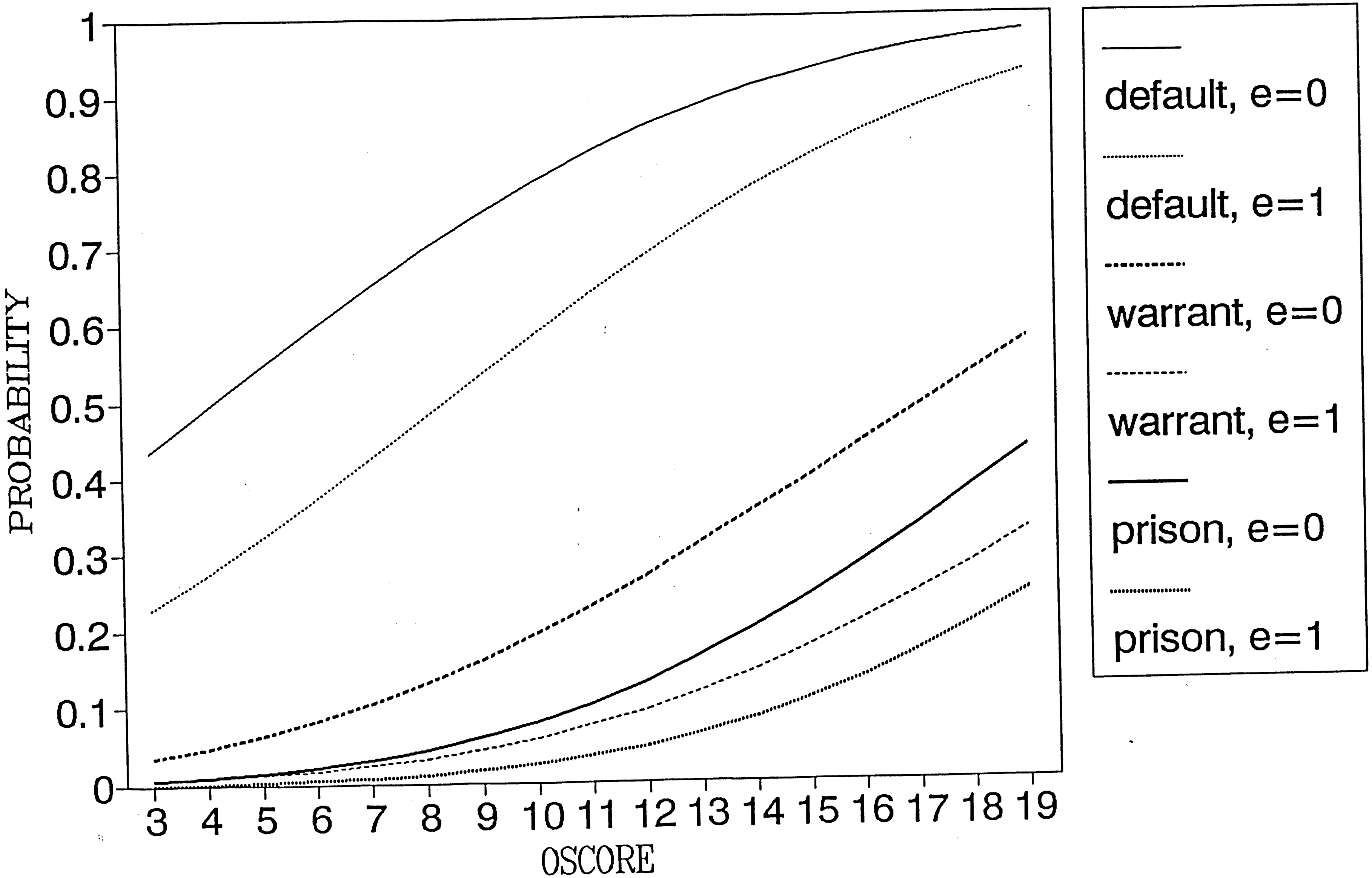


Figure 3

Court 1: Unconditional Probabilities.



25.

Figure 4
Court 4: Conditional Probabilities.

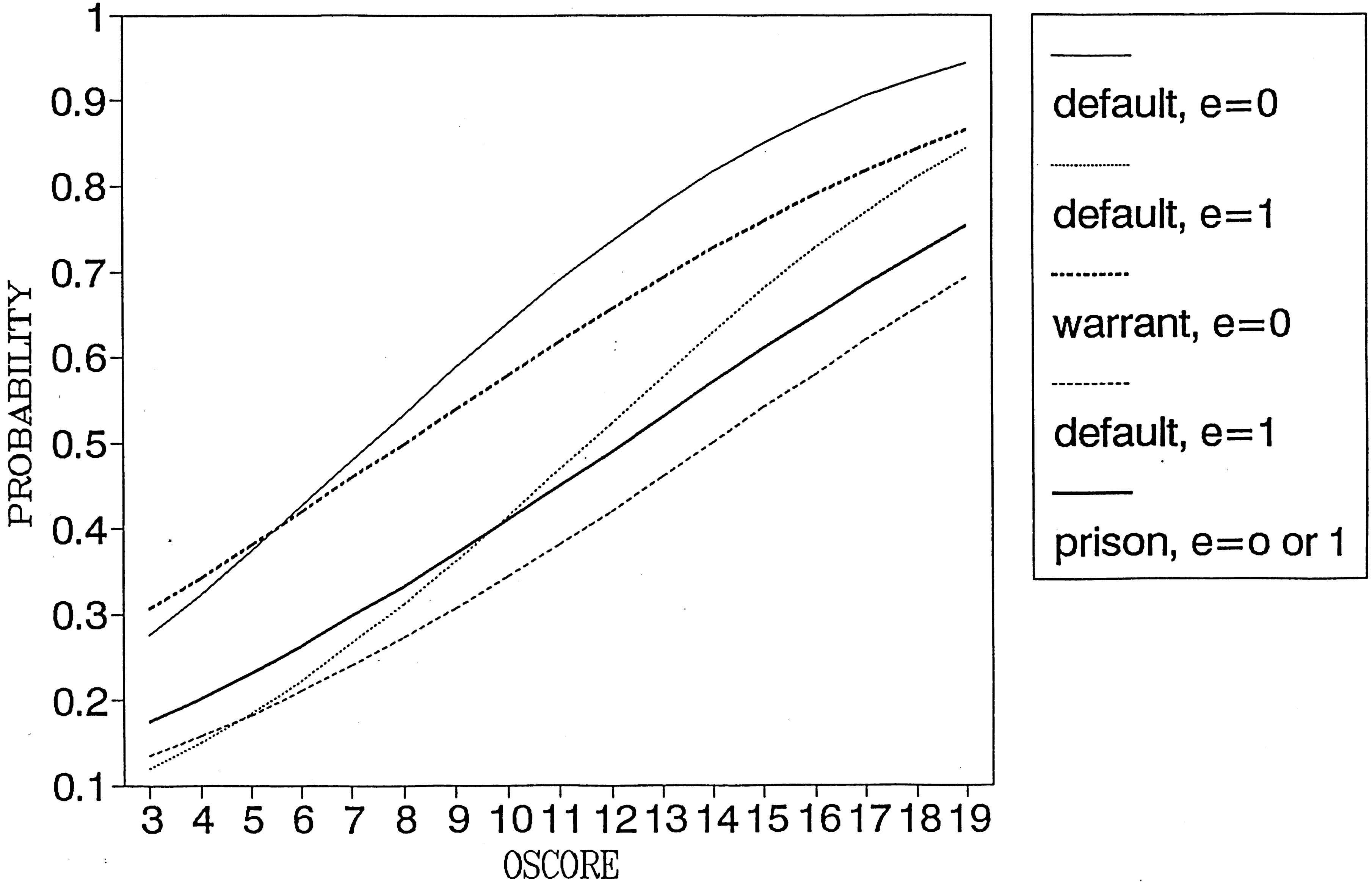


Figure 5

Court 4: Unconditional Probabilities.