Credit Card Pricing and Impact of Adverse Selection

Bo Huang and Lyn C. Thomas

University of Southampton

Abstract

Variable pricing is an attractive way of improving the profitability of credit cards where pricing is essentially the interest rate to be charged. However choosing the appropriate price for each risk grade of default is not straightforward. One of the main problems in applying variable pricing is adverse selection. This is when the lender finds that the set of borrowers who actually take a specific offer have a higher default rate than was expected. We show how modelling the choice of credit card by the borrower as an auction process means that the winner's curse can lead to adverse selection. By calculating the optimal interest rate to charge using a number of simple examples we find how this adverse selection can impact on the profitability of the lender.

Key words: Credit Card, Variable Pricing, Adverse Selection

1. Introduction

Credit cards are probably the most convenient form of credit of all competing financial assets that include both payment and credit devices (Ayadi, 1997). Consumers find credit cards convenient for making purchases as by using the credit methods consumers are able to decide to pay back at the end of the billing cycle or over a longer period (Chakravorti and To, 2006). Variable rate loans have been legal since the early 1980s. In the credit card market, however, a standard rate continued to dominate until the early 1990s. As late as 1990, variable rate credit card companies held less than 5% of the whole market (Stango, 2000).

With a fixed standard rate charged on the loan, lenders used application scoring to determine the default risk of each applicant Their overall objective was to minimize the default risk for a portfolio of borrowers of a given size by choosing an appropriate cut-off application score (Thomas 2008). Since the early 1990s, credit card issuers have recognised that they can improve their profit in terms of segmenting the population depending on their default risk and offering different loan terms to each segment. More recently the development of the internet and the telephone as new channels for loan applications has made the offer process more private to each individual (Thomas 2008). Phillips (2005) in his book outlines a number of reasons why the same product can be sold at different “prices”. The banks are able to “price” their loan products at different interest rates by adopting methods such as channel pricing, group pricing, regional pricing, and product versioning. Meyecord (1994), Sinky and Nash (1993), Sullivan and Worden (1995), Ayadi (1997) and Furletti (2003) have pointed out how such technological innovations and market developments have radically changed the credit card industry. Developments in credit scoring, response modelling, and solicitation technologies (e.g. e-mail, direct mail and telemarketing) have assisted the credit card issuers in marketing their products more efficiently, and in increasing the size of their portfolios of borrowers (Chakravoriti and To, 2006). Ausubel (1991) provided empirical evidences suggesting that credit card issuers obtain higher returns than other banking sectors. Further research by Calem and Mester concluded that credit cards had significantly higher rates and thus higher returns than most of other bank credit products in the 1980s (Calem and Mester, 1995).

However, Ausubel (1991) pointed out that competition in credit card pricing can result in adverse selection. Adverse selection occurs in a trading situation where one side processes information (the informed party) which is relevant to his trading partner who is the uninformed side. Adverse selection has already been investigated in the insurance industry where the probability of higher risk individuals making purchases of insurance policies is higher than those with lower risk (Ausubel, 1999). Akerlof (1970) has given a similar analysis in the second-hand cars market and argued that impact of adverse selection on product quality could be so severe in the market that bad vehicles might drive out good quality vehicles from the market. In the consumer lending context, Thomas (2008) points out that adverse selection is important in estimating the interaction between the quality of the applicant and the chance of them taking the loan. High interest rates charged to borrowers may result in adverse selection on defaulting probability and banks forced to increase their interest rates in an upward spiral. (Stieglitz and Weiss, 1981).

The primary objective of this paper is to model how adverse selection could occur in consumer lending when there is variable pricing of the loans and the credit cards. In the next section we will briefly outline an auction model which is a useful way of thinking about the credit card application process. We show how the winner’s curse which occurs when the successful lender is the one who makes the greatest error in estimating the default risk of the borrower can lead to adverse selection. In section four we develop a simple model of variable pricing for the interest rate charged in consumer lending and apply this in the case of linear and logistic take probability functions. We investigate how the expected and actual profitability of the lender using this model is affected by adverse selection. This is shown using numerical examples in section 5, while some conclusions are drawn in the final section.

2. Auction Model of Credit card Solicitation

Ausubel (1999) suggested that the auction model is a useful analogy to the credit card application process. When a potential customer decides to open a new credit card account, first they collect information including the "price" - interest rate charged, fees - and the benefits - air miles given and free or discounted related products - on the different accounts. To do this they usually have to fill in their details so that the issuers can produce an application score which estimate the default risk of the applicant. Different issuer will have different score cards, and the resultant scores determine not only whether the issuer will accept that customer but nowadays also the interest rate that will be charged. This is what risk based pricing seeks to do. The applicant then evaluates which offer is best, which is often the "cheapest" account. So the credit card application process is akin to a sealed bid auction where the customer plays the role of the auctioneer and the credit card issuers are the bidders.

Consider a simple model where the potential customer applies to N credit card issuers. In the "auction", each lender i, obtains information on the applicant to obtain an application score s_i for that applicant. One can translate the score s_i to obtain p_i which is lender i's probability that the applicant is a 'Good' and will not default on the account in a prescribed time horizon. However these estimates of probability of being Good are likely to have errors ε_i in them. These errors arise because the information required for the application score is not precise enough, or the score card is "ageing" and so becoming less predictive. We assume the applicant has a true probability of being good of $\tilde{p}$, and so $p_i = \tilde{p} + \varepsilon_i$. We also assume that the applicant will choose the credit card offer with the lowest interest rate and that all the firms are using the same risk based pricing approach. This means that each of them has the same relationship $r(p)$ between the interest rate r offered and the probability p of the applicant being Good. So the applicant will choose the firm whose probability $p_i = p^*$ of then being Good is the largest. We thus conclude that the lender who has the most positive error ε_i is the one who will "win" the applicant. This is an example of the winner's curse, in that the lender will have a higher assumed probability of the applicant being a good than is really the case.

Errors in probability of being Good

In order to model how such an error can affect the profitability of the applicant to the lender, assume that lender i, estimates via the application score that the applicant's probability of being good is $p_i = \tilde{p} + \varepsilon_i$ where the errors ε_i are independent random variable with distribution function $F(\cdot)$. We assume that $p_i^* = \max_{1\le i\le N}\{p_i\}, \varepsilon_i^* = \max_{1\le i\le N}\{\varepsilon_i\}$ are the probability of being Good and the error of the lender, whose credit card is chosen by the borrower because the lender made the largest positive error and so offered the best interest rate.

So the distribution of the true probability of being good $\tilde{p}$ of the applicant accepted by the lender who perceives the applicant's probability of being good to be p^*, is given by,

$$G(t) = \Pr\{\tilde{p} \le t\} = \Pr\{p_i^* - \varepsilon_i^* \le t\} = \Pr\{p_i^* - t \le \varepsilon_i^*\}$$

$$= \Pr\{\max_{1\le i\le N}\{\varepsilon_i\} \ge p_i^* - t\} = 1 - \Pr\{\max_{1\le i\le N}\{\varepsilon_i\} \le p_i^* - t\}$$

$$= 1 - \prod_{i=1}^{N} \Pr\{\varepsilon_i \le p_i^* - t\}$$

$$= 1 - F(p_i^* - t)^N$$

So the density function of $\tilde{p}$ is

$$g(t) = N \cdot f(p^* - t) \cdot F(p^* - t)^{N-1}$$

Hence the expected value of $\tilde{p}$ is

$$Exp(\tilde{p}) = \int_{-\infty}^{+\infty} t \cdot g(t) \cdot dt = \int_{-\infty}^{+\infty} N \cdot t \cdot f(p^* - t) \cdot F(p^* - t)^{N-1} \cdot dt$$

Defining $u = p^* - t$, we get

$$Exp(\tilde{p}) = \int_{-\infty}^{+\infty} (p^* - u) \cdot N \cdot f(u) \cdot F(u)^{N-1} \cdot du$$

$$= p^* \cdot \int_{-\infty}^{+\infty} N \cdot f(u) \cdot F(u)^{N-1} \cdot du - \int_{-\infty}^{+\infty} u \cdot N \cdot f(u) \cdot F(u)^{N-1} \cdot du$$

Hence $Exp(\tilde{p}) = p^* - b_N$

since $\int_{-\infty}^{+\infty} N \cdot f(u) \cdot F(u)^{N-1} \cdot du = \left[F(u)^N\right]_{-\infty}^{+\infty}$ and $b_N = \int_{-\infty}^{+\infty} u \cdot N \cdot f(u) \cdot F(u)^{N-1} \cdot du$

The linear relationship in this equation is similar to that discussed in Phillips (2005) and Thomas (2008) where $Exp[\tilde{p}(r,p)] = p - dr, d > 0,$ where it is called the linear probability adverse selection function. If one assumes the error in the probability is a uniform distribution which spreads more the higher the rate charged, i.e. $[-dr, dr]$ then the above calculation given

$$b_N = \int_{-\infty}^{+\infty} u \cdot N \cdot f(u) \cdot F(u)^{N-1} \cdot du = \int_{-dr}^{+dr} \frac{u}{2dr} \cdot N \cdot \left(\frac{u+dr}{2dr}\right)^{N-1} \cdot du = dr \frac{(N-1)}{(N+1)}$$

The argument is that if the lender increases the interest rate, they are willing to accept applicants with a lower probability of being Good and this will lead to a wider range of errors. Note also that the more lenders, N, in the market, the larger is the winner's curse, in that the lender makes even more optimistic errors about the applicant's default risk.

Errors in the score

The probability of the individual applicant being Good is not directly observed by issuers. Instead, the lenders collect data on previous borrowers with similar characteristics and translate this information into a credit score s for that applicant. To model this, suppose the customer with characteristics x will be given credit score of $s(x)$, which relates to the probability of the customer being good. Thomas (2008) imply how use logistic regression to build a score card leads to a log odds score where the relationship between the credit score and the probability of being Good is given by

$$s(x) = \log\left[\frac{p(x)}{1-p(x)}\right] \Rightarrow p(x) = \frac{e^{s(x)}}{1+e^{s(x)}}.$$

In this case suppose the errors that the lenders made are directly in the score they give the applicant, which translates into errors in the probability of the applicant being Good. Let $\tilde{s}$ be the “true” score of the applicant and this corresponds to $\tilde{p}$, the true probability of the applicant being Good. Assume lender i has a scorecard which gives that applicant a score s_i^*, where $\tilde{s} = s_i^* - \varepsilon_i$. Again we assume the applicant will choose the lender who gives the highest score since under risk based pricing this will lead to the offer which the lowest rate required on the credit card. Assume that there are N potential lenders and ε_i the scoring errors made by each lender are independent and have a common distribution with distribution function $F(\cdot)$. Again in this case we are interested in the true probability of being good $\tilde{p}$, of an applicant who has accepted an offer from a lender, who believes the applicant’s probability of being good is p^* .

We can follow the calculations of the previous error type to get the following results.

$$\begin{aligned} G(t) &= \Pr\{\tilde{p} \le t\} = \Pr\left\{\log\frac{\tilde{p}}{1-\tilde{p}} \le \log\frac{t}{1-t}\right\} = \Pr\left\{\tilde{s} \le \log\frac{t}{1-t}\right\} \\ &= \Pr\left\{s_i * - \varepsilon_i * \le \log\frac{t}{1-t}\right\} = \Pr\left\{\log\frac{p*}{1-p*} - \log\frac{t}{1-t} \le \varepsilon_i *\right\} \end{aligned} .$$

Since

$$\begin{aligned} &\Pr\{\varepsilon_i * \ge y\} = \Pr\{\max[\varepsilon_1, \varepsilon_2, \varepsilon_3 ..., \varepsilon_N] \ge y\} = 1 - \Pr\{\max[\varepsilon_1, \varepsilon_2, \varepsilon_3 ..., \varepsilon_N] < y\} \\ &= 1 - \prod_{i=1}^{N} \Pr\{\varepsilon_i < y\} = 1 - F(y)^N \end{aligned} .$$

We have $$G(t) = 1 - F\left(\log\frac{p_i^*}{1-p_i^*} - \log\frac{t}{1-t}\right)^N .$$

Then, the probability density function is

$$g(t) = \frac{N}{t\cdot(1-t)}\, f\left(\log\frac{p^*}{1-p^*} - \log\frac{t}{1-t}\right)\, F\left(\log\frac{p^*}{1-p^*} - \log\frac{t}{1-t}\right)^{N-1} .$$

So, for the lender who has taken the applicant assuming his score is s_i^*, then the expected true credit score of that applicant will be given by

$$E(\tilde{s}) = E(s_i *) - E(\varepsilon_i *) = s_i * - \int_{-\infty}^{\infty} y f(y) F(y)^{N-1} dy = s_i * - b_N$$

In terms of probabilities of being Good this becomes

$$E(\log\left(\frac{\tilde{p}}{1-\tilde{p}}\right)) = E(\log\left(\frac{p*}{1-p*}\right)) - E(\varepsilon_i*) = E\left(\log\left(\frac{p*}{1-p*}\right)\right) - \int_{-\infty}^{\infty} yf(y)F(y)^{N-1}dy = E\left(\log\left(\frac{p*}{1-p*}\right)\right) - b_N$$

In the case when the score errors are uniformly distributed from $-dr$ to dr , where again r is the interest rate charged one gets

$$E(\log\left(\frac{\tilde{p}}{1-\tilde{p}}\right)) = E(\log\left(\frac{p*}{1-p*}\right)) - E(\varepsilon_i*) = \log\left(\frac{p*}{1-p*}\right) - dr\frac{N-1}{N+1}$$

which is strongly related to the linear log odds selection function suggested in (Thomas 2008) and (Phillips 2005).

3. Impact of Adverse Selection on Risk-based Pricing

Risk-based pricing means that the interest rate charged on a loan to a potential borrower depends on the lender's view of the borrower's default risk or equivalently their probability of being Good. We analyse the impact that the errors, we described in the previous section,will have on the lender's profitability when risk based pricing is used. In particular we are interested in the fact that these winner's curse selection errors are a form of adverse selection since they increase as the interest rate charged increases. We use a rate model which looks at the profitability of deciding whether to lending one unit to an applicant (see Thomas 2008).

In such a model the lender seeks to maximise the expected profit from lending. Define p^* to be the lender's estimate of the probability of the borrower being Good given the specific loan with a specific interest rate and define $\tilde{p}$ be the true probability of the borrower being Good on this type of loan. In the previous section we described how the winner's curse can lead to a linear or logistic relationship between these two probabilities.

In this case, the lender is assuming that the probability of the lender being Good is that probability p* that would

$$E(\tilde{p}) = p^* - er,$$

and
$$E(\log\frac{\tilde{p}}{1-\tilde{p}}) = \log\frac{p^*}{1-p^*} - er\ .$$

In general we denote this relationship as $\tilde{p}(r, p^*)$.

Consider the lender deciding what interest rate, r, to charge on a loan of one unit to such a borrower. We assume that the risk free rate at which the lender can borrower the money is r_F and the loss given default (the percentage of defaulted loan finally lost) is l_D. If the lender charges a rate r to an applicant whose probability of being Good is p, then the take probability, (the chance the applicant will accept such a loan) is $q(r, p)$. If the lender believes the borrower has a probability p of being Good, then the lender believes the expected profit if a rate $r(p)$ is charged to be

$$EP(r,p) = q(r,p)\left[\left(r(p) - r_F\right)\cdot p - \left(l_D + r_F\right)\cdot(1-p)\right] \tag{1}$$

In order to find the optimal interest rate, we differentiate this equation with respect to r and set the derivate to zero, to find when the profit is optimised. This gives a risk based interest rate of

$$r^*(p) = r_F + \left(l_D + r_F\right)\cdot\frac{1-p}{p} - \frac{q(r,p)}{\partial/\partial r\, q(r,p)} \tag{2}$$

The reality through is that the lender's estimate of the probability of the borrower being Good is p^*, where the true probability is $\tilde{p}$. Thus the optimal profit the lender would possibly obtain from such a borrower if the lender had the correct view of the borrower's probability of being Good would be

$$EP_{opt}\left[r^*(\tilde{p}),\tilde{p}\right] = q\left(r^*(\tilde{p}),\tilde{p}\right)\cdot\left[\left(r^*(\tilde{p}) - r_F\right)\cdot\tilde{p} - \left(l_D + r_F\right)\cdot(1-\tilde{p})\right] \tag{3}$$

However, the lender's estimate of the borrower's probability of being Good is p^*, and so what the lender expects the profit to be is

$$EP_{\exp}\left[r^*(p^*),p^*\right] = q\left(r^*(p^*),p^*\right)\cdot\left[\left(r^*(p^*) - r_F\right)\cdot p^* - \left(l_D + r_F\right)\cdot(1-p^*)\right] \tag{4}$$

even though the borrower's true probability is $\tilde{p}$.

In fact, the borrower will not live up to this expectation and the true expected profit the lender will get is

$$EP_{true}\left[r^*(p^*),\tilde{p}\right] = q\left(r^*(p^*),\tilde{p}\right)\cdot\left[\left(r^*(p^*) - r_F\right)\cdot\tilde{p} - \left(l_D + r_F\right)\cdot(1-\tilde{p})\right] \tag{5}$$

4. Numerical Examples

Consider two examples, the first is where the take function and the adverse selection function are linear in form and the second is where both are logistic in form. Take functions of those two forms were discussed in Phillip (2005). In both cases we assume the risk free rate is 5%, $r_F = 0.05$ and the loss given default $l_D = 0.5$.

Linear Relationship Model

For the linear, take probability or response rate function define

$$q(r, p) = \min\{\max[0, 1 - b(r - r_L) + c \cdot (1 - p), 1]\}, \text{ for } 0 \le p \le 1.$$

Then the optimal interest rate is

$$r^*(p) = r_F + (l_D + r_F) \cdot \frac{1-p}{p} - \frac{1 - b \cdot (r - r_L) + c \cdot (1-p)}{b}.$$

We choose the value with $r_L = 0.04$, $b = 2.5$, and $c = 2$, . This implies that a 1% increase on interest rate drops the take probability by 0.025 while if the default probability of the borrower goes up by 0.01 (Good drops by this amount) the take probability goes up by 0.02. For borrower with a default rate of 0.01, thus 100% of them would take a loan of rate 6%, while only 50% of them would take a loan with interest rate 25%. If we assume the relationship between $\tilde{p}$ and p^* is given by a uniform error, then we get a linear relationship between $\tilde{p}$ and p^* . So that, from section 2, we have

$$\tilde{p} = p_i^* - dr(\frac{n-1}{n+1}),\ d > 0.$$

and if we assume $d = 0.15$, $N = 500$ then $\tilde{p} = p_i^* - 0.1494 \cdot r$

The results of applying these relationships in $(3), (4)$ and (5) lead to the results in Table 1:

Table 1 shows the impact of adverse selection with a linear probability function model. Column 2 reports the actual profits achieved by the lender. The profits of the lender become positive only if the chance of borrower being good reaches 0.5. Column 5 shows the profits expected by the lender, which are very close to the optimal profit that could be achieved if he knew the borrower's true probability of being Good. Comparing column 2 and column 5, we found that assumed profits are much higher than the true profits. In particular, the lower the borrower's probability of being good, the larger gap between the data from these two columns will occur.

$\tilde{p}$	EP_{true}	EP_{opt}	p^*	$EP_{\exp}$
0.3	-0.05638	0.0000	0.3	0.0000
0.5	0.000257	0.018773	0.5	0.018
0.6	0.035762	0.044867	0.6	0.044204
0.7	0.061176	0.067491	0.7	0.065896
0.8	0.081096	0.085253	0.8	0.085078
0.9	0.091737	0.093626	0.9	0.094044
0.92	0.09291	0.094666	0.92	0.094861
0.94	0.093676	0.095306	0.94	0.095365
0.96	0.09391	0.09548	0.96	0.0955
0.98	0.094048	0.095559	0.98	0.095561

Table 1: Results of a linear probability adverse selection function.

It can be seen from Figure 1, as the probability of being good gradually increase to 1, the difference between expected and actual profits is gradually reduced and eventually the two curves coincide almost exactly. In addition, comparing column 5 with column 3, we can see the assumed profits and the optimal profits almost coincide when the probability of being Good is high. Note that when p^* is below 0.3 although the lender does not expect to make a loss – the loan would not be made in that case - in reality losses do occur.

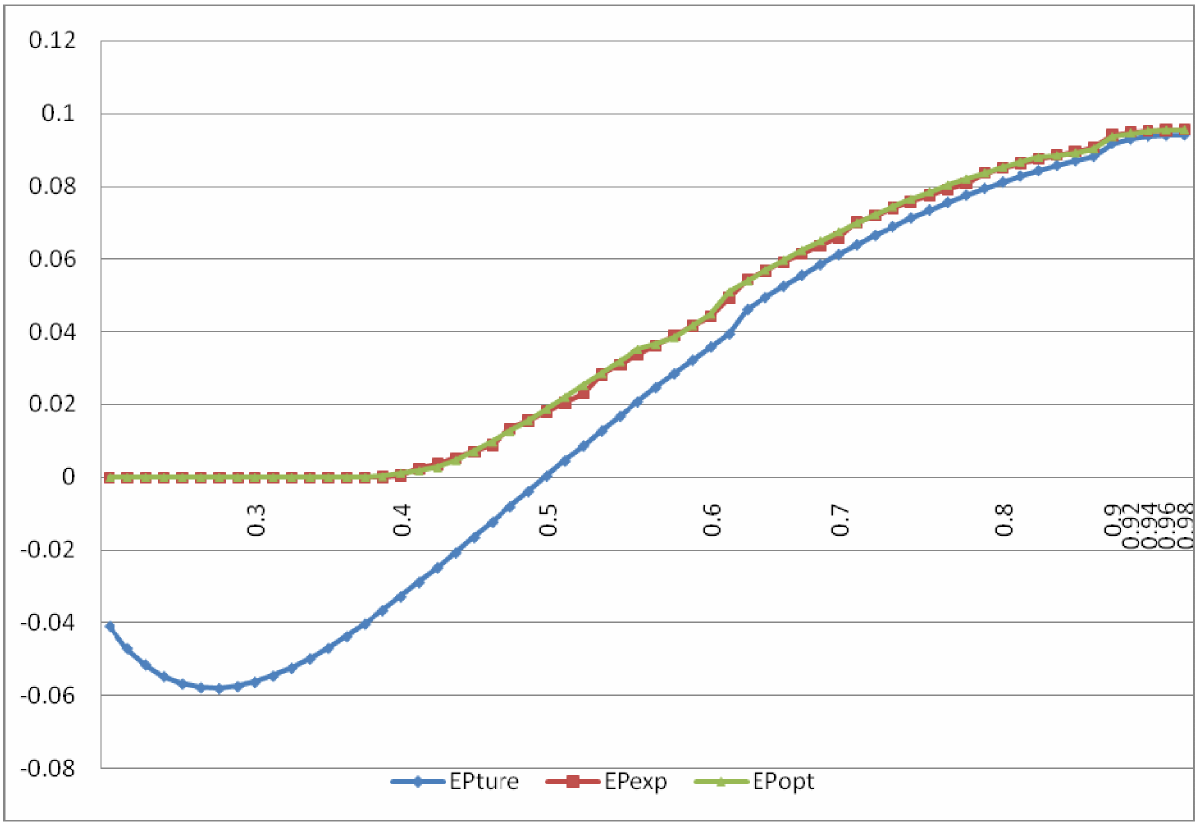

Figure 1: Plot of results of a linear model.

Logistic Model

The logistic risk-based response function or take rate is

$$q(r,p)=\frac{e^{a-br-cp}}{1+e^{a-br-cp}}.$$

In this case the maximum willingness to pay occurs when $r = a/b - (c/b)\cdot p$. This implies the riskier the borrower is, the higher the rate they are willing to pay. The optimal interest rate in this case is

$$r^*(p)=r_F+(l_D+r_F)\cdot\frac{1-p}{p}-\frac{1+e^{a-br-cp}}{b}.$$

Using the cost structure of the previous case with risk-free rate being 0.05 and the loss given default l_D being 0.5, we assume the parameters for the logistic response rate function are $a=54$, $b=32$,and $c=50$. Thus for applicants whose probability of being Good is 0.99

(default rate of 1%), 93% of them will accept a loan at interest rate 6%, while only 30% will accept one at 25%. We also assume the relationship between $\tilde{p}$ and p^* is linear in the log odds corresponding to there being errors in the scores in section 2. We assume the relationship is

$$\log\frac{\tilde{p}}{1-\tilde{p}} = \log\frac{p^*}{1-p^*} - dr(\frac{n-1}{n+1}) \text{, where } d > 0$$

$$\Rightarrow \tilde{p} = \frac{p}{(1-p)\cdot e^{dr\frac{N-1}{N+1}} + p}$$

We take the values $N = 500$ and $d = 4$ so that error between the log odds is

$$\tilde{p} = \frac{p}{(1-p)\cdot e^{3.98r} + p}$$

The results of applying these relationships in (3),(4) and (5) we can get the results in Table 2 and Figure 2.

$\tilde{p}$	EP_{true}	EP_{opt}	p^*	$EP_{\exp}$
0.3	-0.256505902	0.000108971	0.3	0.000108973
0.4	-0.179800649	0.04958824	0.4	0.049588431
0.5	-0.120515218	0.103989042	0.5	0.103988875
0.6	-0.046397856	0.146820976	0.6	0.145201731
0.7	0.00021474	0.15051339	0.7	0.150765621
0.8	0.035509349	0.132797723	0.8	0.133179458
0.9	0.060262605	0.090140422	0.9	0.091745987
0.92	0.060924634	0.078527762	0.92	0.075977514
0.94	0.058631672	0.067225836	0.94	0.065011196
0.96	0.053439103	0.056521742	0.96	0.053937944
0.98	0.046080056	0.046653585	0.98	0.048451123

Table 2: Results of a linear log odds probability adverse selection.

From Table 2, we can see these results are similar to Table 1. Again, the assumed profits and the optimal profits almost coincide, so it seems as if the errors do not matter. Comparing the actual profits and the assumed profits, we can see that a dramatically large gap exists between the two sets of data for small $\tilde{p}$. It gradually reduces and eventually almost disappears, as shown in Figure 2.

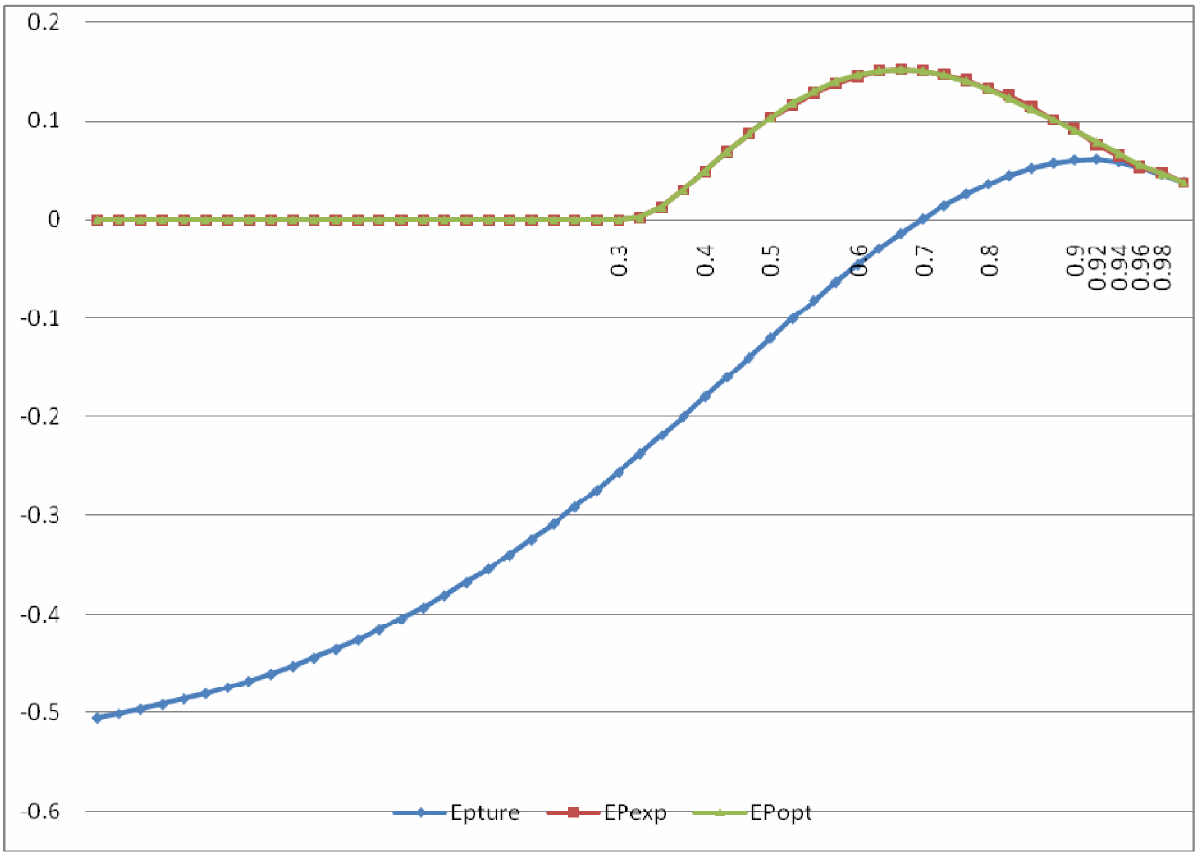

Figure 2: Plot of results of a linear log odds probability adverse selection.

The lender expects to start making a profit when the Probability of being Good is 0.3, and would not lend below that case. The reality is though that the lender only starts to obtain profits when the probabilities of the customer being Good reaches 0.7. It is also interesting to see that after the probabilities of customers being Good reach 0.7 the $EPopt$ and $EP\exp$ curves decrease relatively rapidly. Unlike in the linear case where the optimal profits and expected profits continue to grow as the riskiness of the customers drop, here they start to fall once $\tilde{p} > 0.7$. This is because the rate one needs to offer to attract such good customers is dropping so quickly that the profit from each customer is also dropping. This is a more realestic situation, in that the lender is making more profit from the risker borrowers than from the almost risk free ones. However, it is again the case that the difference between expected and actual profit is large especially for risky borrowers.

5. Conclusions

In the last few years, variable pricing has started to occur in consumer lending. It is surprising that it has taken so long to become established since it has long been the situation in the consumer insurance industry and in transport and hotels. However, variable pricing does mean adverse selection can occur, as lenders do not have the full information about the riskiness of the proposed borrowers. In this paper, we show how modelling the way a borrower selects a loan as an auction, means that winner's curse leads to adverse selection. We show that the relationships between the actual default risk of a borrower and the lender's perceived view of this risk are very simple ones, whatever the distribution of the errors the lender makes. This occurs both if the lender makes errors directly in the default risk or if the errors occur in a log odds score which gives rise to the default risk. By building a simple model of the profit a lender makes from a loan, we are able to examine the effect of these adverse selection errors. This shows that though the profit the lender expects to make is close to the optimal possible profit, the actual profit could be considerable less, particularly for risky borrowers.

One way out of this dilemma is for the lender to allow for the fact he will misrepresent the risk of the borrower, when calculating the optimal rate to charge. However this is like recognising that the application scorecard is 'wrong' and applying an adjustment to it. It is more likely the lender will seek to build a new scorecard to reflect the riskiness of the borrowers who actually takes the loan. The difficultly with this is that the population who take the loan depend critically on the variable rates being offered, and one of the strengths of variable pricing is that one can vary the rates to respond to charges in the market. Thus the population who take the loan is constantly changing.

Variable pricing on consumer lending is here to stay. What this paper to shows is that choosing the appropriate price for a loan is not as straightforward as it may seem – even if one has enough data to build robust take probability functions.

References

Akerlof, G., (1970). The market for lemons: Qualitative Uncertainty and The Market Mechanism, *Quarterly Journal of Economics.* 84, 488-500.

Ayadi, O.F. and Onashile,T. (1994). Taking your plastic card to the limit. *Working paper,* Fayetteville State University.

Ayadi, O.F. (1997). Adverse selection, search costs and sticky credit rates. *Financial Services Review*, 6(1), 53-67.

Ausubel, L. (1991). The Failure of Cometition in the Credit Card Market, *American Economic Review,* 81(1), 50-81.

Ausubel, L. (1999). Adverse Selection in the Credit Card Market, *Working Paper*, University of Maryland.

Calem, P and Mester, L. (1995). Consumer Behavior and the Stickiness of Credit Card Interest Rates, *American Economic Review,* 85(5), 1327-1336.

Chakravoriti, S. and To,T. (2006). A theory of credit cards. *International Journal of Industrial Orgnization*, 25, 583-595.

Furletti,M. (2003). Credit Card Pricing Developments and Their Disclosure. *Federal Reserve Bank*

Keeney, R.L. and Oliver, R. M. (2005), Designing Win-Win Financial Loan Products for Consumers and Businesses. *Journal of the Operational Research Society*, 56, 1030-1040.

Mandell, Lewis. (1990). The credit card industry: A history. *Boston: Twayne Publishers.*

Morgan S.P.,and Teachman, J.D., (1988). Logistic Regression: Description,

Journal of Marriage and the Family, 50(4), 929-936.

Meyercord, A (1994). Recent Trends in the Profitability of Credit Card Banks, *Federal Reserve Bank of New York Quarterly Review*, 107-111.

Pampel, F. C. (2000). Logistic Regression: A Primer, *Sage Publishers.*

Phillips, L.R. (2005), Pricing and revenue optimization, *Stanford University press.*

Sinky,J.F., and Nash, R.C. (1993). Assessing the riskiness and profitability of credit-card banks. *Journal of Financial Services Research*, 127-150.

Stango, V. (2000). Competition and Pricing in the Credit Card Market, The Review of Economics and Statistics. 82(3), 499-508.

Stango, V. (1999) Pricing with Consumer Switching Cost, *University Tennessee, Working paper*

Stango, V. (2002), Pricing with Consumer Switching Costs: Evidence from the Credit Market. *Journal of Industrial Economics*, 50(4), 475-492.

Stieglitz, J. and Weiss, A. (1981) Credit rationing in markets with imperfect information, *American Economic Review*

Sullivan, A.C.and Worden, D.D (1995). Credit cards and the option to default. *Financial Services Review*, 4(2), 123-136.

Thomas, L. (2008), Consumer credit models: pricing, profit, and portfolios. *Oxford University Press.*

To, T.(1996), Multi-Period Competition with Switching Costs, *Journal of Industrial Economics*, 44(1), 81-87.