Adverse Selection And Search In The Bank Credit Card Market

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Abstract

There is little theoretical or empirical literature which relates to adverse selection in consumer credit markets. Stiglitz & Weiss' paper is applicable, but subsequent theoretical developments have considered loans to entrepreneurs. One exception is the study of the US bank credit card market by Calem & Mester (1995). Their argument is that search costs and switching costs result in adverse selection. Specifically if a bank lowers its interest rate it will mainly attract those potential borrowers who search most for low rates. These borrowers are those with low balances who yield low profits. In addition, cardholders with large balances would be less able to transfer their balances to a new bank due to asymmetric information between banks. Their empirical evidence is consistent with these hypotheses. In this paper we repeat C&M's tests using data for a period when the credit card market was more competitive to find no evidence to suggest that those with large balances search either more, or less, than those with low balances. Further, if those who are attracted by a unilateral lowering of an interest rate are those who search most, then additional incites into the degree of adverse selection in this market can be gained by identifying the characteristics of these households. The second part of this paper offers an application of a simple myopic search model of the duration of search a household undertakes when searching for better terms on which to borrow. A household searches for the lowest interest rate, given that it is below a reservation rate. We deduce various comparative static predictions with regard to the duration of search. We then test these predictions using data from the 1998 SCF. We find that some aspects of the model are supported more than others. However those households with poor payment histories do not appear to search more or less than those with better payment histories. This is suggestive that there may be less of an adverse selection problem than is currently thought.

1. Introduction

There is a considerable literature on adverse selection in a variety of markets including labour markets, insurance markets and credit markets. One of the most influential papers concerning credit markets has been that by Stiglitz and Weiss (1981). Stiglitz and Weiss argue, in the context of lending to firms, that there may be an interest rate which maximises a bank's expected return from loans, and that at this rate the demand for loans may exceed the volume a bank is willing to offer, with the result that observationally equivalent applicants are denied a loan: they are credit rationed. Stiglitz and Weiss give two reasons for an optimal interest rate. Firstly if a high interest rate is charged, the less risky firms no longer request loans. With firm risk positively related to firm return, less risky firms do not expect to earn a return sufficient to yield a profit if they pay the higher interest rate. The high risk firms, who realise that if they default the interest rate will not affect their gain, will continue to request loans. This is an adverse selection effect whereby the average riskiness of applicants is higher at higher interest rates. Hellmann & Stiglitz (2000) have shown credit and equity rationing can occur simultaneously if entrepreneurs have private information about both risk and expected returns.

Secondly Stiglitz and Weiss argued that at higher interest rates an adverse incentive effect occurs. At higher interest rates a riskier project will give higher expected profits than a less risky project because the former is less likely to have to repay interest on the loan. At higher interest rates a firm will adopt riskier projects resulting in a decline in the expected return to the bank. Stiglitz and Weiss' adverse selection argument led them to suggest a backward bending supply curve.

These concepts have been developed in a number of ways. For example Cho (1986) and De Meza and Webb (1987) have considered lenders preferences concerning debt and equity. Bester (1985) considered the information indicated by collateral requirements. But much of this literature relates to loans to entrepreneurs and firms. There has been much less consideration of adverse selection in the market for *consumer* loans, beyond the concepts of Stiglitz & Weiss.

Empirical evidence investigating the existence and extent of adverse selection is also limited. A number of studies have however, investigated adverse selection in insurance markets (see for example Cardon and Hendel (2001) and Chiappari & Salanie (2000)). In the case of credit markets there are very few empirical studies. Using time series data for the US for 1968-1989 Martin and Smyth (1991) find evidence for a backward bending supply curve for mortgages both for a representative loan and for aggregate loan volume. Similarly, using UK data for the 1980s, Drake and Holmes (1997) also find a backward bending supply curve for mortgages. They found that the optimum interest rate for lenders was 11.86% which was significant since mortgage arrears rose considerably when the actual interest rate rose above this level. In an earlier study they also found a backward bending supply curve for non-mortgage consumer credit (Drake and Holmes 1995).

There have been few studies which have used cross sectional microdata. One study which has done so is Calem and Mester (1995a and b) (hereafter referred to as 'C&M') who tried to evaluate Ausubel's explanations for an apparently observed 'stickiness' in credit card interest rates. Ausubel (1991) argues that the US credit card industry deviated from perfect competition because cardholders did not switch to lower rate cards when offered the opportunity to do so. According to Ausubel, cardholders did not switch for three reasons: the existence of search costs, of switching costs and irrationality. In the latter case consumers did not switch because they believed they would pay all of their balances before they became liable for interest and because, when this did not happen, they repeatedly failed to adjust their behaviour. C&M used data from the SCF and found that those credit card holders who search most for the best credit or deposit terms have the lowest balances, ceteris paribus, and so are least worth attracting by a reduction in interest rates. A reduction in interest rates would be most likely to attract those with the lowest balances, who yield the lowest profit. They also found that those card holders with the largest balances had the greatest chance of being rejected if they apply for credit and they also have the poorest repayment history. Thus switching costs prevent cardholders switching banks if one bank unilaterally lowers its interest rate.

The aims of this paper are firstly to re-estimate the equations of C&M to investigate whether adverse selection persists in the credit card market which is now considerably more competitive that it was in the late 1980s. We also improve on the statistical methodology of C&M. Second we develop a model of the volume of search for an interest rate and test it using data from the Survey of Consumer Finance.

The structure of the paper is as follows. In the next section we outline C&M's hypotheses and report the results of our tests of them. These tests suggest there is a need for a more thorough analysis of search behaviour by potential borrowers if we wish to fully explore the possible existence of adverse selection. In the third section we present an application of McCall's (1970) theory of job search to the search for a low interest rate by a potential borrower. In section four we present the results of our tests of the theory. Section five concludes.

2. Adverse selection hypotheses and empirical model

C&M argued that a number of empirically testable hypotheses can be deduced from Ausubel's discussion and they also add some of their own.

1. Ausubel (1991) argues that within the set of credit card holders low risk holders search less than high risk holders for lower rates because the former do not intend to borrow. However their expectation is false and they end up borrowing anyway. C&M argue that this leads to adverse selection because, of those credit card holders attracted by a lender who unilaterally lowers its interest, rate a smaller percentage will be low risk than their share in the population of credit card holders. This suggests that amongst credit card holders the degree of search and repayment performance should be negatively correlated.

2. C&M (1995a) also proposed a separate argument. Assume each cardholder maximises, subject to a budget constraint, a two period utility function, where utility depends on consumption in each period and the amount of leisure time, and assume that consumption and leisure are complements. C&M show that a greater desire to borrow may be associated with more borrowing and less search.

3. Following Sharpe (1990) C&M argue that credit card holders who are most desired by a bank would face higher switching costs than less desirable card holders. The reason is that the most attractive cardholders would be granted a lower credit limit by a new bank than their current bank. This is because their current bank has private information about their previous credit history. C&M argue that this would not affect undesirable

cardholders. Therefore a bank which unilaterally lowers its interest rate would attract customers who are less desirable.

4. Applicants for an additional card, who do not reduce the number of cards they hold, may be regarded as wishing to increase their debt outstanding, and so the risk that they will default. Since a bank cannot distinguish between those applicants who wish to close another account and those who do not, it will regard any application with credit card debt outstanding as higher risk than an application with no credit card debt and so be more likely to reject such an application. Empirically, high credit card debt outstanding will be correlated with the probability of rejection.

C&M test hypotheses 1 and 2 by regressing credit card balances outstanding on the degree of search and find a significant negative relationship. If a bank unilaterally lowers its interest rate it will attract those who search most, who are those with low balances and so who yield low profits. C&M test hypotheses 3 and 4 by regressing whether a cardholder was rejected on credit card debt outstanding and credit card line of credit available and find a significant positive relationship. They also regress whether a cardholder was delinquent or not on credit card debt and search to see if banks were rational in rejecting those with large outstanding balances, to find they were. Both sets of empirical tests are taken to indicate the existence of adverse selection.

Our data came from the Federal Reserve Board's 1998 Survey of Consumer Finance. This contains data relating to 4309 households from two samples: a multistage national area probability sample (2813 cases) and a list sample from individual tax files (1496 cases). The publicly available dataset contains only 4305 cases for disclosure reasons. Both samples involved a high degree of stratification and the list sample oversampled high wealth households.

Two aspects of the data need to be noted. First it is impossible to remove the oversampled high wealth cases. However, probability sampling weights corresponding to the inverse of the probability of observation are available for each case. Econometric methodology assumes that, provided the model is complete and the residuals of the statistical models used follow the assumed distributions, the use of sampling weights is unnecessary for parameter estimates (Rogers (1992)). But a sampling statistician, who does not believe he is proposing a complete behavioural model, would argue that sampling weights must be inserted into the estimates of the parameters. If the residuals do not have the assumed distributions, or if use of the sampling weights significantly alters the estimated parameters, then sampling weights should be used. When used, sampling weights make the estimates of the coefficients more efficient and, in principle, make estimates of standard errors unbiased. In this paper we present the results using sampling weights (see Appendix 1).

Secondly, when a respondent fails to answer a question in a survey a value is missing. In the SCF each missing value is imputed in five different ways (see Kinneckell: 1998). Each set of data is known as an implicate. Many users of the SCF report results from one data set alone or refer to similar results from a separate analysis of each implicate. But this procedure underestimates the standard errors of the estimated parameters because it does not incorporate the uncertainty about those data which have been imputed. Below, we give results from all five implicates, suitably combined using formula from Little & Rubin (1987).

Like C&M we estimated three equations. To test hypotheses 1 and 2 we estimated:

$$BCBAL = f(\text{search}, \mathbf{x}) \quad \ldots (1)$$

Where BCBAL is the value of a household's bank card balances outstanding and **x** is a vector of control variables. Search is measured as a dummy variable (SEARCH2) taking on the value 1 when the response to the following question is 4 or 5:

"when making major decisions about credit or borrowing some people shop around for the very best terms while others don't. (What number would you be on the scale?/What number would your family be on the scale?)

1	2	3	4	5
Almost no shopping		Moderate shopping		A great deal of shopping"

The **x** vector includes variables that on a priori grounds, or in other empirical studies (Crook: 2001, Duca and Rosenthal: 1993, Cox and Jappelli: 1993), have been found to affect the demand or supply of debt outstanding to households. Many such variables affect both supply and demand and so their separate effects on demand and on supply cannot be identified (Crook: 1996). We have included almost exactly the same variables as C&M so a comparison can be made. Thus we included three dummy variables which measure the household's attitudes towards credit. In each case a value of 1 indicates a positive attitude towards "buying things on the instalment plan" (ATTGEN), using credit to pay the cost of a vacation

(ATTVAC) and to use credit to finance the purchase of a fur coat or jewelry (ATTFC). Income (INC0) is included since it has been shown to affect demand and it also affects whether or not an applicant will be give a credit card (Crook et al:1992). We include income squared (INC20) since this has been shown to be an appropriate specification. Total household debt less bank card debt as a proportion of income (NDEBT2TOINC), and outgoings on mortgage payments, rent and vehicle loans as a proportion of income (TOUTS1TOINC), are included given their role in credit scoring models. Likewise, whether or not an applicant owns his/her own home has been shown to affect the probability of default in credit scoring models (Crook: 1992) and so is included (OWNSPR). The values of liquid assets (LIQASSETS0) and of stocks and bonds (STCKSBNDS0) are included since some banks would take these into account when credit scoring because these variables indicate assets which can readily be used to repay loans in the event of the borrower experiencing financial difficulty. Similarly, the number of people in the primary economic unit (NPEU), years the head of the household has worked for his/her main employer (YATJOB), and the head of household's age (AGE), all enter credit scoring models. Age would also be expected to affect demand, as may gender (SEX), whether the head of the household is married or living with a partner (MARRIED1) and the level of education completed (GRADE). Since BCBAL is censored at zero we have estimated the parameters of this model using Tobit analysis.

To test hypotheses three and four we estimated the following equations:

$$\text{TURNDN} = f(\text{BCBAL}, \text{AVAIL}, \mathbf{y}) \qquad \ldots . (2)$$

$$\text{DEFAULT} = f(\text{BCBAL}, \mathbf{z}) \qquad \ldots .. (3)$$

Where **y** and **z** are vectors of control variables. In the case of equation (2), AVAIL is the maximum amount a household could borrow on all lines of credit less the amount currently outstanding. The control variables include those which on a priori grounds, or have been found empirically, to indicate the degree of risk of non-payment in the future. Thus we include a dummy indicating whether the respondent was ever behind by 2 or more months on any loan or mortgage payment (DEFAULT), and total debt as a proportion of income (TDEBT2TOINC). The other variables in this equation have been explained above. The control variables in the DEFAULT equation have also been explained above. We have assumed the residuals of both equations are normally distributed and so used a probit model in each case.

Like C&M we have restricted the sample to make it more representative of credit card users. Thus our estimates relate only to those households which have a bank credit card and income of less than or equal to $300,000 and stocks, bonds and liquid assets of less than or equal to $1million. The latter two restrictions removed only 388 cases and had a negligible effect on the results.

Table 1 shows the results. Unlike C&M we do not find that the amount of household search is significantly correlated with household bank card balances outstanding (column 1). C&M found a t-statistic of –5.455 whereas ours is –1.373. Given the importance of this result we also estimated the equation without the sampling weights. The result of this estimation is given in Appendix 2. The t-statistic is -0.009 and significant at only the 99.3% level.

Our result is not consistent with the argument that households with higher balances search less (and therefore it is not consistent with the argument that such households have a higher disutility of search). If, as C&M argue, those households with lower balances provide lower profits, our result does not suggest that a bank which unilaterally lowers its interest rate will attract those households with low balances. In short, this result does not suggest that search costs, as modelled by C&M, led to adverse selection in the late 1990s. In addition, our result is not consistent with the argument that households with large balances often underestimate the value of search: our results are not inconsistent with this interpretation of Ausubel's irrationality hypothesis.

TABLE 1 HERE

There are a number of possible explanations for the difference between our results and those of C&M. One possibility is that the model of utility maximisation dominates for some households, and the argument that those with high balances search more because of the greater benefits they would receive from more search applies to other households, with the latter group increasing over time as a proportion of credit card holders due to greater competition between banks since late 1992. With increased competition, it is possible that the variance of interest rates has increased. A second possibility is that the SEARCH2 variable differs between the two studies. The question in the SCF 1989 (in C&M's study) relates to household search behaviour with regard to borrowing *and* saving whereas the SCF 1998 asks about search behaviour for borrowing *separately* from saving. Our dependent variable relates to borrowing only. A third possibility is that we have used three fewer control variables than C&M. But this is unlikely to be the explanation because none of the three variables is even remotely significant in C&M's results.

Our results for the TURNDN and DEFAULT equations are shown in Table 1 columns 2 and 3. In column 2 it can be seen that we find even stronger support than found in C&M for the switching costs hypothesis: the coefficient on bank card balances is positive and highly significant. In column 3 we also find support for the hypothesis that households with larger credit card balances are more likely to default.

C&M test the irrationality and adverse selection due to search costs hypotheses by regressing bank card balance outstanding on whether or not a household shops for the best credit or savings terms. They initially hypothesise a single period utility maximisation theory of the volume of search. However they do not model the optimal volume of search taking into account the stochastic nature of the possible interest rates offered to a household when it searches. Nor do they try to explain the volume of search for credit terms that a household undertakes. A fuller analysis, both theoretical and empirical, may shed light on who searches most for credit terms and so which households would be most likely to be attracted by a bank which unilaterally lowers it interest rates. The third section of this paper aims to achieve both of these objectives.

3. Search

From section 2 it can be seen that predicted differences in search activity have been used to find empirical support (C&M), or otherwise (our results above), for the adverse selection and irrational borrower hypotheses. But there is almost no published work which explains the degree of search which potential credit borrowers undertake when choosing between suppliers. The aim of this section is to analyse this decision. We begin with a simple search model from which predictions are deduced. We then test these predictions.

We make the following assumptions.

1 Each individual aims to minimise his or her expected interest rate.

2 Each individual knows the distribution of interest rates (s)he faces.

3 An interest rate offer, r, is an independent drawing from the known distribution of interest rates. Let *f* be the probability density function of such offers,

$f \sim N(E(r), \sigma^2_r)$.

4 Search results in one offer per period.

Let r_R be the expected interest rate from searching as given by the optimal stopping rule. Consider the first interest rate offered. It is accepted if $r \leq r_R$ or rejected if $r > r_R$. In the latter case further search in undertaken.

For any offer, the optimum policy is: accept the offer if $r \leq r_R$

search if $r > r_R$

The expected return of this rule is $E[\min(r_R, r)] + c$ where c is the cost to the potential borrower of taking one additional observation.

But r_R is the expected return from best stopping rule.

So $$r_R = E[\min(r_R, r)] + c \qquad \ldots\ldots (4)$$

Now $E\left[\min(r_R, r)\right] = \int_0^{r_R} r f(r) dr + r_R \int_{r_R}^{\infty} f(r) dr$

$$= r_R \int_{r_R}^{\infty} f(r) dr + r_R \int_0^{r_R} f(r) dr + \int_0^{r_R} r f(r) dr - r_R \int_0^{r_R} f(r) dr$$

$$= r_R + \int_0^{r_R} (r - r_R) f(r) dr \qquad \text{. . . .(5)}$$

substituting equation (5) into (4) and simplifying we have:

$$c = \int_0^{r_R} (r_R - r) f(r) dr \qquad \text{. . . . (6)}$$

Equation (6) may be interpreted verbally. The left hand side is the cost of an additional observation of an interest rate. The right hand side is the expected return from an additional observation. Equation 3 may be represented diagramatically as in Fig 1.

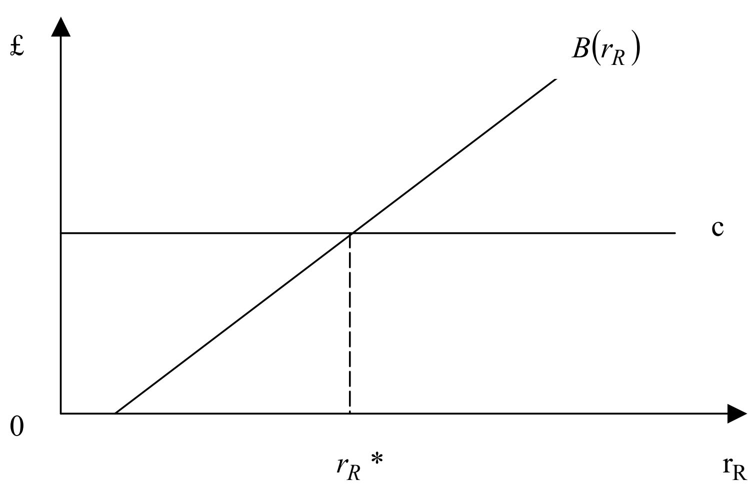

Figure 1

The greater the value of r_R the greater the expected marginal benefit. Therefore the right hand side of equation (6) is positively related to r_R. This is represented by the $B(r_R)$ line. The left hand side of equation (6) is assumed constant with response to r_R and is the horizontal line. The optimum reservation interest rate is r_R * where the lines intersect and equation (6) holds.

A number of comparative static predictions can be deduced. First, the expected number of observations can be related to the optimal reservation interest rate. The probability of finding an interest rate below or equal to the reservation interest rate is: $\int_0^{r_R} f(r)dr = F(r_R)$. The expected number of observations, *E(n),* required to find a rate below the reservation rate is therefore:

$$E(n) = 1/F(r_R). \qquad \text{. . . (7)}$$

Differentiating we gain: $$\frac{\partial E(n)}{\partial r_R} = -\frac{\frac{\partial F}{\partial r_R}}{(F(r_R))^2} < 0 \qquad \text{. . . (8)}$$

So the predicted changes in the expected number of observations have the opposite sign to the changes in the reservation interest rate. Since we assume only one search per time period we can predict the effect of changes in the cost of one more observation and in the marginal benefit of an additional observation on the expected number of periods of search.

Second, an increase in the marginal costs of search will reduce the expected number of additional observations. To prove this, rewrite equation (6) as:

$$G(r_{R,}c) = \int_0^{r_R} (r_R - r) f(r) dr - c \qquad \text{. . . . (9)}$$

rewrite equation (10):

$$E(n) = \frac{1}{\int_0^{r_R} f(r) dr} \qquad \text{. . . (10)}$$

Differentiating equation (10) with respect to c gives:

$$\frac{\partial E(n)}{\partial c} = \frac{\partial E(n)}{\partial c} + \frac{\partial E(n)}{\partial r_R} . \frac{\partial r_R}{\partial c} \qquad \text{. . . (11)}$$

The second term in the right hand side of equation (11) is:

$$\frac{\partial E(n)}{\partial r_R} = \frac{1}{\left(\int_0^{r_R} f(r) dr \right)^2} \left\{ \int_0^{r_R} f(r) dr . 0 - \frac{d}{dr_R} \int_0^{r_R} f(r) dr \right\}$$

$$= \frac{-f(r_R)}{\left[\int_0^{r_R} f(r) dr \right]^2} < 0 \quad \text{using Leibniz's rule} \qquad \text{. . . (12)}$$

The third term on the right hand side of equation (11) is:

$$\frac{\partial r_R}{\partial c} = -\frac{\partial G/\partial c}{\partial G/\partial r_R} = -\frac{-1}{\int_0^{r_R}\left(f(r) + (r_R - r_R)f(r_R) - 0\right)dr}$$

$$= \frac{1}{\int_0^{r_R} f(r)dr} > 0 \qquad \text{using Leibniz's rule} \qquad \text{. . . (13)}$$

Substituting equations (12) and (13) into equation (11):

$$\frac{\partial E(n)}{\partial c} = 0 + \frac{-f(r_R)}{\left[\int_0^{r_R} f(r)dr\right]^2} \cdot \frac{1}{\int_0^{r_R} f(r)dr} < 0 \qquad \text{. . . (14)}$$

So the expected duration of search is lower if the marginal cost of search is greater. Intuitively, in Figure 1, the c line shifts upwards, the optimal reservation interest rate increases and the expected amount of search will decrease.

Third, an increase in the mean of the offer distribution is often said, in the context of unemployed workers searching for a wage above the reservation wage (for example Fallon & Verry: 1988), to increase the marginal benefit function. Applied to the search for an interest rate <u>below</u> the reservation rate, this implies a shift upwards in the marginal benefit function and a decrease in the optimum reservation interest rate, and from equation (8) an increase in the expected number of observations. However, Feinberg (1976) shows, in the context of the wage search problem, that the effect of a change in the mean of the offer distribution can only be signed if the reservation wage is fixed. By analogy we can only sign the effect on the expected number of observations for a lower interest rate if the reservation interest rate is fixed. That is, if we write equation (11):

$$\frac{\partial E(n)}{\partial E(r)} = \frac{\partial E(n)}{\partial E(r)} + \frac{\partial E(n)}{\partial r_R}\frac{\partial r_R}{\partial E(r)} \qquad \text{. . . (15)}$$

and we can only put a sign on this if we set $\partial r_R / \partial E(r) = 0$.

Suppose we do this and we follow Fienberg's general method of proof. We may introduce a parameter α into the offer distribution function such that an increase in α shifts the distribution to the right, increasing the mean. We then define

$$E^*(n) = \frac{1}{\int_0^{r_R} f(r-\alpha)dr} \qquad \text{. . . (16)}$$

Then (see Appendix 3a)

$$\frac{\partial E(n)}{\partial E(r)} = \frac{\int_0^{r_R} \frac{\partial f(r)}{\partial r} dr}{\left[\int_0^{r_R} f(r-\alpha)dr\right]^2} \qquad \text{. . .(17)}$$

The denominator of equation (17) is clearly positive so the sign of equation (17) is that of the numerator.

Suppose $f(r)$ is a symmetric single peaked function.

If $r_R < E(r)$, then $\dfrac{\partial f(r)}{\partial r} > 0$ so $\dfrac{\partial E(n)}{\partial E(r)} > 0$

If $r_R > E(r)$, then $\displaystyle\int_0^{r_R} \frac{\partial f(r)}{\partial r} dr = \int_0^{E(r)} \frac{\partial f(r)}{\partial r} dr + \int_{E(r)}^{r_R} \frac{\partial f(r)}{\partial r} dr > 0$ . . . (18)

(see Appendix 3b)

so $\dfrac{\partial E(n)}{\partial E(r)} > 0$ . . . (19)

An increase in the mean of the interest rate offer distribution will increase the expected number of observations. To interpret this intuitively, a shift to the right in the offer distribution with the reservation interest rate held constant will reduce the probability of the individual observing an interest rate below the reservation rate and necessitate more observations to gain such a rate.

Fourth if we incorporate into equation (6) the volume of debt demanded, D, we have

$$D\int_0^{r_R} (r_R - r) f(r) dr = k \qquad \text{. . . (20)}$$

That is, the expected benefit from one further observation (search period) is now measured as a money amount, and so are the search costs of a further observation. Then following Silberberg and Suen (2001) it can be shown that:

$$\frac{\partial r_R}{\partial D} = \frac{-\int_0^{r_R} F(r)dr}{D.F(r_R)} < 0 \qquad \text{. . .(21)}$$

Given equation (8) we deduce that if the volume of credit demanded is larger then the expected number of observations is larger. Intuitively this is plausible. The greater the volume of credit demanded, the greater the benefit from a further observation. The optimum reservation interest rate is lower and more observations are needed to find a lower rate. This is the opposite to the prediction of the C&M paper.

Fifth, a change in the variance of the interest rate offer distribution can be shown to affect the expected number of observations. We assume that the revised offer distribution has the same expected value as the original: the transformation is a mean preserving spread of r. The method of derivation is again given in Silberberg and Suen (2001). Let β be a parameter of the *f(r)* distribution and which represents its dispersion, but maintains the mean. Denote the right hand side of equation (6) as $H(r_R)$ and differentiate both sides to gain:

$$\frac{\partial H(r_R)}{\partial r_R} \cdot \frac{\partial r_R}{\partial \beta} + \frac{\partial H(r_R)}{\partial \beta} = 0 \qquad \text{. . . (22)}$$

$\frac{\partial H}{\partial \beta}$ is positive because H = E(min (r - r_R),0) = E(max (r_R - r),0). But max(r_R – r, 0) is convex in r and so, as shown in Silberberg and Suen, if r' is a mean preserving spread of r, E(g'(r')) ≥ E(g(r)). Hence the result follows.

$\dfrac{\partial H(r_R)}{\partial r_R}$ is positive as can be seen by differentiating the right hand side of equation (9) and using Leibniz's rule:

$$\frac{\partial H}{\partial r_R} = \int_0^{r_R} f(r)dr > 0 \qquad \text{. . . (23)}$$

Since in equation (22) $\partial H/\partial r_R > 0$ and $\partial H/\partial \beta > 0$ it follows that $\partial r_R/\partial \beta < 0$. For an increase in dispersion the reservation interest rate decreases, and from equation (8) the expected number of observations increases.

We can now summarise the predictions which we have deduced from the simple theory of search behaviour. The expected number of observations, that is periods in which search occurs, is positively related to the mean of the interest rate offer distribution (if the reservation interest rate is constant) and to the volume of debt the potential borrower wishes and to the dispersion of the interest rate offer distribution. The expected number of observations is negatively related to the marginal cost of an additional period of search.

To compare these predictions with cross sectional data we need to identify the characteristics of those people who have different values of these variables and we need to measure the amount of search each person undertakes.

We hypothesize that the following factors would affect the costs of an additional period of search.

1. Age: the more elderly an applicant, the greater the physical difficulty of searching for lower interest rates and so the greater the cost.

2. Income: the greater a person's income which is foregone when search takes place the greater the cost. Similarly the higher is a person's income the greater the monetary value placed on leisure and so the greater the marginal cost of search if the alterative is leisure time.

3. Family commitments: the greater are family commitments the greater the opportunity cost of search.

4. Educational attainment: the greater the level of educational attainment the lower the perceived cost of an additional observation. Better educated households are more likely to have access to search facilities such as the web, phone, published information which reduces the cost of search.

We hypothesise that those people who have a higher mean of their expected offer distribution than do others include the following:

1. those who have a poor repayment performance and who believe that potential lenders will be aware of this record;

2 certain minorities who may also believe they face relatively high expected interest rates. Whilst there is no evidence that such beliefs are held, there is evidence that

certain minorities feel discouraged from applying for credit because they feel they will be turned down (Crook 1999).

We hypothesise that those people who have a higher dispersion of their interest rate offer distribution than others include the following:

1. those who have a poor repayment performance. On average such people would assume that banks will have some information about their past repayment performance and may be less confident than others as to the interest rate they will be offered.

2. those with a higher level of educational attainment. Such people are more likely to believe that the dispersion of interest rate offers is narrower than do people with less education and so the former are likely to believe that the benefits of additional search are greater, ceteris paribus, than the benefits anticipated by the less educated.

We may now summarise the empirical predictions of the search theory outlined in section three:

SEARCH = f(age, income, family commitments, past defaults, membership of

-   -   -   +

minority groups, education, debt outstanding on which interest will be paid)

+   +   +

4. Empirical model and Results

Our measure of the amount of search activity is the household's response to the question described earlier when we explained the variable SEARCH2. However in this work we did not dichotomise the response but used all 5 response values (SEARCH) This measure is clearly not ideal. It is an ordinal rather than a ratio level of measurement and it is possible that two people, identical in their search volume and intensity, may give different answers. The ordinal nature of the measure is specifically accounted for in the likelihood function used to estimate the parameters of the empirical model. We use ordered logistic regression and assume a model of the following form:

$$S_i^* = \beta' x_i + \varepsilon_i \qquad \varepsilon_i \sim \Lambda(1-\Lambda) \qquad \ldots(24)$$

where $\Lambda(1-\Lambda)$ is the lognormal density;

S_i^* is the amount of search activity, case i;

β' is a [1 x j } column vector of parameters to be estimated;

x_i is a [1 x j] column vector of variables, case i;

ε_i is the value of the error, case i;

S_i^* is unobserved (it is continuously measured). But we do observe

$S_i = 1$ if $S_i^* \leq 0$

$S_i = 2$ if $0 < S_i^* \leq k_1$

$S_i = 3$ if $k_1 < S_i^* \leq k_2$

$S_i = 4$ if $k_2 < S_i^* \leq k_3$

$S_i = 5$ if $k_3 \leq Si^*$

The likelihood function is given in standard econometrics texts.

The SCF does not allow us to identify those households who have searched for a new or additional bank credit card in the recent past. In Table 2 we report the results for three different groups of households: all households; those households in which either the head or his/her partner applied for any type of credit or loan in the previous five years; and those households in which either the head or his/her partner had applied for credit in the last five years *and* the household has a bank credit card. We include the first group to indicate the behaviour of households when they seek credit of any type. We report on the second group because those who have applied for credit in the last few years are likely to give a more accurate response to the question asking them to report o their search behaviour than households who have not sought credit recently. The third group is included because it is the closest match to the search behaviour of interest that is possible using data from the SCF. For each sample we have regressed search on selections of the explanatory variables together. We have excluded certain combinations because collinearity would have distorted the results if we had not done so.

TABLE 2 HERE

The results suggest that in the markets for credit, without reference to a particular type of credit product (Tables 2a and 2b), there is no evidence to suggest that those who are poor payers search either more or less than those who do not default. But the search behaviour of those who hold a credit card (Table 2c) is different. For these households, those who have recently defaulted appear to search less than those who have not defaulted. This is consistent with the argument that if a bank unilaterally lowers its interest rate it will attract the better payers rather than poorer payers. This is not consistent with one type of adverse selection.

In none of the samples is the incidence of previous bankruptcy (ever bankrupt) correlated with search behaviour. Nor is a household's balance outstanding on a credit card correlated with search behaviour. But for all three samples, those who reported that they repaid all of their balances on bank credit cards each month did engage in more search activity than those who did not repay all of their balances. This may seem irrational since such people, who have no balance outstanding, would not expect to pay interest and so there would be no reason to search for lower rates. However people may be searching for lower annual fees or for higher credit limits or for additional cards.

For households on average and without regard for any type of credit, being a member of a minority, as represented by WHITE, is unrelated to the amount of search a household undertakes. But being a member of a minority *is* positively correlated with the amount of search for interest rates if the household is a credit card holder. The results also suggest that for those who applied in the last five years and for those who hold a credit card male heads of households search more than female heads of households. In addition and consistent with theory, as age increases so does search activity but eventually search decreases. For all households search reaches a maximum at approximately 40 years of age and for those who have a credit card it reaches a maximum at approximately 38 years of age.

Contrary to the predictions of the theory the level of household income is unrelated to the volume of search activity in all three samples. Households where the head is living with a partner (married or otherwise) search more for low interest rates than households where the head is not married. In addition, those households were the head has completed more years of education also search more actively than other households.

5 Conclusion

The search theory is supported by the results that minorities search more than whites, that the better educated search more than the less well educated, and that after a certain age search activity decreases. The estimated turning point is entirely plausible: around 40 years of age.

But other results are not so supportive. The finding that those who have, in the last years, had a poor repayment record do not search more than those with a good record seems inconsistent with the search theory presented in section 2. However it is possible that those who miss payments may have the type of life style which would cause them to have high search costs and that this effect dominates any increase in the mean of the offer distribution, which they may believe they face. This result suggests more research may be useful.

The lack of an effect for income on search activity could be because those with higher income demand higher debt and so would search actively to reduce the cost of this and this effect counteracts the opportunity cost of search activity effect. The result that households, where the head lives with a partner, search more than others may be due to specialisation of the search activity (see Hassiatosis: 2001 for a similar argument). Alternatively it may be due to lower income per head in such families making the marginal utility of interest payments saved by greater search larger than for families with higher income per head. The overall impression gained form the results is that it is the “efficient” households who search most. These are households where the head is better educated, they repay on time, they are especially keen to reduce either annual fees or any interest they may inadvertently incur and they are relatively young.

Turning now to the implications for the degree of adverse selection, the finding that a poor repayment history does not affect search does not support the notion that, if a bank lowers its interest rate it will, on average, attract poor payers. This particular result was also obtained by C&M. However, our inability to find a significant effect of bank credit card balances on search activity suggests that if a bank unilaterally lowered its interest rate it would not attract a disproportionately large share of low balance (and so low profit) applicants. This result is not consistent with this form of adverse selection and it differs from the result for the late 1980s that was found by C&M.

Variable List

Inc0	Total family income before taxes and other deductions in 1997 (units of \$100,000)
Tdebt2toinc	Total household debt/income where total household debt is debt outstanding on mortgages, home equity loans, HELOCS, other lines of credit, debt for other residential property, credit card debt, instalment loans, loans from pension funds, loans for life policies, margin loans, miscellaneous loans, debt on non residential real estate, loans from businesses.
Ndebt2toinc	Total household debt less credit card balance outstanding / income
Touts1toinc	Outgoings/income where outgoings are outgoings per month on mortgages, property loans, home improvement loans, land contracts, loans for real estate, payments for leased vehicles, payments for owned vehicles and rent.
Ownspr	=1 if household owns its principal residence =0 otherwise
Liqassets0	assets in transaction accounts (checking accounts, savings accounts, money market accounts, call accounts at brokerages), plus value of certificates of deposit plus value of savings bonds (units of \$100,000)

Stckbnds0	value of stocks plus value of bonds (units of $100,000)
Nopeu	Number of people in primary economic unit
Yatjob	Years head of household has worked for main employer
Age	Age of head of household
Sex	=1 if head of household is male =0 if head of household is female
Married1	=1 if head of household is married or living with a partner =0 otherwise
White	=1 if head of household is white =0 otherwise
Grade	highest grade of school or year of college of head of household
Bcbal	for visa, mastercard, discover and optima cards the response to the question 'after the last payments were made on these accounts, roughly what was the balance still owed on these accounts?'
Avail	maximum amount household could borrow on lines of credit less the amount currently owed – on all lines of credit

Default	=1 if answered 'yes' to the question: 'thinking of all the various loan or mortgage payments you made during the last year …were you ever behind in your payments by 2 months or more?'
paybsc	=1 if always or almost always pays off the total balance owed on Visa, Mastercard, Discover, Optima accounts each month. =0 otherwise
degree	=1 if head of household gained a college degre =0 otherwise
Turndn	=1 if in the last 5 years a particular lender or creditor has turned down any request that the head of household or spouse/partner made for credit or if the lender or credit did not give as much credit as was applied for. =0 otherwise
bnkrpt	=1 if head of household or spouse/partner has ever filed for bankruptcy =0 otherwise
Search	The numeric response to the question "when making major decisions about credit or borrowing some people shop around for the very best terms while others don't. (What number would you be on the scale?/What number would your family be on the scale?)

1	2	3	4	5
Almost no shopping		Moderate shopping		A great deal of shopping”

search2 =1 if search is greater than 3

= 0 otherwise

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Appendix 1

Formula used to aggregate estimated parameters across implicates

The following formulae have been used to calculate the coefficients, t-statistics and degrees of freedom from the estimated parameters from all 5 implcates in Tables 1 and 3. They are taken from Little and Rubin (1987) eqns 12.17 to 12.20.

$$X_R = \sum_l \left(X_l \big/ R \right)$$

where X_l, $l = 1, \ldots 5$ is the estimated mean value of X for the complete imputed data set l. The total variance of the estimate, T_R is the sum of the average variance within imputed data sets, W_R, and an adjusted variance between imputed datasets, B_R. Thus:

$$T_R = W_R + ((R+1)/R)B_R$$

where W_R and B_R are given by:

$$W_R = \sum_l \left(W_l \big/ R \right)$$

where W_l is the estimated variance of X calculated using the lth set of imputed values

$$B_R = \frac{\sum \left(X_l - \overline{X_R} \right)^2}{(R-1)}$$

Little and Rubin state that for the scalar X the comparator distribution for significance tests is the t-distribution:

$$\left(X - \overline{X_R} \right) T_R^{-0.5} \sim t_\phi$$

with degrees of freedom

$$\phi = (R-1)\left[1+\left(\frac{1}{R+1}\right)\left(\frac{W_R}{B_R}\right)\right]^2$$

Appendix 2

Tobit regression without using sampling weights

Dependent variable: BCBAL

	Coefficient
SEARCH2	-0.0000
	(-0.009)
ATTGEN	0.0069
	(1.368)
ATTVAC	0.0285
	(4.539)**
ATTFC	0.0153
	(1.680)
INC0	-0.0090
	(-4.598)**
INC20	0.0000
	(3.223)**
NDEBT2TOINC	0.0008
	(1.646)
TOUTS1TOINC	0.0325
	(1.362)
OWNSPR	-0.0067
	(-1.098)
LIQASSETS0	-0.0183
	(-6.474)**
STCKSBNDS0	-0.0039
	(-2.536)*
NOPEU	0.0037
	(1.715)
YATJOB	0.0005
	(1.978)
AGE	-0.0010
	(-5.561)**
SEX	-0.105
	(-1.260)
MARRIED1	0.0187
	(2.309)*
WHITE	-0.0065
	(-1.021)
GRADE	-0.0006
	(-0.663)
CONSTANT	0.0340
	(1.828)

Mean no Of observations: 2827

Ref: st26feq1.xls

Appendix 3a

We then define

$$E^*(n) = \frac{1}{\int_0^{r_R} f(r-\alpha)dr} \qquad \text{. . . (A3i)}$$

Then

$$\frac{\partial E(n)}{\partial E(r)} = \frac{\partial E^*(n)}{\partial \alpha} = \frac{1}{\left(\int_0^{r_R} f(r-\alpha)dr\right)^2}\left\{\int_0^{r_R} f(r-\alpha)dr.0 - \frac{d}{d\alpha}\int_0^{r_R} f(r-\alpha)dr\right\} \qquad \text{. . .(A3ii)}$$

and $\frac{\partial}{\partial \alpha}\int_0^{r_R} f(r-\alpha)dr = \int_0^{r_R} \frac{\partial f(r-\alpha)}{\partial \alpha}dr$ . . . .(A3iii)

But $\frac{\partial f(r-\alpha)}{\partial \alpha} = \frac{\partial f(r-\alpha)}{\partial (r-\alpha)}\frac{\partial (r-\alpha)}{\partial \alpha} = -\frac{\partial f(r-\alpha)}{\partial (r-\alpha)}$ . . . . (A3iv)

and $\frac{\partial f(r-\alpha)}{\partial r} = \frac{\partial f(r-\alpha)}{\partial (r-\alpha)}\frac{\partial (r-\alpha)}{\partial r} = \frac{\partial f(r-\alpha)}{\partial (r-\alpha)}$ . . . (A3v)

so $\frac{\partial (r-\alpha)}{\partial a} = -\frac{\partial f(r-\alpha)}{\partial r}$ . . . (A3vi)

Also $\frac{\partial f\left(r-\alpha\right)}{\partial r}=\frac{\partial f\left(r-\alpha\right)}{\partial\left(r-\alpha\right)}.\frac{\partial\left(r-\alpha\right)}{\partial r}=\frac{\partial f\left(r-\alpha\right)}{\partial\left(r-\alpha\right)}=\frac{\partial f\left(r\right)}{\partial r}$ . . .(A3vii)

Substituting equation (A3vii) into (A3vi): $\frac{\partial f\left(r-\alpha\right)}{\partial\alpha}=-\frac{\partial f\left(r\right)}{\partial r}$ . . . (A3viii)

Substituting equation (A3viii) into (A3iii): $\frac{\partial}{\partial\alpha}\int_0^{r_R} f(r-\alpha)dr=-\int_0^{r_R}\frac{\partial f(r)}{\partial r}dr$ . . . (A3ix)

.

Substituting equation (A3ix) into (A3ii) gives equation (17) in the text.

Appendix 3b

Because $f(r)$ is symmetric and single peaked

$$\int_{0}^{E(r)} \frac{\partial f(r)}{\partial r} dr > 0 \quad \text{and} \quad \int_{E(r)}^{r_R} \frac{\partial f(r)}{\partial r} dr < 0$$

For $2E(r) > r_R$:

$$\left| \int_{0}^{E(r)} \frac{\partial f(r)}{\partial r} dr \right| > \left| \int_{E(r)}^{r_R} \frac{\partial f(r)}{\partial r} dr \right|$$

so $\int_{0}^{r_R} \frac{\partial f(r)}{\partial r} dr > 0$

Table 1

Tests of Adverse Selection

	BCBAL	**TURNDN**	**DEFAULT**
SEARCH2	-0.0006	-0.0818	-2.831
	(-1.373)	(-1.123)	(-2.404)*
BCBAL		3.5757	1.8889
		(5.506)**	(2.422)*
ATTGEN	0.0059	-0.1165	
	(1.472)	(-1.535)	
ATTVAC	0.0233	0.2755	
	(4.296)**	(2.911)**	
ATTFC	0.0111	-0.0194	
	(0.162)	(-0.145)	
DEFAULT		0.8699	
		(5.434)**	
AVAIL		-0.0000	
		(-0.007)	
INC0	0.0003	-0.020	-0.2075
	(0.039)	(-0.537)	(-0.838)
INC20	-0.0000	0.0000	-0.0000
	(-0.980)	(0.663)	(-0.171)
TDEBT2TOINC		0.0114	0.0235
		(0.890)	(1.322)
NDEBT2TOINC	0.0017		
	(0.903)		
TOUTS1TOINC	-0.0060	-0.1458	-1.9759
	(-0.101)	(-0.291)	(-1.102)
OWNSPR	-0.0084	-0.2809	-0.4345
	(-1.414)	(-3.157)**	(-3.325)**
LIQASSTES0	-0.0017	-0.1605	-0.4765
	(-3.689)**	(-2.158)*	(-1.035)
STCKSBNDS0	-0.0026	-0.0337	-0.0654
	(-1.364)	(-0.908)	(-0.526)
NPEU	0.0034	0.1090	0.1558
	(2.035)*	(3.407)**	(3.400)**
YATJOB	(0.0004)	-0.0052	-0.0000
	(2.035)*	(-1.176)	(-0.012)
AGE	-0.0008	-0.0253	-0.0099
	(-5.516)**	(-9.013)**	(-2.614)**
SEX	-0.0071	0.2066	0.2900
	(-1.191)	(1.769)	(1.678)
MARRIED1	0.0133	-0.3512	-0.3835
	(2.059)*	(-2.908)**	(-2.142)*
WHITE	-0.0002	-0.0092	-0.0635
	(-0.045)	(-0.933)	(-0.493)
GRADE	-0.0001	-0.0378	-0.0344
	(-0.0154)	(-2.583)**	(-1.530)

CONSTANT	0.0254 (1.543)	0.8838 (3.126)**	-0.5635 (-1.432)
Mean Pseudo R^2	NA	0.1832	0.1252
Mean no of observations:	2827	2826	2826

* = significant at 5%. ** = significant at 1%.

All regressions use probability sampling weights and Huber standard errors.

Ref:	st26feq2.xls	st21feq2.xls	st20feq2.xls

Table 2 (a)

Search activity by all households

Dependent variable: SEARCH

	Coefficient	Coefficient	Coefficient
DEFAULT	0.074	0.067	-0.008
	(0.517)	(0.468)	(-0.050)
BNKRPT	0.112	0.111	0.023
	(0.924)	(0.916)	(0.140)
PAYBSC	0.354	0.364	
	(4.648)**	(4.784)**	
BCBAL			0.000
			(0.452)
WHITE	0.037	0.040	0.029
	(0.425)	(0.453)	(0.220)
SEX		0.122	0.189
		(1.493)	(1.688)
AGE	0.052	0.055	0.056
	(4.383)**	(4.629)**	(4.242)**
AGE2	-0.001	-0.001	-0.001
	(-5.809)**	(-6.045)**	(-5.055)**
INC0	0.004	0.009	0.023
	(0.336)	(0.757)	(1.626)
INC20	-0.000	-0.000	-0.000
	(-0.386)	(-0.809)	(-1.669)
MARRIED1	0.194		
	(2.707)**		
GRADE	0.073	0.072	0.084
	(5.590)**	(5.531)**	(5.663)**
C1	0.631	0.662	0.742
	(2.052)*	(2.149)*	(1.567)
C2	0.999	1.029	1.135
	(3.243)**	(3.336)**	(2.655)*
C3	2.720	2.748	2.893
	(8.715)**	(8.792)**	(7.752)**
C4	3.350	3.378	3.544
	(10.646)**	(10.715)**	(9.964)**
ref	sst33feq1.xls	sst33feq2.xls	sst33feq3.xls

Table 2 (b)
Search activity by households who applied for credit in the last 5 yrs

Dependent variable: SEARCH

	Coefficient	**Coefficient**	**Coefficient**
DEFAULT	-0.049	0.006	-0.043
	(-0.271)	(0.033)	(-0.252)
BNKRPT	-0.135	-0.089	-0.101
	(-0.886)	(-0.593)	(-0.580)
PAYBSC		0.384	
		(4.130)**	
BCBAL	-0.000		-0.000
	(-0.396)		(-0.118)
WHITE	-0.112	-0.152	-0.084
	(-0.993)	(-1.346)	(-0.596)
SEX		0.261	0.273
		(2.424)*	(2.182)*
AGE	0.048	-0.048	0.052
	(2.749)**	(-2.786)**	(3.138)**
AGE2	-0.001	-0.001	-0.001
	(-3.219)**	(-3.336)**	(-3.564)**
INC0	0.019	0.007	0.023
	(1.078)	(0.442)	(1.344)
INC20	-0.000	-0.000	-0.000
	(-1.110)	(-0.479)	(-1.378)
MARRIED1	0.305		
	(3.264)**		
GRADE	0.078	0.062	0.079)
	(4.172)**	(3.326)**	(4.322)**
C1	0.074	-0.054	0.323
	(0.165)	(-0.120)	(0.577)
C2	0.576	0.448	0.797
	(1.284)	(1.008)	(1.543)
C3	2.518	2.400	2.692
	(5.567)**	(5.358)**	(5.781)**
C4	3.272	3.160	3.421
	(7.181)**	(6.999)**	(7.646)**
Ref	sst32feq1.xls	sst32feq2.xls	sst32feq3.xls

Table 2 (c)

Search activity by households who applied for credit in the last 5 years and who have a bank credit card

Dependent variable: SEARCH

	Coefficient	Coefficient	Coefficient
DEFAULT	-0.439 (-1.961)	-0.400 (1.807)	-0.462 (-2.071)*
BNKRPT	-0.031 (0.164)	0.010 (0.053)	-0.027 (-0.144)
PAYBSC		0.334 (3.307)**	
BCBAL	-0.000 (-0.384)		-0.000 (-0.363)
WHITE	-0.358 (-2.643)**	-0.384 (-2.838)**	-0.364 (-2.686)**
SEX		0.300 (2.375)*	0.331 (2.619)**
AGE	0.033 (1.730)	0.034 (1.752)	0.036 (1.846)
AGE2	-0.000 (-2.183)*	-0.000 (-2.266)*	-0.000 (-2.263)*
INC0	0.022 (1.236)	0.013 (0.720)	0.024 (1.310)
INC20	-0.000 (-1.265)	-0.000 (-0.751)	-0.000 (-1.336)
MARRIED1	0.277 (2.554)*		
GRADE	0.044 (1.964)	0.033 (1.497)	0.043 (1.940)
C1	-1.154 (-2.112)*	-1.143 (-2.099)*	-1.030 (-1.876)
C2	-0.566 (-1.054)	-0.555 (-1.029)*	-0.442 (-0.813)
C3	1.472 (2.703)**	1.493 (2.748)**	1.595 (2.918)**
C4	2.268 (4.139)**	2.295 (4.197)**	2.391 (4.347)**
ref:	sst31feq1.xls	sst31feq2.xls	sst31feq3.xls

The number in parentheses is the t-statistic. The coefficients and t-statistics have been calculated from all 5 implicates using formula given in the Appendix from Little & Rubin (1987).

* denotes significance at 5%. ** denotes significance at 1%.