Self-control and debt: evidence from data on credit counselling.

Very preliminary, comments are welcome.

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ABSTRACT. Counselling agencies assist borrowers in financial difficulties by administering repayment plans, the so-called debt management plans (DMPs). This paper explores the effect of self-control problems on the debt repayment behavior of borrowers on a DMP. We develop a simple model of a DMP performance which predicts that borrowers, who have self-control problems and are naive about it, are more likely to default on a DMP. We use unique data from a major credit counselling charity in the UK to test this prediction. Two different indicators are constructed to identify individuals with self-control problems, self-reported reason for falling into unmanageable debt, and smoking. To compare the debt repayment behavior of the individuals with and without self-control problems, we use the Cox proportional hazard model to estimate a probability of defaulting on a DMP. Our results suggest that self-control problems increase the probability of defaulting by 12% and 31% respectively, as measured by the two different self-control problems indicators.

Keywords: time preferences, self control, credit behaviour, credit counselling, debt management plans

JEL Classification Codes: G2, G21, D14, D91.

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1 Introduction

People run into financial difficulties for various reasons. Is overindebtedness always caused only by unexpected adverse events such as loss of job, drop in income, illness or divorce? Can it also be merely a result of lack of financial planning? Chakravarty and Rhee [6] using PSID data for the U.S. between 1984-95, for example, reported that among people who filed for bankruptcy, around 40 percent stated credit misuse as the reason. We reproduce Panel B of Table 1 from their paper below:

<table>
<thead>
<tr>
<th>Reason for filing (chapter 7)</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job Loss</td>
<td>12.17</td>
</tr>
<tr>
<td>Marital distress</td>
<td>14.28</td>
</tr>
<tr>
<td><strong>Credit Misuse</strong></td>
<td>41.26</td>
</tr>
<tr>
<td>Health care bills</td>
<td>16.40</td>
</tr>
<tr>
<td>Lawsuits and Harassments</td>
<td>15.87</td>
</tr>
</tbody>
</table>

Source: Table 1, Panel B from Chakravarty and Rhee [6]. U.S. between 1984-95, PSID.

One possible reason for credit misuse may-be the lack of financial literacy. If debt mismanagement problems are due to lack of financial literacy, then the financial education should play a key role in helping people take “better” (from the economic theory point of view, “optimal”) decisions. However, as reported in Durkin [8] and discussed in Bertaut and Haliassos [3], there is survey evidence suggesting that people are generally familiar with basic financial concepts, i.e. they are aware of APR (annual percentage rate) and other terms of the credit card contracts. If we are to describe “unaware” as not knowing the APR on a bank type credit contract, the level of “awareness” is around 80 percent among the people surveyed.

*Self control problems* represent an alternative and entirely different reason for debt mismanagement. The 2001 Survey of Consumers (U.S.) reveals that about forty percent of the households regard self-control as a general problem, and they believe that availability of credit cards might trigger overspending and overborrowing. Interestingly, a significant percentage of people think that this is a problem for others but not for themselves (Durkin [8], Bertaut and Haliassos [3]).
Credit counselling assists heavily indebted borrowers by setting up and administering repayment plans, so called debt management plans (DMPs). In this paper, we use a unique administrative data set of a major consumer credit counselling charity in the UK to explore the effect of self-control problems as well as the effect of various other individual characteristics on the debt repayment behavior of borrowers in financial difficulties.

Despite the fact that the credit counselling industry has been growing rapidly, the economic research in this area is still scarce. To our knowledge, there are only two papers on credit counselling that provide quantitative analysis, each with a rather different focus: Staten et. al. [18] use detailed credit bureau information from the U.S. to explore the effect of credit counselling on borrowers’ credit scores and future repayment behavior. They find that credit counselling has a significant positive effect on borrowers’ credit worthiness, in particular for those borrowers who have low initial credit scores. They also document improvement in many aspects of borrowing behavior of people who received counselling. Beltz [1] on the other hand analyzes the relationship between counselling agencies and creditors. He concludes that a closer co-operation between creditors and the counselling agencies would be preferable to current status where competition is used to lower the fair-share contribution rates.

In this paper we focus on the counselling process itself. Namely, we ask who are the borrowers that are more likely to succeed in a DMP and therefore benefit from the counselling most, and who are the ones who do not. We begin by developing a simple model of repayment behavior of a borrower in a debt management plan. We model the self-control problems by hyperbolic discounting and compare the results to the exponential discounting benchmark. The model predicts that sophisticated hyperbolic discounters would have the same DMP drop-out rates as exponentials whereas naive hyperbolic discounters would drop out from the DMP more often.

We use the dataset of clients of a major consumer credit counselling charity in the UK to test the predictions of our model. Our estimation sample consists of all the borrowers who started a DMP between January 2003 and November 2006 (60,495 individuals). We observe their debt repayment behavior (DMP performance) as well as various individual characteristics, budget information (income and expenditures), and DMP terms (amount of debt, duration, monthly payment). We construct two indicators of self-control problems using two types of information: self-reported reasons for
running into financial troubles and smoking. Individuals who reported difficulties in managing their finances (poor shopping habits, lack of financial planning, no budget etc.) as the reason for running into financial troubles, and smokers are both regarded as suffering from self-control problems. We than compare the debt repayment behavior of individuals with and without self-control problems. We estimate a Cox proportional hazard model of the probability of dropping out from a DMP as a function of various individual characteristics including the two self-control indicators.

Preliminary results show that self-control problems increase the drop-out probability at any time by 12 % and 31 % respectively, depending on the self-control indicator used. We also find that the drop-out probability decreases with age and that women are substantially more likely to stay on DMP than men. A single woman is almost 40% less likely to drop than a single man. A couple is more likely to stay on the DMP if it is a woman who contacts CCCS. Having a mortgage decreases the probability of the DMP drop-out. While being self-employed increases the probability of dropping out, working as a full-time employee reduces it.

The paper is organized as follows. In the next section we introduce a very simple theoretical model of a DMP and analyze the behavior of the exponential, naive and sophisticated borrowers. Section 3 describes the data and the estimation method. In Section 4 we present the results, and in Section 5 we conclude. Appendix A describes the variables that are used in the estimation. In Appendix B we discuss the role of credit counselling as a commitment mechanism to help borrowers overcome their self-control problems.

2 A simple model of a DMP

We construct a simple model of a DMP repayment behavior with income uncertainty that serves to illustrate the repayment performance of different types of borrowers while on a DMP. We consider borrowers that differ only with respect to their time preferences as explained below.

Discounting. We assume that borrowers have quasi-hyperbolic discount function (Strotz [19]; Phelps and Pollack [17]; Laibson [11]; O’Donoghue and Rabin [14], [15]). The quasi-hyperbolic discount function for time \( s \) evaluated at period \( t \), equals to 1 for \( s = t \) and is equal to \( \beta \delta^{s-t} \) for \( s = t + 1, t + 2, ... \) where \( \beta \in (0, 1] \) and \( \delta \in (0, 1] \). The case of \( \beta = 1 \) corresponds to time-
consistent, exponential discounting. When $\beta < 1$, the consumer has time-inconsistent discounting. Consumers with time inconsistent preferences are like different selves at different times (preferences change over time). We refer to consumer’s self in period 0 as self-0, and that of period two and period three as self-1 and self-2 respectively. With quasi-hyperbolic discount function, self-0 time preferences are given as $\{1, \beta \delta, \beta \delta^2, \ldots\}$. Suppose that self-0 thinks that the future selves’ time preferences are $\{1, \hat{\beta} \delta, \hat{\beta} \delta^2, \ldots\}$. A consumer with preference parameters $(\beta, \hat{\beta}, \delta)$ is said to have time-consistent exponential discounting if $\beta = 1$ with $\hat{\beta} = 1$. We will consider the following cases of time-inconsistency: if $\beta < 1$ with $\hat{\beta} = \beta$, the consumer is said to be sophisticated and if $\beta < 1$ with $\hat{\beta} = 1$, the consumer is naive. That is, sophisticated consumer is fully aware of her hyperbolic preferences and correctly anticipates that her future selves will have hyperbolic preferences. In contrast, naive consumer is completely unaware of her time-inconsistency and she thinks that her future selves will discount exponentially. Note that these are the two extreme cases. If consumer’s self-0 believes that her future selves’ preferences are $\{1, \hat{\beta} \delta, \hat{\beta} \delta^2, \ldots\}$ with $\beta < \hat{\beta}$, then she is said to be partially naive. The difference $\hat{\beta} - \beta$ can be interpreted as the degree of naivete. Similarly, the difference $\beta - 1$ reflects the degree of time-inconsistency.

### 2.1 Borrower behavior in a DMP

We assume that the time is discrete and there are three periods (0,1,2). We consider a borrower with preference parameters $(\beta, \hat{\beta}, \delta)$ and a given debt level $P$ at $t=0$. We define the DMP as an agreement between the debt counselor and the borrower such that the borrower promises to pay $P$ at $t = 1$ upon accepting the DMP at $t = 0$. We assume for simplicity that the consumption takes place only in period 1 and the per period utility $u_t(c_t) = c_t$ is linear in $c_t$. The income at $t = 1$ is a random variable that takes the value $y_h \geq P$ with probability $\alpha$ and the value $y_l < P$ with probability $1 - \alpha$. There is no saving or borrowing while on a DMP.

At time $t = 0$ the borrower decides whether to accept a DMP (debt management plan) or reject it and default on his debts. If the borrower rejects the DMP and defaults, he incurs a cost $\overline{d}_0$ at $t = 1$. If the borrower accepts the DMP and if the realization of the income $y$ at $t = 1$ is $y_l$ then the borrower cannot meet his payment obligation and drops out. In this case the borrower gets the utility $u(y_l) = y_l$ from consuming $y_l$ at $t = 1$
and incurs the cost $d_1$ at $t = 2$. If the realization of income is $y_h$ then the borrower decides whether to stay in DMP or drop out. If he stays, he consumes $u(y_h - P) = y_h - P$ at $t = 0$. If he drops out, he incurs the cost $d_1$ at $t = 2$.

We compute the conditional drop-out probability, namely the probability that a borrower with $(\beta, \hat{\beta}, \delta)$ preferences drops out from a DMP at $t = 1$ conditional on accepting a DMP at $t = 0$ under the following assumptions:

**Assumption 1** At $t = 0$, expected benefit of rejecting the DMP is higher than the expected benefit of accepting and then dropping-out next period if $y = y_h$.

**Assumption 2** At $t = 0$, paying the debt when $y = y_h$ is preferred to dropping-out when $y = y_h$.

The assumptions imply that the no borrower has strategic default motives at $t = 0$ when signing the DMP. That is, dropping out from a DMP when
there is a positive shock to income is never ex-ante optimal. We believe this assumption is justifiable in the context of credit counselling, since DMPs are voluntary agreements. We will now show that, under Assumptions 1 and 2, naive and sophisticated borrowers drop only if \( y = y_l \). All the naive and the sophisticated borrowers who share the same \( \beta \) either accept the DMP and drop out only if \( y = y_l \) or only the naive borrower accepts and drops out if \( y = y_h \).

**Proposition 3** Under Assumptions 1 and 2, all the exponential borrowers accept the DMP and drop out with probability \( \alpha \). If the naive and sophisticated borrowers share the same \( \beta > \frac{P}{\delta d_1} \), they both accept the DMP and drop out with probability \( \alpha \). If they share the same \( \beta \leq \frac{P}{\delta d_1} \), sophisticated borrower rejects the DMP whereas the naive borrower accepts the DMP and drops out with probability \( 1 > \alpha \).

**Proof:** We begin by deriving the condition that any borrower prefers rejecting the DMP to accepting it at \( t = 0 \) with the intention of dropping out at \( t = 1 \) if \( y = y_h \):

\[
-\beta \delta \bar{d}_0 + \beta \delta [\alpha y_l + (1 - \alpha) y_h] > \beta \delta \left[ \alpha (y_l - \hat{\beta} \delta \bar{d}_1) + (1 - \alpha)(y_h - \hat{\beta} \delta \bar{d}_1) \right],
\]

which implies that

\[
\hat{\beta} > \frac{d_0}{d_1 \delta}.
\]

We will now derive the condition for accepting a DMP, namely the condition that the expected benefit of agreeing a DMP at \( t = 0 \) with the intention of staying at \( t = 1 \) when \( y = y_h \), exceeds that of rejecting the DMP, both evaluated from the perspective of \( t = 0 \):

\[
-\beta \delta \bar{d}_0 + \beta \delta [\alpha y_l + (1 - \alpha) y_h] \leq \beta \delta \left[ \alpha (y_l - \hat{\beta} \delta \bar{d}_1) + (1 - \alpha)(y_h - P) \right]
\]

After some algebra the condition above simplifies to another condition on \( \hat{\beta} \):

\[
\hat{\beta} \leq \frac{d_0 - (1 - \alpha)P}{\alpha d_1 \delta}.
\]
When $t = 1$ arrives, the condition for staying in DMP becomes,

$$y_h - P \geq y_h - \beta \delta \bar{d}_1$$

which after some algebra simplifies to

$$\beta \geq \frac{P}{\delta \bar{d}_1}.$$  \hspace{1cm} (2.1)

Assumptions 1 and 2 imply that any exponential borrower with $\delta > \frac{d_0}{\delta \bar{d}_1}$ and $\delta \leq \frac{d_0 - (1 - \alpha)P}{\delta \bar{d}_1}$ accepts the DMP and drops out only when $y = y_l$. Assumption on $\delta$ implies that $d_0 > P$ and therefore $\frac{d_0 - (1 - \alpha)P}{\delta \bar{d}_1} > 1$. Thus, all the time-inconsistent borrowers with $\hat{\beta} \in \left(\frac{d_0}{\delta \bar{d}_1}, 1\right)$ accept the DMP and drop out with probability $\alpha$ only if $\beta \geq \frac{P}{\delta \bar{d}_1}$. The sophisticated borrower with $\beta < \frac{P}{\delta \bar{d}_1}$ rejects the DMP and the naive borrower who shares the same true $\beta$ accepts the DMP and drops out with probability $1 > \alpha$. This concludes the proof.$\Box$

The following example illustrates the proposition by assuming a particular joint distribution on $\beta$ and $\hat{\beta}$.

**Example Distribution for $\beta$ and $\hat{\beta}$**

Consider the population of borrowers with their $(\beta, \hat{\beta})$ jointly uniformly distributed as follows

$$f_{\beta, \hat{\beta}}(\beta, \hat{\beta}) = \begin{cases} 2 & \text{if } 0 \leq \beta \leq \hat{\beta} \leq 1, \\ 0 & \text{otherwise}. \end{cases}$$

The marginal distribution of $\hat{\beta}$ can be calculated as

$$f_{\hat{\beta}}(\hat{\beta}) = \int_{\beta}^{1} f_{\beta, \hat{\beta}}(\beta, \hat{\beta}) d\beta = 2\hat{\beta}$$

if $0 \leq \hat{\beta} \leq 1$ and $f_{\hat{\beta}}(\hat{\beta}) = 0$ otherwise.

Figure 2 illustrates the behaviour of a borrower with $(\beta, \hat{\beta}, \delta)$ preferences as $\beta$ and $\hat{\beta}$ vary.

Insert figure here.
Figure 2: DMP outcome for different combinations of $\beta$ and $\hat{\beta}$

The point $(1, 1)$ on the upper corner represents the exponential borrowers, if $\delta \in \left[\frac{d_0}{\delta d_1}, \frac{d_0-(1-\alpha)P}{\alpha d_1}\right]$, they accept the DMP and stay if $y = y_h$. The line segment joining the points $(\frac{d_0}{\delta d_1}, \frac{d_0}{\delta d_1})$ and $(1, 1)$ represents the sophisticated borrowers who accept and stay if $y = y_h$. The area with coordinates $(\frac{d_0}{\delta d_1}, 0), (1, \frac{P}{\delta d_1}), (1, 0)$ represent the naive borrowers who accept the DMP thinking they would stay but end up dropping at $t = 1$ when $y = y_h$.

The sophisticated hyperbolic discounters and exponentials do not drop from the DMP at $t = 1$ once they have accepted a DMP at $t = 0$, unless the realization of $y$ is $y_l$ (negative shock). Therefore for this type of borrowers the drop out probability is given by $\alpha$.

The probability (for a naive borrower) of dropping out at $t = 1$ conditional on accepting the DMP at $t = 0$ can be calculated as follows:
\[
\alpha + (1 - \alpha) Pr(\beta \leq \frac{P}{\delta d} \mid \tilde{\beta} > \frac{d_0}{\tilde{d}_1}) = \alpha + (1 - \alpha) \int_0^{P/\delta d} \int_{d_0/\delta d_1}^{1} 2 \beta \tilde{d} d\beta \int_0^{1} 2 \tilde{\beta} d\tilde{\beta}
\]

Thus, if the income shock is distributed randomly across types, we observe the same drop out rates for exponentials and sophisticates and higher drop out rate for naives.

3 Empirical analysis

3.1 About CCCS

In this paper, we use the client database of the Consumer Credit Counselling Service (CCCS), the leading provider of the free debt counselling service in the UK.\footnote{1} CCCS acts as a mediator between borrower/debtor and typically “many lenders” by negotiating a debt consolidation plan known as debt management plan (DMP) with lenders on behalf of consumers.

People in financial difficulties reach CCCS through their free phone number or their website.\footnote{2} An assessment of the situation is performed over the phone and consumers are offered one of the following: financial and budget advice (providing self-help material) or a counselling interview.\footnote{3} If the client is a candidate for a debt management plan (DMP), CCCS negotiates a repayment plan with creditors on behalf of the consumer (creditors are asked to freeze interest, stop penalties, and accept a longer repayment period and sometimes a reduced sum). Therefore DMP is essentially a debt consolidation plan. CCCS only deals with unsecured debt (debt accumulated on credit cards, store cards, catalogue orders etc.).\footnote{4}

\footnote{1}CCCS is a registered debt charity and therefore has a non profit status. It is funded by fair share contributions form credit industry.

\footnote{2}Almost half of CCCS clients are recommended to CCCS by their lenders.

\footnote{3}The interview can take place over the phone or face to face in one of the centres and it consists of a full review of the credit and debt situation followed by a recommendation.

\footnote{4}Secured debts (mortgages) are considered as “priority debts” and monthly payment obligations on such debts are taken into account when agreeing a monthly budget with the client.
CCCS was introduced into the UK in 1993.\textsuperscript{5} Table below shows the number of people who started a DMP and the total number of people who were on a DMP at the end of each year between 2003-2006. Note that, these numbers take into account that there were borrowers who successfully completed their DMPs or who found other means of paying their debt and therefore left CCCS.

<table>
<thead>
<tr>
<th>Year</th>
<th># people started a DMP</th>
<th># people on DMP at year’s end</th>
<th>average debt per client</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>13,448</td>
<td>30,399</td>
<td>£27,565</td>
</tr>
<tr>
<td>2004</td>
<td>16,984</td>
<td>37,825</td>
<td>£29,341</td>
</tr>
<tr>
<td>2005</td>
<td>24,444</td>
<td>51,133</td>
<td>£30,763</td>
</tr>
<tr>
<td>2006</td>
<td>35,135</td>
<td>73,655</td>
<td>£31,370</td>
</tr>
</tbody>
</table>


In 2006, a typical CCCS client on a DMP is in mid-30’s, married with children with an average debt of just over 31,000 pounds.

### 3.2 Data Description and Key Variables

Our raw data contains information on all CCCS clients who have started a DMP between January 2003 and January 2007 (approximately 75,000 individuals) when the data was extracted. For the reasons we explain in section 3.3, our estimation sample uses 60,495 of these individuals.

Besides individual characteristics (such as age, gender, marital status, no of dependants, smoking, employment status, type of housing etc.), information about the debt (total amount owed to creditors, no of debts, information on each debt, debt type, creditor name etc.), and the agreed DMP budget (income, expenditures) and terms (amount of debt on which the DMP is set up, duration, monthly payments), we also have a self-reported reason of why the individuals ran into financial difficulties (i.e. why they have built up an amount of debt they cannot repay or handle without CCCS help).

\textsuperscript{5} It started with a pilot scheme in Leeds. During 1996 new centres opened in Nottingham, Birmingham and Cardiff, Glasgow, Newcastle, Chester, London and Limavady in Northern Ireland. Last year the charity opened new centers in Eastbourne, Sussex and more recently a center in Halifax.
3.2.1 Reason for Debt Indicator

Corresponding to the theoretical model, we are in particular interested in the repayment behavior of borrowers who may be classified as the ones with self-control problems, and how they compare to the rest of the CCCS clients. The fact that the self-control problems are rather difficult to measure is an obstacle to this objective. We use smoking as a potential indicator of general self control problems, as risky behaviors (such as substance abuse including smoking and alcohol consumption) are traditionally associated with low self control in psychology literature. We also consider some of other individual characteristics which may be correlated with self control problems such as age and gender, since being older is usually associated with increased financial discipline whereas being a single female or a single mother are usually associated with increased likelihood of financial troubles.\(^6\)

However, we also use a new indicator of self-control problems, which is based on a unique information contained in our data - (self-reported) reasons for running into financial troubles. We propose and construct an indicator that identifies individuals who have self-control problems as the ones who ran into financial troubles purely due mismanagement of their debts, rather than for any exogenous reason. Tables below summarize the variable “reason for debt” for our estimation sample. Although multiple reasons can be stated, around 74 percent of the clients state only a single reason for their debt.

Insert Tables 1 and 2 here.

Unfortunately, the reason for debt - although revealed during the over-the-phone counselling session and immediately reported (entered to the computer) by the counselor - is subject to two types of distortions/biases and a considerable change during 2005. In addition, the indicator also includes several categories that do not have clear interpretation, such as “overcommitted on credit”. The “reason for debt” information is automatically added in the letters that are sent to creditors along with a proposed repayment plan (DMP). During our discussion with the counsellors regarding the interpretation of each reason for debt, we discovered that there was a change in the trend of its reporting at the beginning of year 2005. The first bias come from the fact that the clients are reluctant to admit that they could not manage their finances well, and the counsellors are less likely to report these reasons

\(^6\)See Bertaut and Haliassos [2] for a discussion.
### Table 1: Reason for debt variable

<table>
<thead>
<tr>
<th>Category</th>
<th>Reason for debt</th>
<th>Freq.</th>
<th>Percent.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC_prob</td>
<td>No Budget</td>
<td>1663</td>
<td>2.09</td>
</tr>
<tr>
<td></td>
<td>Lack Of Money Education</td>
<td>182</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>Poor Shopping Habits</td>
<td>23</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>Bank Account Problems</td>
<td>286</td>
<td>0.36</td>
</tr>
<tr>
<td>NS_job</td>
<td>Unemployment</td>
<td>4238</td>
<td>5.34</td>
</tr>
<tr>
<td></td>
<td>Change In Employment</td>
<td>1848</td>
<td>2.33</td>
</tr>
<tr>
<td></td>
<td>Failed Business</td>
<td>706</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Spouse/Partner Not Working</td>
<td>238</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>Temporary Layoff/Strike</td>
<td>100</td>
<td>0.13</td>
</tr>
<tr>
<td>NS_ill</td>
<td>Injury/Illness</td>
<td>5175</td>
<td>6.52</td>
</tr>
<tr>
<td></td>
<td>Caring For Relatives/Friends</td>
<td>755</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Death In The Family</td>
<td>813</td>
<td>1.02</td>
</tr>
<tr>
<td>NS_preg</td>
<td>Pregnancy/Childbirth</td>
<td>1172</td>
<td>1.48</td>
</tr>
<tr>
<td>NS_incshock</td>
<td>Reduced Income</td>
<td>13840</td>
<td>17.43</td>
</tr>
<tr>
<td></td>
<td>Lost Part Time Income</td>
<td>151</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>Reduced Benefits</td>
<td>510</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>Reduction In Hours/Overtime</td>
<td>854</td>
<td>1.08</td>
</tr>
<tr>
<td></td>
<td>Salary Fluctuates/Commission</td>
<td>707</td>
<td>0.89</td>
</tr>
<tr>
<td>NS_sep</td>
<td>Separation/Divorce</td>
<td>6455</td>
<td>8.13</td>
</tr>
</tbody>
</table>

Table continues at the other page.

unless the client specifically mentions it. The reason for the later is that the reason for debt is part of the information pack each client receives as the summary of the counselling session and clients may not be happy to be advised of their financial illiteracy. This means that financial-mismanagement-type reasons for debt are likely to be underreported in our data.\(^7\) The second bias and the change in 2005 have the following reason. As CCCS discovered that creditors were willing to accept the negotiated DMP terms more readily when a specific reason for debt, and in particular, clear negative shock (such as loss of job, drop in income etc.) was stated as the justification for the borrower’s inability to repay, in 2005 CCCS started encouraging its coun-

\(^7\)Variables such as “no-budget” are rather infrequently populated.
<table>
<thead>
<tr>
<th>Category</th>
<th>Reason for debt</th>
<th>Freq.</th>
<th>Percent.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other</td>
<td>Over Committed On Credit</td>
<td>25008</td>
<td>31.5</td>
</tr>
<tr>
<td></td>
<td>Used Credit For Living Exp.</td>
<td>9209</td>
<td>11.6</td>
</tr>
<tr>
<td></td>
<td>Used Credit For Business Exp.</td>
<td>273</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>Expenditure Excessive</td>
<td>499</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>Utility Arrears</td>
<td>62</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>School Expenses</td>
<td>123</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>High Mortgage/Rent</td>
<td>273</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>High Vehicle Costs</td>
<td>136</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>Home Repair Expenses</td>
<td>264</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>Housing Cost Arrears</td>
<td>175</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>Increased Housing Payments</td>
<td>726</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>Insurance Problems</td>
<td>8</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>Legal Expenses</td>
<td>56</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>Child Support Problems</td>
<td>343</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>Missed Work-Bad Weather</td>
<td>26</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>Moving/Relocation Expenses</td>
<td>883</td>
<td>1.11</td>
</tr>
<tr>
<td></td>
<td>Low Paid</td>
<td>294</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>Part Time Work Only</td>
<td>451</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>Vehicle Accident</td>
<td>81</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>Vehicle Repairs</td>
<td>101</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>Substance Abuse</td>
<td>24</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>Unknown</td>
<td>667</td>
<td>0.84</td>
</tr>
</tbody>
</table>

| Total             | 79,398                              | 100.00|

sellors to try to track down and report more specific reason for debt, and avoid using less clear categories. For example, if the client said I was over committed to credit, the counsellors would ask for a more specific reason. \(^8\)

Despite these limitations, we believe we can still make use of the indicator in the following “conservative” way. First, this indicator allows us to distinguish individuals who ran into financial difficulties for a particular exogenous negative shock. The key categories of these shocks are: unexpected illness, divorce, pregnancy, loss of job, and reduced income. These are clear facts

\(^8\)We observe that if the client does not report a clear negative shock, “reduced income” is chosen more often as the reason for debt.
that took place and are less likely to be subject to the above mentioned biases. Second, we use the categories, although less frequently populated, that suggest that the main reason for the financial troubles was mismanagement of the debt, as a proxy for the self-control problems. These are the reasons that suggest that the clients did not manage their finances (had no budget), lack financial education etc. which led them to have financial difficulties in the absence of a negative shock. We keep in mind the fact that this indicator is underreported and interpret the estimated effect of self-control problems on the debt repayment behavior as the lower bound. We use reasons which suggest a clear negative shock to construct indicators for specific negative-shock sub-groups and the debt mismanagement indicator and compare the DMP performances of these sub-groups to the rest of the population (the mix of the CCCS clients that are on a DMP and stated a reason for debt that has a less clear interpretation). We interpret the effect of the specific negative shocks (prior to starting a DMP) on DMP performance to capture either their permanent nature or correlation overtime. We interpret the coefficient of the debt mismanagement indicator in the model of the DMP performance as the effect of the self-control problems on the debt repayment behavior.

In addition, in order to capture the potential changes in the trend of the reason-for-debt reporting, we include a set of dummy variables that identify the year-month when the DMP started in our estimation.

### 3.2.2 DMPs and DMP performance measures

During the counselling appointment, a budget is agreed and the monthly surplus is calculated. The monthly surplus equals monthly disposable in-

#### Table 2: Number of reasons stated

<table>
<thead>
<tr>
<th>Number of reasons</th>
<th>Freq.</th>
<th>Percent.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>45,063</td>
<td>74.49</td>
</tr>
<tr>
<td>2</td>
<td>12,474</td>
<td>20.62</td>
</tr>
<tr>
<td>3</td>
<td>2,509</td>
<td>4.15</td>
</tr>
<tr>
<td>4</td>
<td>391</td>
<td>0.65</td>
</tr>
<tr>
<td>5</td>
<td>53</td>
<td>0.09</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>0.02</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>60,495</strong></td>
<td><strong>100.00</strong></td>
</tr>
</tbody>
</table>
come minus the regular monthly expenditures and the payments for secured debts. The DMP is based on the monthly surplus, i.e. it constitutes the required monthly payment of the borrower towards the DMP. Given the monthly surplus and the total amount owed to creditors, the DMP length is determined. Individuals’ debt-repayment behavior (their performance on the DMP) is captured by the DMP status of the client at the date the data was extracted. The DMP status of a client may be active (still on DMP), self administration (an individual found other means of paying the debt and left CCCS), successful completion (debt is paid off under the DMP) or non payer (dropped from DMP). As the amount of debt owned is usually high and the available monthly surplus is only limited, the typical DMP length is over 10 years and most of the clients who have not dropped yet or exited in another way are still on a DMP. A non-payer (an individual dropped from the DMP) is a client that either missed 2 consecutive payments, or 4 payments in 12 months.

3.3 Estimation Sample

The estimation sample consists of individuals started a DMP between January 2003 and November 2006. We consider only individuals who were on a DMP for at least 3 months. There are two reasons to do that. First, given the definition of the drop out (two consecutively missed payments which can be observed only in the third month information), for these individuals - unless they explicitly tell CCCS that they discontinue the DMP - it cannot be determined whether they dropped or not. Also, intuitively, it is hard to assess the DMP performance during such a short period. Even more importantly, the three month rule excludes the borrowers who have agreed a DMP but never started paying. We consider this to be a special case, which may not be comparable with the DMP drop out after some repayments have been made. Further, we consider and compare only the regular DMP repayment versus default. We therefore exclude all other alternative ways of exiting DMP before the planned ending date, i.e. successful self-administration.\footnote{The DMP information in CCCS database is updated on a continuous bases as new clients (new DMPs) are added every day. The data we have has monthly frequency. We are able to keep track of whether the client has made the payments since the start of the DMP.}

\footnote{The most typical case being an earlier repayment of the debt via selling of one’s property.}
However, individuals who chose (had to chose due to no other alternative) self-administration due to inability of paying the monthly payments required by the DMP are left in the sample and classified as DMP drop-outs. Finally, we drop individuals with missing information on any of the key variables and obvious outliers such as negative or zero income, age exceeding 120 etc.\textsuperscript{11} This leaves us with 60,495 individuals who have started or have been observed on the DMP during the analyzed period.

### 3.3.1 Summary Statistics

The following tables provide summary statistics for the variables that are used in the estimation.

Insert Tables 3, 4 here

<table>
<thead>
<tr>
<th>Stats</th>
<th>Mean</th>
<th>Var</th>
</tr>
</thead>
<tbody>
<tr>
<td>smoker</td>
<td>0.221</td>
<td>0.172</td>
</tr>
<tr>
<td>woman</td>
<td>0.555</td>
<td>0.247</td>
</tr>
<tr>
<td>couple</td>
<td>0.476</td>
<td>0.249</td>
</tr>
<tr>
<td>#dependants</td>
<td>0.476</td>
<td>0.249</td>
</tr>
<tr>
<td>mortgage</td>
<td>0.214</td>
<td>0.168</td>
</tr>
<tr>
<td>selfempl</td>
<td>0.030</td>
<td>0.029</td>
</tr>
<tr>
<td>fulltime</td>
<td>0.605</td>
<td>0.239</td>
</tr>
<tr>
<td>age</td>
<td>38.941</td>
<td>147.887</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stats</th>
<th>Mean</th>
<th>Sd</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expenditure*</td>
<td>1126.52</td>
<td>548.54</td>
<td>5.00</td>
<td>3369.00</td>
</tr>
<tr>
<td>Income*</td>
<td>1336.04</td>
<td>598.70</td>
<td>30.00</td>
<td>3500.00</td>
</tr>
</tbody>
</table>

* In British Pounds.

About 55 % of the individuals who contacted CCCS are women and the average age is 39.\textsuperscript{12} There is about 48 % of couples and the average number

\textsuperscript{11} We didn’t find any systematic pattern in the observations that were dropped form the data.

\textsuperscript{12} Some of them, however, represent a bigger household.
of dependants is 0.48 in the sample. 6% of the contact individuals are self-employed, while 61% work full-time. There are 22% of households with smokers and 21% of households who have mortgage. A typical household in our sample has a monthly income of about 1,336 pounds per month and spends about 1,127 pounds a month. Table 5 below summarizes the specific-reason-for-debt variables that we use in the estimation. While 25.5% of the CCCS clients state reduction in income as the reason why they built up debt which they have troubles repaying, for 11.5% of the clients it is loss of job, for 10.9% it is illness or death in the family, for 10.7% it is separation or divorce, and for about 1.9% it is pregnancy. We classify 3.5% of clients as the ones who have self-control problems, based on the reported reasons that suggest debt mismanagement.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Freq.</th>
<th>Percent.</th>
</tr>
</thead>
<tbody>
<tr>
<td>NS_inshock</td>
<td>15,425</td>
<td>25.50</td>
</tr>
<tr>
<td>NS_job</td>
<td>6,933</td>
<td>11.46</td>
</tr>
<tr>
<td>NS_ill</td>
<td>6,582</td>
<td>10.88</td>
</tr>
<tr>
<td>NS_sep</td>
<td>6,455</td>
<td>10.67</td>
</tr>
<tr>
<td>NS_preg</td>
<td>1,172</td>
<td>1.94</td>
</tr>
<tr>
<td>SC_prob</td>
<td>2,140</td>
<td>3.54</td>
</tr>
</tbody>
</table>

As will be explain in the next section, typical DMP is over 10 years long and in our sample there are only very few regular successful completions of the DMP. To simplify the Cox proportional hazard model (described in the next session) that we use to analyze the DMP performance (duration and the probability of dropping from the DMP) we classify the individuals who has already successfully paid their debt off (309 individuals) as “active”.

Given our classification of the active and the non-payers, the distribution of the DMP outcomes (performance) in our estimation sample is as follows: There are 48,075 (about 80%) of active DMPs and 12,420 (about 20%) of non-payers, i.e. drop outs. See table below:

### 3.4 Empirical methodology: survival analysis

We use the conjectures of the theoretical model presented in section 2.1 to analyze the DMP performance of different types of CCCS clients (borrowers).
Table 6: DMP status

<table>
<thead>
<tr>
<th></th>
<th>Freq.</th>
<th>Percent.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active</td>
<td>48075</td>
<td>79.47</td>
</tr>
<tr>
<td>Nonpayer</td>
<td>12420</td>
<td>20.53</td>
</tr>
<tr>
<td>Total</td>
<td>60495</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Namely, we explore who successfully completes his or her DMP and repay their debts and who is not being able to make use of the DMP and drops out.

If we observed only the successfully completed DMPs or the drop outs, we could use a binary variable model for the estimation of the probability of dropping from a DMP versus successful completion, as done in the theoretical model. However, the structure of the data and the time interval in which we observe the DMPs make this approach infeasible. As the average DMP is designed to last over 10 years and our data start only in 2003, vast majority of the DMP plans in our data are still on-going. We observe only very little instances of success - when the DMPs were completed, and certain proportion of failures - plans that stopped because the client dropped out. In most cases, the plans are still on and it is not yet known whether they will become a success or failure. However, even in these instances, it is possible to make meaningful comparisons of how long have the DMPs been on and compare them to the failures.

The best way to estimate the probability of DMP failure with this type of data is the duration analysis. It is based on the estimation of the hazard rate - the rate at which a failure happens given that it hadn’t happened yet. This methodology takes into account the duration of the DMPs as well as whether they failed or were censored. The censoring date in our data is January 2007, when the data was extracted. We observe all the DMPs of the CCCS clients who started a DMP after 2003 up to either their failure or the censoring date. The DMP duration corresponds to what is named as “spells” in the duration analysis. We observe the starting date for all the DMPs, but the ending date is observed only for the few successful completions\(^\text{13}\) and for the DMPs that failed. In the duration analysis terminology, we have the so-called flow data, in which we observe complete spells for the individuals who dropped from a DMP for a very long time, so that in the limit their drop out probability approaches zero.

\(^{13}\)To keep things simple, we classify the few successful completions as being still on a DMP for a very long time, so that in the limit their drop out probability approaches zero.
DMP prior to January 2007, while the rest of the spells are right-censored in January 2007.

There is a range of models available for the estimation of the hazard rate (or the corresponding survival rate), both parametric and non-parametric, and with continuous or discrete time. Given the theoretical model, the empirical analysis has the following preferences: 1. We are interested only in the overall effect of various time-invariant individual characteristics and debt circumstances. 2. We do not want to impose any particular shape (functional form) on the hazard function.

3.5 Cox’s proportional hazard model

We choose a simple proportional hazard model estimated by semiparametric estimator proposed by Cox [7], which doesn’t impose any restrictions on the baseline hazard function of the model. Cox suggested a partial likelihood estimator for a model with the following specification\(^\text{14}\): the hazard rate of an individual \(i\) with the spell length \(t_i\), i.e. the probability that a spell ends at a particular time, given it lasted until that moment,

\[
\lambda(t_i) = \lim_{\Delta s \to 0} \frac{\text{Prob}(s \leq t \leq s + \Delta s / t \geq s)}{\Delta s}
\]

is defined in the Cox’s proportional hazard model as

\[
\lambda(t_i) = \exp(-x t_i \beta) \lambda_0(t_i).
\]

where \(x\) are individual or spell-specific characteristics and \(\lambda_0\) is the baseline hazard function. Cox’s partial likelihood estimator allows to estimate \(\beta\) (the effect of the covariates \(x\) on the hazard rate) without estimating the baseline hazard \(\lambda_0(t_i)\).

The partial likelihood estimator is based on the expression for a probability that a particular spell ends among the corresponding risk set (set of spells that have not ended yet). It therefore estimates the probability that a given individual drops from the DMP divided by the sum of the probabilities that any of the individuals that are still on the plan drop from the DMP. It is this conditioning on being one of the individuals from the risk set that allows \(\lambda_0(t_i)\) be unconstrained, as it drops out from the expression that is estimated. The censored observations are included in the traditional way, as

\(^\text{14}\)The exposition of the model here is based on Greene [9].
described for example in Cameron and Trivedi [5]. As we know the exact
date when a spell starts, ends, or is censored, we measure the spells in days.
This allow us to regard the model as the one with a continuous time and to
avoid the presence of spells with exactly the same length. However, if ties
still occur, they are treated by the method suggested in Breslow [4].

4 Estimation Results

Table 7 presents the results from the estimation of the Cox proportional
hazard model. The three pairs of columns correspond to three different
specifications that we estimate. In the first one, we explain the failure to
stay on the DMP plan only with the set of the variables describing the
various reasons why individuals ran into financial difficulties, so that they
had to seek CCCS’s help. In the second, we also add various demographic
characteristics, indicator for smoking, having a mortgage, self-employment
and full-time employment status as well as logarithm of monthly income
and household expenditures. In the third specification, we also add dummy
variables that control for the starting point (year and month) of the DMP in
calendar time.

We focus on the impact of the various reasons for debt on the probability
of dropping out of the DMP. The key indicator that describes the individuals
who ran into financial troubles because of the mismanagement of their debt
(no budget, lack of financial education etc.) is presented in the first row of
the table. Its coefficient is always positive and significant for all the three
specifications, ranging from 0.186 in the first specification to 0.122 in the third
one. The effect somewhat declines when we control for additional variables
(moving from the first to the second specification), but the magnitude is fairly
robust across all the three specifications. The preferred third specification
suggests that individuals, who reported mismanagement as the reason for
debt, drop out from the DMP with 12% higher probability than the rest of
the CCCS clients. We interpret the debt-mismanagement indicator as a sign
of self-control problems. If our interpretation is correct, the result we find
supports the prediction of our theoretical model that the naive hyperbolic
discounters are more likely to drop from the DMP.

The estimates of the other reasons for debt are more sensitive to the
inclusion of additional variables. Namely, the effect of experiencing illness
changes sign from negative to positive and the effect of pregnancy and of
the reduction in income cease to be significant when we move from the first
to the second and third specification. The occurrence of the specific shocks
is highly correlated with age, gender, marital status, number of dependence
and possibly also smoking. It is likely that in the first specification these
shocks capture also the effect of these other factors that are not present in
the estimation. The results in the preferred third specification suggest that
individuals who experienced a particular negative shock, namely loss of job,
ilness in the family or divorce, that led them into debt, are more likely to
drop from the DMP than the rest of the CCCS clients.\footnote{Insignificance of the reduced income is not surprising, knowing that it is often chosen -given the relatively vague definition - to explain the reason to the creditor in the absence of a clear negative shock.} This outcome is
likely to be driven either by the permanent nature of these shocks or by
the high probability of subsequent shocks, when the shocks are correlated
over time. In terms of our theoretical model, we interpret this finding as
follows: the individuals who were hit by this kind of shock may have, as a
consequence or even a priori, a higher probability of the occurrence of a low
income state (the bad state of the world) than the rest.

As mentioned earlier, for some individuals, we observe multiple reasons
for debt, meaning that the same person may be observed to have mismanaged
their debt and experienced a negative shock at the same time. We also try to
interact the debt mismanagement indicator with the negative shock indica-
tors to be able to see, whether individuals with self-control problems handle
negative shocks worse or better than the rest of the population. However,
neither of these interactions has been found significant.\footnote{The results, not presented here, are available form the authors on request.}

Another result that we focus on in relation to the predictions of our model,
is smoking, as it may be an alternative measure of self-control problems. The
effect of smoking is highly significant and more than twice as big as the debt
mismanagement indicator. It suggests that smoking increases the probability
of dropping out from the DMP by 31 %. Again, provided that individuals
who smoke have self-control problems, the finding is consistent with our
expectations as well as with the predictions of our model.

However, when looking at debt mismanagement and smoking together, we
find that their interaction of the two variables is not significant in the model,
suggesting that they are two alternative measures of self-control problems,
rather than two complementary or substitutable indicators. In addition to measuring self-control problems, smoking is also likely to have a direct income effect: given the high and still rising tobacco prices, smoking expenditures substantially increase the monthly “indispensable” spending, leaving smaller amount of income available to repay one’s debt and, in general, making households more vulnerable to income fluctuations.

We next focus on the demographic characteristics. We observe that the probability of the DMP drop-out decreases with age, although at a decreasing speed. Result that we find in particular interesting, is that women are much more likely to stay on DMP than men. As sometimes the CCCS client represents (in terms of debts, income and expenditures) the whole family, we interact the female indicator with marital status (couple) to see if the results are not driven only by the fact that women are more (or less) likely to be representing the couple and dealing with CCCS. The results however show that women indeed don’t drop from the DMP as often as men. A single woman is 28 % less likely to drop than a single man, and a married man is 12 % less likely to drop than a single man. It is also clear that the family is more likely to stay on the DMP if it is a woman who contacts CCCS. Married women are about 14% (female indicator plus the interaction term) less likely to drop out than married men.

Having a mortgage decreases the probability of the DMP drop-out by 14 %, suggesting that the cost of default (namely loss of home) has a positive effect on repayment.

While being self-employed increases the probability of dropping out by 17 %, working as a full-time employee reduces it by 12 % when compare to the rest of the population. The high volatility and uncertainty of the income of the self-employed is likely to increase their sensitivity to various shocks that may lead to inability to repay. Steady stream of income of the full-time employees, on the other hand, makes the regular repayment easier.

The last two indicators, the logarithm of monthly income and the logarithm of monthly expenditure of the financial unit (whether it is an individual or a household), describe the regular financial inflow and outflow. As mentioned before, the DMP monthly payment is determined at the initial counselling session by deducting the regular expenditures from the regular monthly income. The effect of the two variables is in line with our prior

17 The results, not presented here, are available form the authors on request.
18 Including necessary payments such as repayment of secured debt.
expectations: while the amount of regular expenditure increases the probability of dropping out of the DMP, the amount of regular income makes individuals more likely to stay.

Finally, in the third specification, we also include dummy variables that indicate the year and month of the beginning of the DMP, to capture any changes that take place overtime, including the changes in the total state of the economy, the changes in the consumer credit availability, price changes as well as the potential changes in the composition of the CCCS’s clientele. Comparing the second and the third specification suggest that while improving the fit of the model, the starting date indicators do not change the results substantially.

We have so far discussed the effect of the various factors on the DMP dropout rate but haven’t explored how the probability of dropping out evolves overtime. This is captured by the baseline hazard function, evaluated at the means of the variables, presented in Figure 3. The duration on the y-axis is measured in days.

The Figure 3 shows that overall the hazard rate of dropping out of the DMP is not monotonic, although it is predominantly declining with the time spent on the DMP. After peaking at about 220 days (7 months) since the starting date, the hazard rate steadily declines up to about 650 days (around 2 years), when the decline somewhat slows down. The very short durations (less than 60 days) are omitted in the model. The reason is the institutional features of the DMP and the conditions for dropping out: unless clients contact CCCS themselves, telling them that they want to drop out from the DMP, they are not dropped until one of the two conditions is met: they either miss 4 individual payments in 12 months or they miss two consecutive payments. It is the latter which basically implies that nobody (unless they purposefully do so) can drop from the DMP before the two month period of the two consecutive missed payments elapse. We believe that this is also the reason that drives the initial increase in the hazard rate, so we attribute it a purely institutional interpretation.

The predominately declining hazard rate may imply the presence of negative duration dependence, i.e. negative effect of time spent on DMP on the probability to drop. However, the observed shape of the hazard rate may be equally likely driven by unobserved heterogeneity (at the absence of any duration dependence): if the non-repaying people drop early on, the remaining pool of individuals who are at risk of dropping may, as a result, be less
Table 7: Estimation results - Cox Proportional Hazard

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>(SE)</th>
<th>Coef.</th>
<th>(SE)</th>
<th>Coef.</th>
<th>(SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC_prob</td>
<td>0.186*</td>
<td>(0.044)</td>
<td>0.123**</td>
<td>(0.045)</td>
<td>0.122**</td>
<td>(0.045)</td>
</tr>
<tr>
<td>NS_job</td>
<td>0.154**</td>
<td>(0.028)</td>
<td>0.101**</td>
<td>(0.028)</td>
<td>0.103**</td>
<td>(0.029)</td>
</tr>
<tr>
<td>NS_ill</td>
<td>-0.077*</td>
<td>(0.031)</td>
<td>0.096**</td>
<td>(0.032)</td>
<td>0.100**</td>
<td>(0.033)</td>
</tr>
<tr>
<td>NS_preg</td>
<td>0.118†</td>
<td>(0.065)</td>
<td>-0.080</td>
<td>(0.065)</td>
<td>-0.077</td>
<td>(0.065)</td>
</tr>
<tr>
<td>NS_inshock</td>
<td>-0.085**</td>
<td>(0.022)</td>
<td>-0.026</td>
<td>(0.022)</td>
<td>-0.013</td>
<td>(0.022)</td>
</tr>
<tr>
<td>NS_sep</td>
<td>0.075**</td>
<td>(0.029)</td>
<td>0.075*</td>
<td>(0.031)</td>
<td>0.077*</td>
<td>(0.031)</td>
</tr>
<tr>
<td>smoker</td>
<td>0.322**</td>
<td>(0.020)</td>
<td>0.311**</td>
<td>(0.020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>woman (W)</td>
<td>-0.269**</td>
<td>(0.024)</td>
<td>-0.279**</td>
<td>(0.024)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>couple (C)</td>
<td>-0.112**</td>
<td>(0.030)</td>
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<td>W x C</td>
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<td>(0.037)</td>
<td>0.136**</td>
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<td>(0.005)</td>
<td>-0.067**</td>
<td>(0.005)</td>
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<td>(0.006)</td>
<td>0.047**</td>
<td>(0.006)</td>
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<td>0.036**</td>
<td>(0.010)</td>
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<td>(0.027)</td>
<td>-0.143**</td>
<td>(0.028)</td>
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<td>(0.059)</td>
<td>0.171**</td>
<td>(0.060)</td>
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<td>(0.021)</td>
<td>-0.119**</td>
<td>(0.025)</td>
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<td>(0.060)</td>
<td>0.329**</td>
<td>(0.060)</td>
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<td>-0.429**</td>
<td>(0.067)</td>
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<td>Start. Month</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>and Year In</td>
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N                  | 60495   | 60495   | 60495   |
Log-likelihood     | -128427.722 | -127329.08 | -127147.51 |
χ²(1)              | 80.193  | 2288.971 | 2578.277 |

Significance levels: †: 10%  *: 5%  **: 1%

The degrees of freedom of the χ²(1) distribution for the three models are 6, 18, and 64.
Robust standard errors are calculated according to Lin and Wei (1989).
likely to drop. In this paper, we do not try to distinguish which of the two interpretation is correct.

The shape of the hazard rate also confirms our choice of the estimation model with a fully flexible baseline hazard rate, as we find that it is neither constant, nor monotonic. As this is a proportional hazard model, the baseline hazard function does not vary across individuals and the effect of the respective covariates only shifts the hazard rate up and down. The effects of the RHS variables therefore hold at any point in time during the DMP. Figures 4 and 5 further illustrate how the hazard rate of the individuals who have self-control problems (as measured by the debt-mismanagement indicator and smoking indicator respectively) differ from the hazard rate of the rest of the CCCS clients.

5 Conclusion

Consumer credit counselling assists heavily indebted borrowers by providing financial advice and by setting up and administering repayment plans, so called debt management plans (DMPs). In this paper we explore the effect of self-control on the debt repayment performance of borrowers who have been enrolled in a DMP. We develop a simple model of a DMP and analyze the repayment behaviour of borrowers with and without self-control problems. We model self-control by hyperbolic discounting and allow the borrower to be fully aware or partially naive about her self-control problems. We compare the results to the exponential discounting benchmark. The model predicts that sophisticated hyperbolic discounters would have the same DMP dropout rates as exponentials whereas naive hyperbolic discounters would drop out from the DMP more often.

We use administrative data from a major consumer credit counselling charity in the UK to test the predictions of our model. We identify the individuals with self-control problems using two different self-control indicators: self-reported reasons for running into financial troubles and smoking. We explore the debt repayment behavior of individuals who are on a DMP, comparing the group of individuals we identified as the ones that have self-control problems to the rest of the CCCS clientele. Specifically, we use Cox proportional hazard model to estimate the probability of staying on a DMP vs. the probability of a DMP drop out. We control for the occurrence of specific negative shocks as reasons for financial difficulties prior to entering
a DMP, as well as other household-specific characteristics.

Preliminary results show that self-control problems increase the drop-out probability at any stage of the DMP by 12% and 31% when reason for debt and smoking are used as indicators respectively. We also find that the drop-out probability decreases with age and that women are substantially more likely to stay on a DMP than men. Having a mortgage as well as working as a full-time employee decreases the probability of the DMP drop-out, whereas being self-employed increases it.

We conclude that, when we control for the permanent negative shocks, borrowers who admit that they cannot manage their finances well, (i.e. reported reasons for debt suggesting debt misuse) and borrowers who smoke, are more likely to drop from a DMP. To the extend that these indicators can be used as a valid proxy for self-control problems, our results suggest that self-control problems have adverse effect on the debt repayment behavior.

Figure 3: Hazard Rate from the Cox’s Model - at Means of the Variables
Figure 4: Hazard Rates for Individuals with Self-control Problems (Who Mismanaged their Debt) and for Individuals without Self-control Problems
Figure 5: Hazard Rates for Smokers and Non-Smokers
References


Appendix

A  List of Variables used in the estimation

SC_prob  Indicator for self control problems, Dummy, 1 if the reason for
debt stated is; no budget or lack of money education or poor shopping
habits or bank account problems

NS_job  Indicator for job loss, Dummy, 1 if the reason for debt stated is; un-
employment or change in employment or failed business or spouse/partner
not working or temporary layoff/strike

NS_ill  Indicator for illness, Dummy, 1 if the reason for debt stated is; in-
jury/illness or caring for relatives/friends or death in the family

NS_preg  Indicator for pregnancy, Dummy, 1 if the reason for debt stated is
pregnancy/childbirth

NS_incshock  Indicator for shocks to income, Dummy, 1 if the reason for
debt stated is; reduced income or lost part time income or reduced
benefits or reduction in hours/overtime or salary fluctuates/commission

NS_sep  Indicator for separation or divorce, Dummy, 1 if the reason for debt
stated is seperation

smoker  Dummy, 1 if the CCCS client smokes

woman  Dummy, 1 if the client is female

couple  Dummy, 1 if the client is married or has a partner

age  Indicator for the client age

# dependants  Indicator for the no of dependants the client has

mortgage  Dummy, 1 if the client has mortgage

selfempl  Dummy, 1 if the client is self-employed

fulltime  Dummy, 1 if the client is employed full time

lnexpend  Indicator for monthly expenditures, in British Pounds, in loga-

rithm.
lnincome Indicator for monthly income, in British Pounds, in logarithm.

Start. Month and Year In Set of binary indicators of the year and the month client has started the DMP.

Appendix

B Counselling as a commitment mechanism

If the counselling agencies are in fact able to renegotiate better repayment terms with lenders than the borrowers themselves, the DMPs can in principle help people hit by a negative shock. As for the people who are financially illiterate, the role of credit counselling should be providing financial education and advice. Can credit counselling help borrowers with self control problems?

A DMP is essentially a debt consolidation plan. It transfers for example, credit card debt- which is a line of credit- to a closed end credit paid over a stipulated amount of time in equal installments. That is, it changes the type of the loan agreement and the repayment scheme. One might argue that this particular repayment arrangement as well as the counselling provide the borrower with some spending and repayment discipline, if the borrower manages to stop borrowing on credit cards completely. In principle, being in DMP limits the chances of people borrowing further from the current lenders who agreed to re-negotiate the original debt contract. There is still a chance to borrow from other lenders who lack information about borrower’s repayment capabilities. This depends on the availability information sharing among these other lenders and counselling agency. In the UK the DMPs are not registered in a credit report, however borrowing further while on a DMP, if detected, results in the termination of the DMP agreement by the credit counselling agency.

If the credit counselling does help borrowers with self-control problems, there are two interesting questions one can ask: to what extent does being in a DMP serve as a commitment mechanism for borrowers who suffer from self control problems or to what extend it is possible to teach self-control? In this section, given our choice of modelling self control problems by hyperbolic discounting, we will discuss the limitations associated with testing these questions. Let us begin by describing the implications of different scenarios regarding the contractual environment.
By definition, sophisticated hyperbolic consumers (rational but time-inconsistent consumers) are aware of their time inconsistency and therefore they would like to “commit” whenever possible. However, commitment may not always be possible since the capability to constrain the future selves and to commit depends on the availability of commitment mechanisms and the contracting environment.

As for the contracting environment, two scenarios are possible. The first scenario is to assume that there are commitment devices, including credit counselling, that would help sophisticates to control the effect of their self-control problems (i.e. control spending, commit to debt obligations etc), which would prevent them from running into financial difficulties purely due to self control problems. That is, the CCCS clientele would consist of exponentials and sophisticates who were hit by a negative shock and we would not be able to distinguish exponentials from sophisticates. However, by definition we would not expect naives to make use of the counselling services as a commitment mechanism. Assuming that the negative shocks occur randomly across different types of people, naives would have higher drop out rates.

The second scenario is to assume that there are no commitment devices available except for the counselling which plays the role of the imperfect commitment device possibly through controlling spending and further borrowing and helping to figure out a better forecast of repayment capabilities. If this is the case, then sophisticates, using the commitment mechanism, would have similar drop out rates as exponentials whereas naives would drop out more often due to same reason explained above.

If the post-DMP data on individuals (who either successfully completed or failed a debt management plan) were available we could be able to test whether the effect of counselling on the future financial performance is temporary or permanent. If the affect of being on a DMP is helping borrowers commit their budget and pay their debt, by acting as an imperfect commitment device, the improvement on self-control problems would be temporary. If the effect is through teaching (learning) self-control then the effect would be permanent. Unfortunately, we do not have post-DMP data on individuals and therefore we can not test whether the effect of counselling is temporary or permanent.

As long as the counselling is voluntary, it can best be an ‘imperfect” commitment mechanism.

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