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SELF-CONTROL AND DEBT: EVIDENCE FROM DATA ON CREDIT COUNSELLING

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

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ABSTRACT.

Counselling agencies assist borrowers in financial difficulties by administering repayment plans, the so-called debt management plans (DMPs). In this paper, we use unique administrative data from a major credit counselling agency in the UK to analyze the determinants of debt repayment performance of approximately 60.000 borrowers who are enrolled on a DMP. Employing survival analysis, we estimate that borrowers who smoke and who reported poor financial management as the reason for their repayment difficulties at the enrollment stage are significantly more likely to fail on a DMP even when controlling for a rich set of covariates including monthly DMP payments, income, expenditures, self-reported experiences of negative shocks prior to DMP (ilness, job loss, divorce, pregnancy), gender, age, marital status, having a mortgage, and whether the consumer is self or full time employed. In particular, smoking increases the probability of failing on a DMP by 31 percent and admitting bad financial management increases it by 12 percent. Our findings lend considerable support to the view that self-control considerations play a role in households' indebtedness and consequent repayment difficulties.

Keywords: quasi-hyperbolic discounting, self control, households' repayment difficulties, 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 [12] 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:

Reason for filing (chapter 7)	Percentage
Job Loss	12.17
Marital distress	14.28
Credit Misuse	41.26
Health care bills	16.40
Lawsuits and Harassments	15.87

Source: Table 1, Panel B from Chakravarty and Rhee [12]. U.S. between 1984-95, PSID.

Similarly, Warren et al. [46] reports that bad financial management was among the most important five reasons reported by US borrowers for filing bankruptcy in 1999.[1] Jentzsch and Amparo [26] compile survey evidence from a number of European countries (Austria, Belgium, Spain, France) on the reported reasons for repayment difficulties. A significant percentage of respondents in these surveys report that poor financial management, excessive charges or, excessive borrowing have contributed to them defaulting or being in financial difficulties. Jentzsch and Amparo [26] argue that while "inadequate information" might be consistent with life-cycle or permanent income models of debt, reporting poor financial management or excessive charges cannot be.

In this paper, using a unique administrative data from a major credit counselling charity (CCCS) in the UK, we provide direct empirical evidence for the impact of reporting poor financial management and smoking on the subsequent debt repayment performance of borrowers in financial troubles. CCCS assists heavily indebted borrowers by setting up and administering repayment plans, so called debt management plans (DMPs). These are essentially debt consolidation plans. Our estimation sample consists of all the borrowers who started a DMP between January 2003 and November 2006 (60,495 individuals). We observe the debt repayment behavior (DMP performance) overtime. Employing survival analysis, we estimate

[1] According to the results of a "survey of 1,974 individual bankruptcy petitioners conducted during the first quarter of 1999 in eight federal judicial districts".

that borrowers who smoke and who reported poor financial management as the reason for their repayment difficulties at the enrollment stage are significantly more likely to fail on a DMP even when controlling for a rich set of covariates including monthly payment towards DMP, income and expenditures recorded at the start of the DMP and various individual and demographic characteristics such as age, gender, having a mortgage, marital status, number of dependents, whether the consumer is self or full time employed, and self-reported reasons for debt (which are used to construct proxies for negative shocks experienced prior to start of DMP).

The reason we focus on the two variables, admitting bad financial management as the reason for debt and smoking, is because we treat the former as a proxy for self-control problems in the financial domain and the latter as a proxy for more general self-control problems. Assuming that self-control preferences are stable over time, we conjecture that these two variables recorded at the enrollment stage would predict the future debt repayment performance on a DMP. In other words, we conjecture that individuals who are identified as suffering from lack of self-control would be more likely to fail on a DMP.

We introduce a very simple theoretical model of a DMP to illustrate our conjecture when self-control problems are modelled by quasi-hyperbolic discounting ((Strotz [43]; Phelps and Pollack [42]; Laibson [29]; O'Donoghue and Rabin [39], [40]).[2] Time-inconsistency of preferences (due to the assumption of quasi-hyperbolic discounting) requires us to make assumptions on the consumers' analysis of their own future behavior. More specifically, we distinguish two types of consumers with dynamically inconsistent preferences: a *sophisticated* consumer who is fully aware of her self-control problems and a *naive* consumer who is partially or completely unaware of her self-control problems. We compare the results to the exponential (time-consistent) discounting benchmark. The simple 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.[3]

It can be argued that it is not clear what exactly reporting "debt misuse" or "poor financial management" reveals about borrower behaviour (that is, it does not necessarily reflect self-control problems). It does suggest that factors other than unanticipated negative

[2]On the theory front, there are a variety of approaches to model self-control: temptation and self-control model of Gul and Pesendorfer [22]; models with time inconsistent discounting by Strotz [43] and Laibson [29], the dual-self models of Thaler and Shefrin [44], Benabou and Pycia [4], Fudenberg and Levine [18], Benhabib and Bisin [5], Loewenstein and O'Donoughe [33] and the model of cue-triggered mistakes of Bernheim and Rangel [6].

[3]It would be very interesting to see whether our indices of self-control are correlated with the subjective rates of time-discount, but unfortunately we are unable to directly test the assumption of quasi-hyperbolic discounting due to limitations of the data.

shocks are playing a nonnegligible role in household's overindebtness but these factors could also be strategic default motives (if bankruptcy costs are not sufficient to deter people from defaulting on their debts) or financial illiteracy.

The counselling data has a natural advantage in that it allows us to credibly rule out financial illiteracy as the main driver of poor DMP performance. Individuals who are selected for a DMP get substantial debt and budgeting advice prior to the start of the DMP. In fact, counselors do the budgeting for them asking for detailed information on income, expenditures and spending habits during lengthy phone interviews. Consumers are able to contact CCCS while on DMP to get further debt advice and are encouraged to inform CCCS when their circumstances change for good or for worse. Total debt on DMP is repaid in equal monthly installments over a fixed period of time (over the duration of the DMP) making DMP terms simple and leaving little room for confusion. Thus, if admitting poor financial management were to proxy for low financial literacy rather than self-control issues, we would not expect this indicator to be a significant predictor of DMP default. We also argue that, individuals in our sample who admitted poor financial management as the reason for debt are not likely to be the ones who accumulated so much debt because they had strategic default in their mind. It is in the interest of the counselling agency to select individuals who show a commitment to repay their debts and are likely to succeed doing so through a DMP (service is free to the clients but CCCS gets a commission from lenders out of the debt repaid by consumers, known as "fair share" contribution). It is true that contacting CCCS is not entirely on a voluntary basis: approximately half of the consumers are referred to CCCS by their lenders. In either case, however, bankruptcy was an option but borrowers showed a preference for trying to repay their debts first. One counter argument would be that CCCS ask lenders freeze interest for debts on DMP and this could create an incentive for borrowers to enroll a DMP even though they do not have the intention to repay their debt. However, the DMP agreement is an informal one and CCCS does not (can not) guarantee that lenders will agree to freeze interest rates.[4]. Thus, in our sample, individuals who reported difficulties in managing their finances (poor shopping habits, no budget etc.) as the reason for running into financial troubles are regarded as suffering from self-control problems.

We also use smoking to proxy for general self control problems. Becker and Murphy's [3] model of rational addiction has been the standard approach to modelling consumption of addictive goods such as cigarettes.[5] However, Gruber and Kozsegi [20] show that forward looking

[4]Moreover, as it will be discussed in more detail in section 3, we drop individuals who were on a DMP for less than 3 months from our sample in order to exclude cases where a person enrolled and never paid, or enrolled but failed very early on DMP.

[5]Indices of self-control has been linked to substance use (including tobacco) in psychology literature. See, for example, Audrain-McGovern et al. [2] and references there in.

behaviour (future prices matter for today's consumption) does not imply time-consistency.[6] In fact, a model that incorporates time-inconsistent discounting in Becker and Murphy framework is also consistent with forward looking consumption decisions. Morover, Gruber and Kozsegi [20] argue that smokers' demand for commitment devices, their unrealized intentions to quit and repeated (unsuccessful) attempts at quitting all provide "indirect" evidence that preferences with respect to smoking are time-inconsistent. Gruber and Mullainathan [21], based on individual-level cross-sectional data from Canada and the U.S., find that smokers' happiness rises with cigarette taxes (cigarette taxes serve as a commitment device to help consumers solve their self-control problem). Hersch [25] uses data from Current Population Survey Tobacco Use Supplements for the period of 1992 to 2002 to demonstrate that (i) smokers who plan to quit are more supportive of regulations than other smokers (ii) smokers who failed to quit but plan to try again are more supportive of restrictions than those who plan to quit for the first time. Hersch's findings suggest that regulatory restrictions work as a self-control mechanism to help reduce costs of quitting. Kan [27] finds, using survey data from Taiwan, that a smoker's intention to quit has a positive effect on the smoker's support for smoking bans and a cigarette excise tax increase. These empirical findings challenge the validity of rational addiction model and supports the view that smokers are better described as suffering from self-control problems. Della Vigna and Paserman [15] use smoking and heavy drinking as measures of impatience. They claim that both activities provide immediate rewards and delayed costs and should indirectly reveal a preference for early gratification.

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: admitting poor financial management as the reason for debt and smoking. We 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 DMP drop-out probability decreases with age. Rather surprisingly, we found 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.

Our findings lend considerable empirical support to the view that self-control considerations play a role in households' over-accumulation of debt and consequent repayment dif-

[6] See, Gul and Pesendorfer [23] for another recent approach to modelling addiction.

ficulties.[7] If, as our results suggest, financial capability has a "behavioral" dimension, then the policy implications would be major. In particular, if cognitive biases such as lack of self-control play a role in shaping household credit behaviour, the regulatory response of imposing disclosure rules or providing financial education alone are unlikely to have long lasting and significant effects on improving consumer financial decision making.

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 Self-control and borrower behavior in a DMP: an illustrative model

Here we illustrate with a simple model how "time-preference interpretation" of self-control problems could result in higher DMP drop out rates. In particular, we show that if self-control problems were due to the difference between long run and short run discount rates with present bias, then naive borrowers (who are only partially aware of their present bias) would fail on a DMP more often.

We construct a very simple model of a DMP repayment behavior with income uncertainty and consider borrowers which differ only with respect to their time preferences. In particular, we assume that borrowers have quasi-hyperbolic discount function (Strotz [43]; Phelps and Pollack [42]; Laibson [29]; O'Donoghue and Rabin [39], [40]). 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

[7] Previous research has found a link between self-control (in particular present bias) and accumulation of credit card debt. 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 [16], Bertaut and Haliassos [8]). Laibson et al. [31] estimate that the co-existence of substantial illiquid wealth and credit-card debt can only be explained by present-biased time preferences (when short-term discount rate is higher than long-term discount rate). Meier and Sprenger [36] test in a field study whether present-biased time preferences (revealed through incentivized choice experiments) correlate with credit card borrowing and document (even controlling for disposable income, other socio-demographics, and credit constraints) that present-biased individuals are in fact more likely to have significantly higher amounts of credit card debt. Ameriks et. al. [1] identify a robust relationship between measured self-control (using Gul and Pesendorfer's [22] model of temptation) and the level of liquid wealth. For further discussions and additional references see Della Vigna [14] and Heidheus and Kozsegi [24].]

$s = t+1, t+2, ...$ 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 $\{1, \beta\delta, \beta\delta^2, ...\}$. Suppose that self-0 thinks that the future selves' time preferences are $\{1, \hat{\beta}\delta, \hat{\beta}\delta^2, ...\}$. 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 $\beta < \hat{\beta}$, the consumer is *naive*. That is, the sophisticated consumer is fully aware of her hyperbolic preferences and correctly anticipates that her future selves will have hyperbolic preferences. In contrast, the naive consumer is partially or completely unaware of her time-inconsistency. She thinks that her future selves will either discount exponentially (fully naive) or she overestimates her true β (partially naive). The difference $\hat{\beta} - \beta$ can be interpreted as the *degree of naivete*. 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 α 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 $\overline{d}_1$ 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 $\overline{d}_1$ at $t = 2$.

We would like to 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*

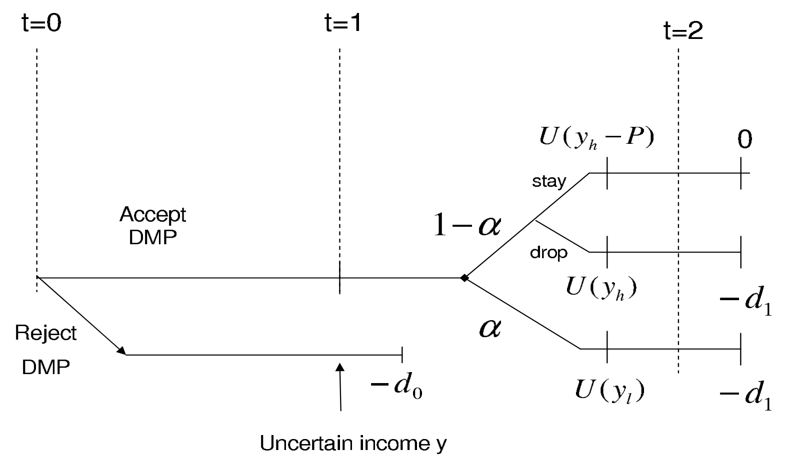

Figure 1: The model

accepting a DMP at $t = 0$, absent strategic default motives. For this purpose, we need to rule-out strategic default by assuming that dropping out from a DMP when there is a positive shock to income is never ex-ante optimal. We also need to assume that there will be some borrowers who accept a DMP. In particular, we make 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 *Expected benefit of accepting the DMP with the intention of staying at $t = 1$ when $y = y_h$, exceeds that of rejecting the DMP, both evaluated from the perspective of $t = 0$.*

Assumptions 1 and 2 ensure that no borrower has strategic default motives at $t = 0$ when signing the DMP and imply the following condition on $\hat{\beta}$:

$$\frac{\overline{d}_0}{\overline{d}_1 \delta} \leq \hat{\beta} \leq \frac{\overline{d}_0 - (1-\alpha)P}{\alpha \overline{d}_1 \delta}. \tag{2.1}$$

When $t = 1$ arrives, the condition for staying in DMP becomes,

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

which after some algebra simplifies to a condition on β:

$$\beta \geq \frac{P}{\delta \overline{d}_1}. \tag{2.2}$$

Proposition 3 *Assume that Assumptions 1 and 2 hold. The exponential and the sophisticated borrowers drop out of the DMP only if $y = y_l$ whereas it is possible for the naive borrower to drop out when $y = y_h$.*

Proof: First, note that 2.1 implies $d_0 \geq P$. Recall that the exponential borrower has $\beta = \hat{\beta} = 1$. It follows from (2.1) and (2.2) that (i) the exponential borrower accepts the DMP iff $\delta \in (\frac{\overline{d}_0}{\overline{d}_1}, \delta \leq \frac{\overline{d}_0-(1-\alpha)P}{\alpha \overline{d}_1})$ and drops out only when $y = y_l$ (ii) the sophisticated borrower $(\beta = \hat{\beta})$ with $\beta \in (\frac{\overline{d}_0}{\delta \overline{d}_1}, \frac{\overline{d}_0-(1-\alpha)P}{\alpha \overline{d}_1 \delta})$ accepts the DMP and drops out with probability α (iii) the naive borrower who has the same true β, accepts the DMP if $\hat{\beta} \in (\frac{\overline{d}_0}{\delta \overline{d}_1}, \frac{\overline{d}_0-(1-\alpha)P}{\alpha \overline{d}_1 \delta})$ and drops out with probability α (iv) the sophisticated borrower with $\beta < \frac{\overline{d}_0}{\delta \overline{d}_1}$ rejects the DMP and (v) the naive borrower who shares the same true β accepts the DMP if $\hat{\beta} \in (\frac{\overline{d}_0}{\delta \overline{d}_1}, \frac{\overline{d}_0-(1-\alpha)P}{\alpha \overline{d}_1 \delta})$ and drops out with probability $1 > \alpha$ if $\beta < \frac{P}{\delta \overline{d}_1}$.

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

Consider the population of borrowers with $\delta \in (\frac{\overline{d}_0}{\overline{d}_1}, \frac{\overline{d}_0-(1-\alpha)P}{\alpha \overline{d}_1})$ and with $(\beta, \hat{\beta})$ 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 β and $\hat{\beta}$ vary.

Insert figure here.

The point $(1, 1)$ on the upper corner represents the exponential borrowers. Since $\delta \in (\frac{\overline{d}_0}{\overline{d}_1}, \frac{\overline{d}_0-(1-\alpha)P}{\alpha \overline{d}_1})$, they accept the DMP and stay if $y = y_h$. The line segment joining the points $(\frac{d_0}{\delta \overline{d}_1}, \frac{d_0}{\delta \overline{d}_1})$ and $(1, 1)$ represents the sophisticated borrowers who accept and stay if $y = y_h$. The area with coordinates $(\frac{d_0}{\delta \overline{d}_1}, 0)$, $(\frac{d_0}{\delta \overline{d}_1}, \frac{P}{\delta \overline{d}_1})$, $(1, \frac{P}{\delta \overline{d}_1})$ and $(1, 0)$ represent the naive borrowers who accept the DMP thinking they would stay but end up dropping at $t = 1$ when $y = y_h$.

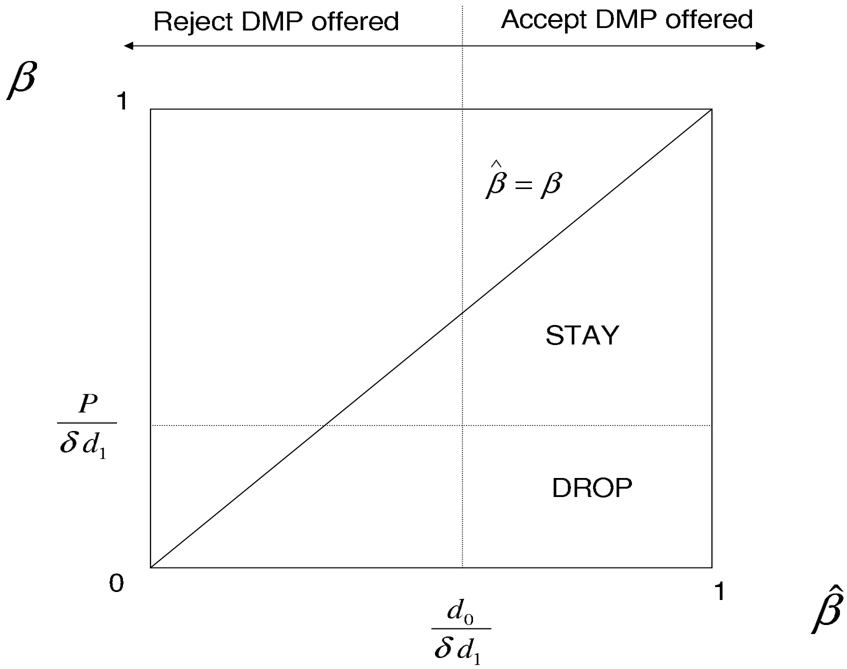

Figure 2: DMP outcome for different combinations of β and $\hat{\beta}$

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 α. 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:

$$\begin{aligned} \alpha + (1-\alpha) Pr(\beta \leq \frac{P}{\delta \overline{d}} \quad | \quad \hat{\beta} > \frac{\overline{d}_0}{\delta \overline{d}_1}) &= \alpha + (1-\alpha) \frac{\int_0^{P/\delta \overline{d}} \int_{\overline{d}_0/\delta \overline{d}_1}^1 2 \, d\hat{\beta} d\beta}{\int_{\overline{d}_0/\delta \overline{d}_1}^1 2\hat{\beta} \, d\hat{\beta}} \\ &= \alpha + (1-\alpha) \frac{2P}{\overline{d}_0 + \delta \overline{d}_1}. \end{aligned}$$

Thus, if the income shock is distributed randomly across types, we obtain the same drop out probability for exponentials and sophisticates and a higher drop out probability 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.[8] 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.[9] 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.[10] 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.).[11]

CCCS was introduced into the UK in 1993.[12] 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.

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

Source: CCCS Statistical Yearbooks 2005, 2006.

[8] CCCS is a registered debt charity and therefore has a non profit status. It is funded by fair share contributions from credit industry.

[9] Almost half of CCCS clients are recommended to CCCS by their lenders.

[10] 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.

[11] 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.

[12] It started with a pilot scheme in Leeds. During 1996 new centres opened in Nottingham, Birmingham and Cardiff, Galsgow, 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.

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), and the agreed DMP budget (income, expenditures) and DMP 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).

3.2.1 Reason for Debt variable

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. We use smoking as a proxy for general self-control problems. In addition, we propose and construct an indicator of self-control, using a unique information contained in our data - (self-reported) reasons for debt. In particular, we identify individuals who reported reasons which are suggestive of poor financial management and treat them as suffering from self-control problems.

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

Table 1: Reason for debt variable

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

Table 1 continues at the other page.

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 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. [13] 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.)

[13]Variables such as "no-budget" are rather infrequently populated.

Table 1: Reason for debt variable

Category	Reason for debt	Freq.	Percent.
Other	Over Committed On Credit	25008	31.5
	Used Credit For Living Exp.	9209	11.6
	Used Credit For Business Exp.	273	0.34
	Expenditure Excessive	499	0.63
	Utility Arrears	62	0.08
	School Expenses	123	0.15
	High Mortgage/Rent	273	0.34
	High Vehicle Costs	136	0.17
	Home Repair Expenses	264	0.33
	Housing Cost Arrears	175	0.22
	Increased Housing Payments	726	0.91
	Insurance Problems	8	0.01
	Legal Expenses	56	0.07
	Child Support Problems	343	0.43
	Missed Work-Bad Weather	26	0.03
	Moving/Relocation Expenses	883	1.11
	Low Paid	294	0.37
	Part Time Work Only	451	0.57
	Vehicle Accident	81	0.10
	Vehicle Repairs	101	0.13
	Substance Abuse	24	0.03
	Unknown	667	0.84
	Total	79,398	100.00

was stated as the justification for the borrower's inability to repay, in 2005 CCCS started encouraging its counsellors 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. [14]

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

[14]We observe that if the client does not report a clear negative shock, "reduced income" is chosen more often as the reason for debt.

Table 2: Number of reasons stated

Number of reasons	**Freq.**	**Percent.**
1	45,063	74.49
2	12,474	20.62
3	2,509	4.15
4	391	0.65
5	53	0.09
6	4	0.02
7	1	0.00
Total	60,495	100.00

are clear facts 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 income 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. [15] 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.[16] 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.[17] This leaves us with 60,495 individuals who have started or have been observed on the DMP during the analyzed period.

[15] 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.

[16] The most typical case being an earlier repayment of the debt via selling of one's property.

[17] We didn't find any systematic pattern in the observations that were dropped form the data.

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 3: Summary statistics-I

Stats	**Mean**	**Var**
smoker	0.221	0.172
woman	0.555	0.247
couple	0.476	0.249
#dependants	0.476	0.249
mortgage	0.214	0.168
selfempl	0.030	0.029
fulltime	0.605	0.239
age	38.941	147.887

Table 4: Summary statistics-II

Stats	**Mean**	**Sd**	**Min**	**Max**
Expenditure*	1126.52	548.54	5.00	3369.00
Income*	1336.04	598.70	30.00	3500.00

* In British Pounds.

About 55 % of the individuals who contacted CCCS are women and the average age is 39.[18] There is about 48 % of couples and the average number 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.

[18]Some of them, however, represent a bigger household.

Table 5: Percentage reasons for debt

Variable	Freq.	Percent.
NS_incshock	15,425	25.50
NS_job	6,933	11.46
NS_ill	6,582	10.88
NS_sep	6,455	10.67
NS_preg	1,172	1.94
SC_prob	2,140	3.54

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:

Table 6: DMP status

dropDMP	**Freq.**	**Percent.**
Active	48075	79.47
Nonpayer	12420	20.53
Total	60495	100.00

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). 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[19] 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 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 [13], 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[20]: 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,

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

is defined in the Cox's proportional hazard model as

[19] 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.

[20] The exposition of the model here is based on Greene [19].

$$\lambda(t_i) = \exp(-x\prime_i\beta)\lambda_0(t_i).$$

where x are individual or spell-specific characteristics and λ_0 is the baseline hazard function. Cox's partial likelihood estimator allows to estimate β (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 described for example in Cameron and Trivedi [11]. 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 [10].

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 due to bad financial management (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 poor financial management as the reason for debt problems, drop out from the DMP with 12 % higher probability than the rest of the CCCS clients.

The estimates of the other reasons for the initial debt (proxies of negative shocks) 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 dependents 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, illness 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.[21] 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 overtime. 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 poor debt management and experienced a negative shock at the same time. We also try to interact the indicator for poor debt management with the negative shock indicators 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.[22]

Another result that we focus on in relation to the predictions of our model is smoking (as a proxy for self-control problems). The effect of smoking is highly significant and more than twice as big as the indicator for poor debt management. It suggests that smoking increases the probability of dropping out from the DMP by 31 %.

It could be objected that smoking might also be capturing other individual traits such as educational attainment (and thus financial literacy), earning growth and risk preferences. The fact that we do not have data on education or risk preferences is an important drawback of our analysis. However, the evidence on the link between financial literacy and education is not strong. [23] Moreover, as discussed in more detail in the introduction, we do not expect financial

[21] 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.

[22] The results, not presented here, are available form the authors on request.

[23] The survey evidence shows that low income is a predictor for low debt literacy (Lusardi and Tufano [35]) and those with low educational attainment are "disproportionately less likely to be financially literate"

literacy to matter for DMP outcomes as consumers get substantial debt and budget advice and the DMP terms are simple. We are also able to control for monthly DMP payments, current income, and negative shocks (reported prior to start of DMP). Nevertheless, we recognize that smoking is an imperfect proxy for self-control problems and we can not rule out the possibility that strong predictive power of smoking on DMP performance could be due to a combination of all of the factors above.[24] In our defence, there has been a number of studies which support the view that smoking correlates with lack of self-control in the context of financial decision making. Bertaut et al. [8] documents that smokers are significantly more likely to revolve credit card balances even after controlling for age, race, education, and income which lends support to the idea that spending-control considerations play a role. Khwaja et al. [28] also finds that impulsivity and lack of financial planning are related to smoking decision.

Smoking is also likely to have a direct income effect: given the high and still rising tobacco prices, smoking expenditures 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. However, we were told by CCCS that the reason for collecting information on smoking is to account for the smoking expenditure when calculating monthly disposable income (income used towards paying debt on DMP). CCCS advice people to cut on smoking and if people are over-optimistic about their odds of quitting, smoking expenses could create income fluctuations. This would reinforce our argument that self-control problems, as proxied by smoking, have a negative effect on DMP performance.

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 particularly 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 even the single women do not 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

(Lusardi and Mitchell [34]). Yet, as a large percentage of respondents with university education display low financial literacy, the education can at best be an imperfect proxy for financial literacy (Van Rooji et al.[45]).

[24] The non-zero correlations have been reported between time-preference and smoking, education and smoking, smoking and wage growth, and time-preference and education (See Munasinghe and Sicherman[38] and references there in). Moreover, Mischel [37] has shown that ability to resist temptation correlates with academic achievement. The complex correlations between these variables make it difficult to draw casual inferences.

married men.

The results on gender and age differences in DMP performance contrast with previous findings on differences in financial literacy across demographic groups. Lusardi and Tufano [35], for example, provide survey evidence that elderly and woman display low debt literacy. Therefore, one would not expect them to perform better on a DMP. [25]

Having a mortgage decreases the probability of the DMP drop-out by 14 %. The interpretation of this result is not clear as default on DMP does not mean loss of home (only unsecured debts are included in DMPs). It could be that those with a mortgage "feel more pressure" to keep their finances in order (keep their credit risk scores higher etc.).

While being self-employed increases the probability of dropping out by 17 %, working as a full-time employee reduces it by 12 % when compared 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 [26] from the regular monthly income. The effect of the two variables is in line with our prior 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 drop-out 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

[25]If, as we argue, the counselling does help neturalise the negative effects of illiteracy, we would not expect them to differ in their DMP performance from the rest of the clients. Thus, our results seem to suggest that other factors such as risk preferences might be playing a role here.

[26]Including the payments for secured debt.

Table 7: Estimation results - Cox Proportional Hazard

Variable	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
SC_prob	0.186**	(0.044)	0.123**	(0.045)	0.122**	(0.045)
NS_job	0.154**	(0.028)	0.101**	(0.028)	0.103**	(0.029)
NS_ill	-0.077*	(0.031)	0.096**	(0.032)	0.100**	(0.033)
NS_preg	0.118†	(0.065)	-0.080	(0.065)	-0.077	(0.065)
NS_incshock	-0.085**	(0.022)	-0.026	(0.022)	-0.013	(0.022)
NS_sep	0.075**	(0.029)	0.075*	(0.031)	0.077*	(0.031)
smoker			0.322**	(0.020)	0.311**	(0.020)
woman (W)			-0.269**	(0.024)	-0.279**	(0.024)
couple (C)			-0.112**	(0.030)	-0.123**	(0.030)
W x C			0.143**	(0.037)	0.136**	(0.037)
age			-0.068**	(0.005)	-0.067**	(0.005)
agesq100			0.048**	(0.006)	0.047**	(0.006)
# dependants			0.044**	(0.010)	0.036**	(0.010)
mortgage			-0.170**	(0.027)	-0.143**	(0.028)
selfempl			0.204**	(0.059)	0.171**	(0.060)
fulltime			-0.053*	(0.021)	-0.119**	(0.025)
lnexpend			0.343**	(0.060)	0.329**	(0.060)
lnincome			-0.470**	(0.067)	-0.429**	(0.067)
Start. Month and Year In	no		no		yes	
N	60495		60495		60495	
Log-likelihood	-128427.722		-127329.08		-127147.51	
$\chi^2_{(.)}$	80.193		2288.971		2578.277	

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

The degrees of freedom of the $\chi^2_{(.)}$ distribution for the three models are 6, 18, and 64.

Robust standard errors are calculated according to Lin and Wei (1989).

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 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

This paper investigates the predictors of the debt repayment performance of over 60,000 borrowers who are in financial troubles and have been enrolled in a debt management plan (DMP) administered by a major credit counselling charity in the UK.

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 prior to enrolling a DMP as well as other household-specific characteristics such as, monthly payment towards DMP, income and expenditures recorded at the start of the DMP and various individual and demographic characteristics such as whether the individual is self or full-time employed, age, gender, having a mortgage, marital status, number of dependents etc. We find that smoking and reporting of poor financial management as the reason for financial troubles increase the likelihood of failing on a DMP by 30 and 12 per cent respectively. We also find that the DMP 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.

The finding that poor financial management and smoking are strong predictors of default on a DMP, even when controlling for the occurrence of specific negative shocks and a rich set of individual characteristics, is striking. Our results highlight a need to consider models of default which account not only for unexpected negative shocks (e.g. income shocks) but also for behavioral biases (in our case, lack of self-control). If behavioral biases are important drivers of poor financial management, then conventional financial education policies are unlikely to have lasting effects on changing consumer attitudes.[27]

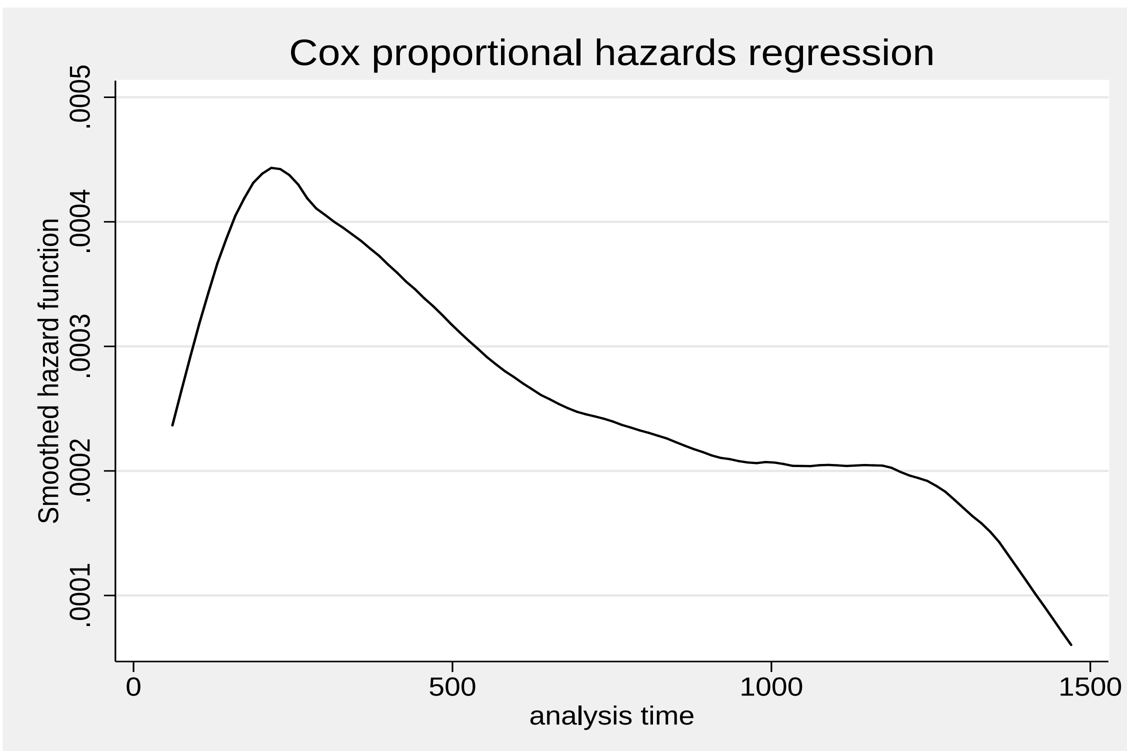

Figure 3: Hazard Rate from the Cox's Model - at Means of the Variables

[27]Regulators in the UK are increasingly taking into account the possible implications of "behavioral biases" for policy design. A recent independent review commissioned by UK's regulator FSA [17] concludes that "psychological rather than informational differences may explain much of the variation in financial capability reported in the FSA's financial capability survey".

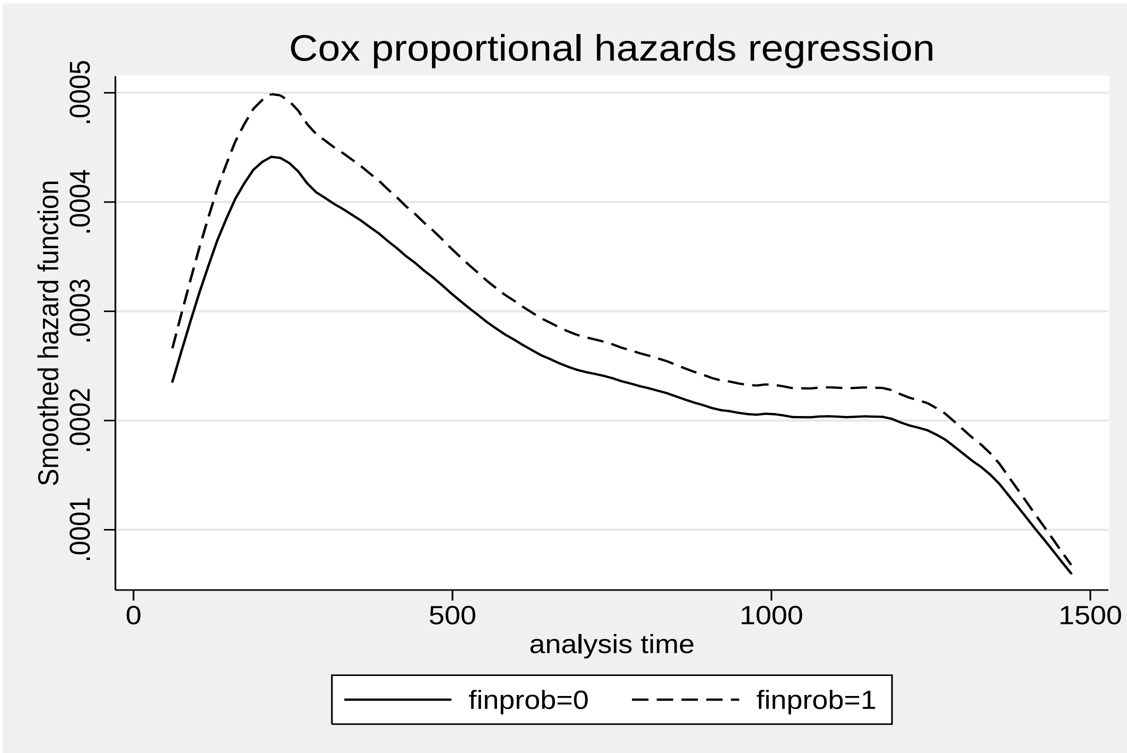

Figure 4: Hazard Rates for Individuals with Self-control Problems (Who Mismanaged their Debt) and for Individuals without Self-control Problems

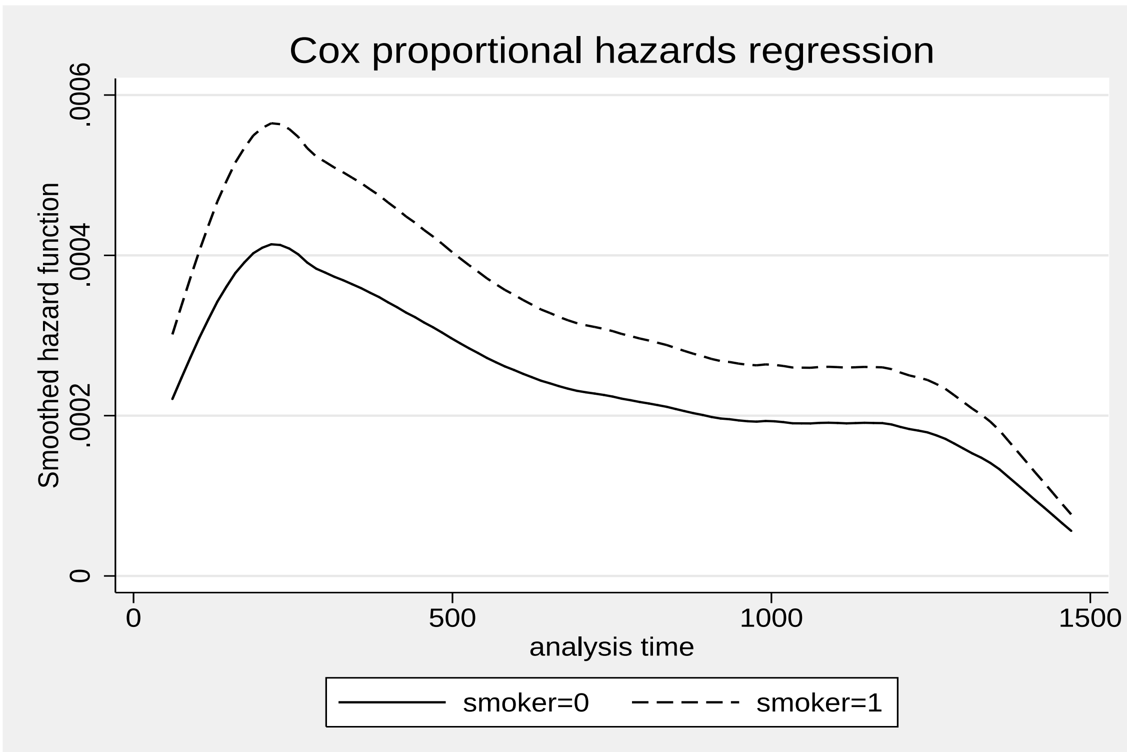

Figure 5: Hazard Rates for Smokers and Non-Smokers

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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; unemployment 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; injury/ilness 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 logarithm.

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 borowers 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 exponential 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.[28] 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.

[28]As long as the counselling is voluntary, it can best be an 'imperfect" commitment mechanism.