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The Success and Failure of Counseling Agency Debt Repayment Plans

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This paper investigates whether success on a counseling agency-administered Debt Management Plan (DMP), as measured by the amount of original debt repaid, can be predicted at the time of counseling based on observable client and debt attributes. The paper utilizes a unique database of over 17,000 consumers who were counseled and recommended for a DMP by a large non-profit credit counseling agency during 2003. Of particular interest to counseling agencies and creditors is the finding that the magnitude of the interest rate reduction offered by creditors to consumers on a DMP has a significant, positive influence on debt repayment.
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INTRODUCTION

Millions of American consumers seek advice and assistance from a credit counseling organization each year. Upwards of one-third of these consumers enroll in voluntary repayment plans, called Debt Management Plans (DMPs), as an alternative to bankruptcy. Counseling agencies broker these unique plans by getting creditors to voluntarily exercise mutual forbearance in the form of concessions on finance charges and repayment terms, a halt to late fees and collection calls, and a re-aging of accounts to "current" status while the consumer is on the repayment plan. But, the majority of DMPs terminate prior to completion. Creditors worry that some borrowers opportunistically enroll (with the tacit approval of counseling agencies that act as screeners) just to get a temporarily lower interest rate with no intention of sticking with a plan to its conclusion. The moral hazard risk has contributed to creditor reluctance to make deep concessions on plans. But, a DMP can be a far less costly debt relief option for many consumers than either bankruptcy or debt settlement.[1] Creditor reluctance to make concessions leaves many consumers unable to qualify for a beneficial DMP, as will be explained below.

This paper investigates whether success on a DMP, as measured by the amount of original debt repaid, can be predicted at the time of counseling based on observable client and debt attributes. One objective of building such a model is to identify the impact of creditor concessions on DMP participation and completion. In addition, a

predictive model accessible to both counselors and creditors could be used to move the industry away from the typical one-size-fits-all DMP and toward a system in which creditors are more willing to make deeper concessions for those consumers with a demonstrated greater need. A predictive model could also help to boost DMP completion rates by giving agencies a tool to make operational adjustments to allocate more resources to clients who are likely to need extra assistance as they work through their repayment plans.

We are not aware of any prior econometric studies of the determinants of DMP payment experience. With more than 1.5 million households projected to file for bankruptcy in 2010, at the same time that credit card chargeoffs for the largest issuers have soared about 10 percent of outstanding balances, there is clear need for creditors and counseling agencies to reduce the barriers to making DMP products available to a wider segment of consumers in order to prevent bankruptcies and lower losses.[2] This paper examines the factors that determine the repayment of debt through a DMP using data on over 17,000 consumers who were counseled and recommended for a DMP by a large non-profit credit counseling agency during 2003. The objective is to identify attributes observable at the time of counseling that predict which consumers will be more likely to do well on DMPs, among the pool of clients for whom a counselor recommended a DMP at the end of the initial counseling session.

The paper is organized as follows. We first provide background on the DMP and the resulting partnership between consumers, counselors, and creditors. Then a brief literature review regarding the potential determinants of DMP success is given. The methodology underlying the research is then discussed. Next, the data used in the empirical models are described. Regression model estimates of DMP repayment are subsequently analyzed. We then acknowledge and explore sample selection issues and provide additional insight into the effectiveness of the counseling agency's screening process. Finally, we offer concluding thoughts.

BACKGROUND ON THE DMP RELATIONSHIP BETWEEN CONSUMERS, COUNSELORS, AND CREDITORS

In uniquely American fashion, the credit counseling industry in the United States began in the late 1960s as a market-driven, creditor-sponsored effort to advise financially troubled consumers on alternatives to personal bankruptcy [Hunt 2005; Staten 2006]. Major national creditors organized a network of non-profit counseling agencies to offer in-person, individualized counseling sessions through which consumers received budgeting analysis and advice. The rapid expansion in both credit availability and serious loan delinquencies during the 1990s caused demand for counseling services to soar, and led to the entry of hundreds of new competitors. The number of credit counseling agencies mushroomed from fewer than 250 agencies operating about 800 offices in 1992 to over 900 agencies operating as many as 2,000 offices by the end of 2003 [U.S. Senate 2004]. Up to 9 million people sought advice and assistance from a credit counseling organization in 2003 [Loonin and Plunkett 2003].

A core service of each agency (and the primary motivation for creditor financial support) is to negotiate with a consumer's creditors to set up voluntary repayment plans, called DMPs. These plans are unique in getting creditors to exercise mutual forbearance by offering concessions on finance charges, late fees, minimum monthly payments, and a halt to collection calls. When successful, these agency-administered DMPs provide a valuable service to consumers by helping them to resolve their debts while avoiding the stigma associated with filing for bankruptcy.

DMPs also help creditors, mostly issuers of unsecured credit cards. The oldest network of non-profit credit counseling agencies, those operating as members of the National Foundation for Credit Counseling (NFCC), returned $2.3 billion to creditors in 2002 through the DMPs they structured for their consumer clients. Industry-wide statistics are elusive, but up to $17 billion in outstanding balances from the 10 largest US bank credit card issuers were being serviced through credit counseling DMPs in 2002 [Furletti 2003]. To put this in perspective, total credit card charge-offs industry-wide in 2002 were $35 billion. Clearly, balance recovery through DMPs can substantially reduce total losses.

Typically, creditors pay counseling agencies a "fair-share" contribution as a percentage of the funds recovered under the DMPs. Fair-share payments linked to DMP performance constitute the single largest source of agency revenues for the typical counseling agency. This revenue-sharing arrangement gives the agency an increased incentive to work with debtors (e.g., follow-up contacts, re-evaluations) to keep them on a plan, and to enroll them on plans that have a good chance of being successful. However, the revenue model also increases the agency's incentive to sign up lower-risk/less needy consumers for DMPs (and creditor financial concessions) to increase the probability that they'll pay more through the plan. Creditors are at a disadvantage in policing this opportunistic behavior because of an informational asymmetry inherent in the counseling process.

The initial counseling "intake" interview allows the agency to know more about the client's financial condition than does the creditor. Both creditors and the counseling agency can purchase a variety of commercially available bankruptcy risk scores for consumers. But, the counseling agency deals directly with consumers, sees a fuller picture of their overall debt exposure, and has greater insight as to the client's financial situation as a result of conversation with the client during the initial counseling interview. Consequently, the agency can better assess a consumer's financial predicament than can creditors. In particular, the informational asymmetry makes it difficult for creditors to know whether consumers who enroll in DMPs actually need the concessions on finance charges and fees that are offered as virtually a standard feature of all DMPs.[3]

Staten [2006] noted that if a predictive model could be developed that would give *both* the agency and the creditor a similar indication of who is more likely to complete a DMP, then the informational asymmetry would be reduced and concessions and other assistance could be targeted at debtors who appear to need them most.[4] The model could also be used to calibrate the creditor fair-share payment to the agency, in essence awarding greater compensation for the toughest (highest risk) cases, thereby increasing agency incentives to work with debtors toward plan success.

Remarkably, given the widespread use of credit scoring over the past decade to drive loan acceptance decisions and individualized risk-based pricing of loans, the counseling industry has not developed and implemented such a model. Certainly as of the time our data were collected in 2003, counseling agencies still offered one-size-fits-all DMP products to consumers [Ludwig 2005]. The next section examines potential components of a model to predict success on a DMP.

POTENTIAL DETERMINANTS OF DMP SUCCESS

There has been little research on the factors that influence these repayment plan outcomes. Regarding debtor repayment plans under bankruptcy Chapter 13,

Norberg [1999] and Bermant [2005] report total amounts paid to creditors, but do not analyze the factors that contribute to higher payments. Loibl et al. [2006] examined factors that influence the self-reported expectations of success for debtors who had recently started Chapter 13 repayment plans after filing for bankruptcy protection, and found limited evidence that certain financial behaviors (e.g., good organization of financial records) were associated with debtor optimism regarding plan success, but the researchers did not observe actual success rates of the Chapter 13 plans. However, what is known is that the majority of Chapter 13 plans do not pay the full amount proposed by the bankruptcy court at the outset of the plan. Eraslan et al. [2007] examine some factors that influence bankruptcy court approval of Chapter 13 repayment plans and ultimate payout to creditors. Using Delaware court docket data from 2001 to 2002, the authors found that whether debtors were first-time filers, the magnitude of their past-due balances at the time of filing, and income in excess of that required for basic maintenance all significantly affected the distribution of creditor recovery rates. However, the bankruptcy court records had limited socio-demographic data on debtors and no credit report information, thus limiting the range of variables available to the authors to predict repayment experience.

DMPs are similar in length to Chapter 13 repayment plans, but differ significantly in that DMPs are entirely voluntary on the part of both debtors and creditors. Since the late 1990s, DMPs have typically been set up as 60-month repayment plans.[5] Most of these plans terminate before completion. According to statistics from the NFCC for its member counseling agencies, of the 273,473 DMPs terminated during 2002, 47 percent were due to clients who simply stopped making payments, 21 percent were attributable to clients choosing to "self-administer" (i.e., take over payments to creditors outside the credit counseling plan), 4 percent ended in client bankruptcy, and 21 percent were successful completions.

Kim et al. [2003 and 2005] found that indices of self-reported financial management habits and the existence of financially stressful events (both measured at the time of initial counseling) were associated with the likelihood that consumers were still actively participating after 18 months on a DMP. Using agency data on client characteristics and plan completion rates for 660 DMPs initiated in 1988, Staten [1993] found that creditor reductions in finance charges for DMP clients were a significant, positive determinant of whether a plan was still active after 4 years. Although outside the context of a counseling DMP, Agarwal et al. [2008] examined the success of one creditor's internally administered debt workout programs (of length similar to counseling DMPs) for its account-holders who had fallen seriously delinquent. The authors found that the borrower's Fair Isaac Corporation (FICO) risk score at the outset of the workout plan was a significant predictor of plan success.

Building on these limited findings from prior research and extensive discussions with credit counselors and counseling industry leaders, several categories of factors emerged that are likely to influence success of DMPs. Some factors refer to the characteristics of borrowers who agree to enroll in plans after being recommended by a counselor. Other factors involve the nature of the plan itself, counseling agency procedures, creditor actions, and life events that impact borrowers during the repayment period. Events that occur after a DMP has formed certainly also influence a client's success, but such factors are difficult to predict. The objective of this research is to predict the amount of debt that will be repaid given the factors that are observable at the time of the initial counseling.

METHODOLOGY

We designate four broad categories of factors that are likely to influence the success of a client (*REPAY*). The categories are the relevant interest rates (*INT*), the client's financial (*FIN*) and demographic (*DEM*) characteristics, as well as other pertinent information (*OTH*), such as the client's perceived ability to manage debt. One can express the relationship as follows,

$$REPAY = \alpha + \beta \cdot INT + \gamma \cdot FIN + \delta \cdot DEM + \lambda \cdot OTH + e \quad (1)$$

Endogeneity likely exists in equation (1) since the independent variables, such as the original interest rate set by credit card companies, are tailored to the expectations of repayment. Similarly, if the composition of creditors for a particular borrower is based on the creditors' expectations of repayment, even one-size-fits-all repayment plans offered by each creditor may yield DMP interest rates that are correlated with the expectations of the client's ability to repay debt.

Ideally, the problem of endogeneity is overcome via identification methods, the most common of which is two stage least squares. Unfortunately, few variables in consumer finance are legitimate instruments since so many could be used to form expectations. Therefore, we proceed with a second-best solution of estimating equation (1) and assume that the specification sufficiently controls for *all* of those factors underlying the counselor's and creditors' expectations of debt repayment at the time of counseling.[6]

On the face of it, the assumption that the specification controls for these expectations may seem untenable due to the limitations of most data sets. However, the data used for this paper are substantially more robust than most data available to academic researchers for estimating credit and payment behavior. In particular, a full credit bureau profile is available for each client prior to the DMP, as well as situation-specific information gathered by the counselor (but not available to creditors) during the initial interview. These controls mitigate the extent to which endogeneity might bias the estimation of equation (1).

DATA

A large national credit counseling agency supplied demographic and financial data on over 24,000 clients who received financial counseling during March or April of 2003. The agency provided counseling session data for all clients along with DMP performance data as of May 2007 for the subset of clients who began a DMP. One of the three major national credit reporting agencies appended archived credit report information to the counseling agency data and returned the depersonalized files to the research team for analysis. The archived credit report variables provide snapshots of the client's credit report at the time of counseling in 2003 and again in 2007. Table 1 lists variable descriptions, means, and standard deviations for all relevant variables.

The counseling agency provided the date the first plan payment was made and how many dollars the client had repaid as of May 2007. Therefore, client repayment (*REPAY*) is defined as the total amount of dollars paid as of May 2007 divided by the total amount of dollars that were scheduled to be paid at that time.[7] On average, DMP starters repaid 45.3 percent of their scheduled payments.

Table 1 Description and number of observations ($N = 6{,}065$)

Name	*Description*	*Mean*	*Std. dev.*
REPAY	Total percent of scheduled payments made by June 2007	0.453	0.384
O_IR	Weighted average interest rate of debt prior to joining DMP	0.201	0.045
P_IR	Weighted average interest rate of debt on DMP	0.107	0.033
AST	Total assets reported at the time of counseling	60,770.1	81,647
LIAB	Total liabilities reported at the time of counseling	62,786.8	73,174.4
INC	Monthly income at the time of counseling (incl. spousal income)	2,465.1	1,397.8
EXP	Monthly expenses on home, automobiles, and utilities	1089.2	747.1
PREV	Client has previously been on DMP	0.034	0.181
EMP	Client is employed	0.879	0.326
MAR	Client's marital status is reported to be married	0.463	0.499
DIV	Client's marital status is reported to be divorced	0.083	0.277
SIN	Client's marital status is reported to be single	0.381	0.486
M_OTH	Client's marital status is widowed, other, unreported, or unknown	0.073	0.259
MALE	Client is male	0.319	0.466
FEM	Client is female	0.59	0.492
G_NA	Client's gender is not reported	0.091	0.288
AGE	Age of client	41.1	13.5
DEP1	Client reports one dependent (including self)	0.198	0.399
DEP2	Client reports two dependents (including self)	0.293	0.455
DEP3	Client reports three dependents (including self)	0.218	0.413
DEP4	Client reports four dependents (including self)	0.124	0.329
DEP5UP	Client reports five or more dependents (including self)	0.167	0.373
OWN	Client is a homeowner	0.469	0.499
RENT	Client rents or partially rents their home	0.462	0.499
HOMLS	Client is homeless	0	0.018
PARNT	Client lives with parents	0.009	0.093
H_NA	Client does not report housing status	0.06	0.238
METRO	Client lives in a metropolitan area	0.864	0.343
CHAP7	Percent of state bankruptcy filings declaring Chapter 7 in 2003	0.705	0.139
ΔBNK	Percent change of state bankruptcy filings between 2002 and 2003	0.123	0.055
SRC1	Client was referred by a credit counseling agency	0.005	0.074
SRC2	Client was referred by community or employer	0.008	0.088
SRC3	Client was referred by a creditor	0.267	0.443
SRC4	Client was referred by family or friends	0.275	0.447
SRC5	Client was referred by an internet site	0.282	0.45
SRC6	Client was referred by legal advice	0.004	0.064
SRC7	Client was referred by other	0.001	0.031
SRC8	Client was referred by paid advertisements	0.121	0.326
SRC9	Client was referred by paid leads	0.024	0.152
SRC10	Client was referred by public service announcements	0.012	0.109
SRC11	Client was referred by social work or other government agency	0.001	0.034
ACMP	Client was accompanied with another person in counseling	0.338	0.473
HAB	Self-reported cause of financial difficulty is deemed habitual	0.518	0.5
SIT	Self-reported cause of financial difficulty is deemed situational	0.45	0.497
UNKN	Self-reported cause of financial difficulty is unknown	0.032	0.176
FACE	Client was counseled in person	0.292	0.455
TELE	Client was counseled on the telephone	0.529	0.499
NET	Client was counseled over the internet	0.179	0.383
RISK	Client′s risk score	600.7	78.1
HI_DLNQ	Highest delinquency ever on trade (in months)	5.082	3.22
LAT_TRD	Number of currently past due balances	1.297	1.849
DRG_TRD	Number of derogatory public records	0.212	0.634
LAT_MOR	Client is late on mortgage	0.049	0.216
SAT_RV	Number of satisfactory revolving trades	6.777	5.377
PCT_CUR	Percent of trades not delinquent	67.6	24
ACTV_TRD	Number of currently active bankcard trades	2.872	2.406

The counseling agency also provided details about the DMPs, including two important interest rates. The first is the weighted average interest rate on the client's unsecured debt before he or she contacted the counseling agency (*O_IR*). This interest rate would apply to the debt if the client stopped making payments to the agency. The second rate reflects the weighted average interest rate for the debt on the DMP (*P_IR*). The latter rate incorporates creditor concessions in terms of a lower interest rate that applies to the debt so long as the client continues to pay as agreed on the plan.

A priori, and holding *P_IR* constant, one would expect *O_IR* to directly (and positively) impact repayment, because it is the penalty for failing the DMP. On the other hand, because today's credit markets are characterized by risk-based pricing, the initial interest rate is likely influenced by the client's perceived creditworthiness. Higher original interest rates could signal a low ability to repay debt. If this ability is captured by the residual of the repayment equation, endogeneity would bias the coefficients.

However, credit risk scores are dynamic and can undergo substantial changes in a relatively short period of time. The credit risk profile that the lender observed at the time of loan origination (and that determined the loan interest rate) may be substantially different from the customer's subsequent risk profile observed at the time of counseling. Importantly, it is the latter profile that is available in our data. Coupled with the counseling interview data, the combined set of variables captures multiple dimensions of the client's perceived creditworthiness at the time the DMP is formed.

By the same token, one expects *P_IR* to negatively affect the amount of debt repaid: less progress is made toward repayment of principal when monthly finance charges are higher. But, the relationship could be endogenous if creditors tailored interest rates on the DMPs so as to give lower rates to those clients needing greater assistance. However, this potential problem is mitigated because of the institutional characteristics of the credit counseling industry as of 2003. As discussed earlier in the paper, in 2003 and for at least several years thereafter, counseling agencies were offering one-size-fits-all DMP products to clients. Concessions were not tailored to client creditworthiness. From a single counseling agency's perspective, it was quite typical for all DMP clients with a balance from Bank X to get the same interest rate from Bank X, independent of their original contract interest rate, so long as they continued paying on the plan [Ludwig 2005].[8]

The agency also provided information on the size of each monthly payment (*PMT*) and the number of payments scheduled to be paid (*LNG*). However, these variables were deemed to be poor controls because the total amount of the debt and the interest rates directly influence the monthly payment size and the number of payments. Including these variables in the specification introduces a problem of interpretation.

For example, suppose *PMT* was included in equation (1). Suppose also that two clients are observationally equivalent, except that one client has been granted a lower plan interest rate than the other client. The lower interest rate implies this client could have chosen a lower payment while keeping the plan length equal to other client, but instead opted for a relatively higher monthly payment and a relatively shorter plan length. Therefore conditional on *PMT*, the client with the lower interest rate may be more financially responsible.[9]

The financial information vector *FIN* includes the client's total assets (*AST*) and liabilities (*LIAB*), monthly income (*INC*), monthly expenses (*EXP*), and whether the

client had ever been on a DMP in the past (*PREV*).[10] Another variable indicated whether the client was employed (*EMP*), though unfortunately the type of employment could not be determined.

Demographic information (*DEM*) indicated marital status (*MAR*, *DIV*, *SIN*, *M_OTH*), gender (*MALE*, *FEM*, *G_NA*), age (*AGE*),[11] number of dependents (*DEP1*, *DEP2*, *DEP3*, *DEP4*, *DEP5UP*), housing status (*OWN*, *RENT*, *HOMLS, PARNT, H_NA*), and whether the client lived in a metropolitan area (*METRO*). We accounted for differences across state bankruptcy laws with two variables. The first variable is the percent of total state bankruptcy filings in 2003 that were filed under Chapter 7 (*CHAP7*) and the second was the percent change in total bankruptcy filings between 2002 and 2003 (ΔBNK).

Other information (*OTH* in equation (1)) includes variables from the counseling session and from the credit profile. During the counseling session, the client reported who had recommended the agency (*SRC1*, *SRC2*, …, *SRC11*) and whether someone accompanied the client to the counseling session (*ACMP*). Information was also revealed during the counseling session regarding the underlying cause of the client's financial distress. The underlying cause may be "situational" (*SIT*) if the distress is primarily attributed to an income or expense shock, "habitual" (*HAB*) if the distress is due to poor money management behavior (consistent overspending or addictive behaviors), or "unknown" (*UNKN*) if the counselor did not record a reason. The omitted group represents those clients who were referred to the counseling agency by a creditor, went to counseling unaccompanied, and declared an habitual reason for financial distress.

Data from the credit bureau describe the financial health of the client at the time of counseling. The variables were categorized into four separate categories. One variable (*RISK*) is an overall measure of credit health. Risk score is the credit bureau's proprietary equivalent of the widely used FICO score, with a similar but slightly different numerical scale. Four negative measures of financial health include the highest delinquency the client ever had on a trade (*HI_DLNQ*), the number of trades that were currently past due (*LAT_TRD*), the number of trades that were derogatory (*DRG_TRD*), and whether the client was currently behind on a mortgage (*LAT_MOR*). The positive aspects of financial health were captured by the number of satisfactory revolving trades (*SAT_RV*) and the percent of debt that was not delinquent (*PCT_CUR*). Credit utilization was captured by the number of active bankcard trades (*ACTV_TRD*).

The variables in the *OTH* vector should mitigate the effects of endogeneity. Recall that endogeneity can arise when the expectations are based on unobservable information that materially affects both the expected amount of debt that will be repaid in the future and the independent variables. For example, if the client's previous repayment history has been bad, the creditor would likely have set a high interest rate on the original debt. However, such history would likely manifest as a low value of *RISK*, presence of derogatory public record items on the credit report, late payments, etc. Similarly, the situational, habitual, and unknown indicator variables reflect personal information known only to the client and counselor that may affect the terms of the plan. The *ACMP* variable indicates a degree of support the client is receiving from another person.[12]

Many practical considerations reduced the number of useable observations. First, the credit bureau was able to match 23,213 observations with the counseling agency's data. Of this sample, the agency offered a DMP to 18,239 clients.[13] Due to missing data and outliers, the sample was further reduced to 17,991 observations, of

which 6,294 clients commenced the DMP by sending a payment to the agency within 6 months of counseling. Of these 6,294 observations, 174 recorded a zero weighted-average interest rate on their total unsecured liabilities and 55 recorded a zero weighted-average interest rate for their debt on the plan. These 229 observations were eliminated from the sample.[14] Equation (1) will be estimated using the repayment behavior of the remaining 6,065 observations.

MODEL RESULTS

Selected coefficients from the full specification described by equation (1) are reported in Table 2. The results indicate that both interest rates are statistically significant and their coefficients have the expected signs. The original weighted average interest rate was positively related to the amount of DMP debt repaid. A 10 percentage point increase in this rate, other things equal, is associated with a 4.7 percent increase in the amount of debt repaid. The original interest rate is the penalty for failing to maintain payments on the DMP. A higher original interest rate would induce a greater effort to retain the DMP concessions and repay debt through the plan. In contrast, the DMP interest rate was negatively correlated with client

Table 2 Conditional repayment of scheduled debt

Selected variables	*Coefficient*	*Robust standard error*	*Control variables*
Original interest rate	0.466***	0.104	Age
DMP interest rate	−0.543***	0.140	Gender
Total assets	5.86e-07***	1.28E-07	Dependents
Total liabilities	−1.31e-06***	1.56E-07	Marital status
Monthly income	4.08e-05***	7.20E-06	Housing status
Monthly expenses (house, car, utilities)	−3.48e-05***	1.34E-05	Source of DMP recommendation
Prior DMP experience	0.00683	0.0243	
Employment status	0.000503	0.0161	
Lives in metropolitan area	−0.0508***	0.0144	
Percent of state filing for Chapter 7	−0.00266	0.0352	
Percent change of state bankruptcy filing	−0.175*	0.0901	
Accompanied to counseling	0.0143	0.0148	
Situational cause of financial distress	−0.0215**	0.00970	
Unknown cause of financial distress	0.0166	0.0266	
Credit profile			
Risk score	0.00108***	8.91E-05	
Highest delinquency ever on trade (in months)	−0.00457**	0.00193	
Number of past due balances	−0.00848***	0.00283	
Number of derogatory trades	−0.0261***	0.00709	
Late on mortgage payments	−0.0469**	0.0212	
Number of satisfactory revolving trades	0.00380***	0.00140	
Percent of debt not delinquent	−0.00115***	0.000304	
Number of active bankcard trades	0.000790	0.00286	
Adjusted R^2	0.110		
Observations	6,065		

***$P<0.01$, **$P<0.05$, *$P<0.1$.

success. As this interest rate increased 10 percentage points, the amount of debt expected to be repaid fell by 5.4 percent, other factors held constant. This result is also consistent with expectations, since a higher interest rate on DMP debt increases the price of debt and makes bankruptcy relatively more attractive.[15]

Financial variables were important predictors of debt repayment and estimated coefficients had the expected signs. For example, assets (liabilities) were positively (negatively) correlated with repayment. An additional $10,000 in assets raised the amount of debt repaid by 0.59 percent, while a $10,000 increase in liabilities lowered the amount of DMP debt repaid by 1.3 percent.[16] In other words, liabilities are approximately twice as important to client success as are assets. Asset illiquidity likely explains this phenomenon. On the other hand, an additional $1,000 in monthly income raised the amount of debt repaid by 4.1 percent, but increasing the monthly expenses by the same amount decreased repayment by 3.5 percent.[17]

Although most of the non-demographic variables obtained in the counseling session were insignificant, area of residence played an important role. A client living in a metro area was found to repay nearly 5 percent less of his or her scheduled debt than a client living in a non-metro area. Also, recent increases in statewide bankruptcy reduced the expected repayment, though the effect is only marginally significant.

If the primary cause of financial distress was situational, the client repaid approximately 2.2 percent less debt than if the reported cause of financial distress was habitual. The direction of this coefficient suggests that counseling and structured DMP programs are more helpful in addressing habitual causes of financial distress than they are in treating distress that results from external income and expense shocks. That is, counseling may be more effective for a client who accumulates debt due to poor financial management than for one who accumulates debt because of a job loss or an expensive divorce.

The estimated coefficients on many of the credit bureau variables were significant and consistent with *a priori* expectations. The client's risk score at the time of counseling in 2003 was positively related to the amount of debt repaid. Debt repayment was predicted to increase with the number of satisfactory revolving trades, and decrease with the highest delinquency on any account, the number of currently past due balances and the number of derogatory public record items. If the client was late on a mortgage payment, the predicted amount of repayment on the DMP fell by 4.7 percent.[18] All of these variables were statistically significant at the 5 percent level or better. Credit utilization, as captured by the number of active trades, was not statistically significant.

According to the model estimates, the percent of debt that was not delinquent was negatively correlated to repayment. This is contrary to initial expectations, because we expected this variable to reflect a better ability to manage credit. However, a client in trouble on only a small amount of debt may have less incentive to remain on a DMP rather than self-administering his/her own repayment plan.

SAMPLE SELECTION

To obtain the empirical results we estimated an OLS regression to examine factors that influence the amount of debt repaid under a credit counseling DMP. In this section we address econometric issues that arise from the non-random incidence of DMPs across the population of consumers who seek counseling.[19]

Several decisions occurring before a client can start a DMP. At the conclusion of counseling the agency may or may not offer the client a DMP. The client may or may not accept the DMP if it is offered. Consequently, DMPs observed in the sample are not randomly assigned and borrowers who choose to begin DMPs may differ in important ways from those who do not. Both of these characteristics of the sample could introduce selection bias, and a discussion of both is important for interpreting the empirical results.

The first issue stems from the fact that clients are typically not randomly offered a DMP after counseling. Of course, on the face of it this result is expected since the purpose of the budget and financial counseling process is to assess a borrower's financial condition and recommend the most appropriate solution to alleviate the financial distress. In some cases the counselor determines that the client is financially unable to afford the monthly payments and can't qualify for a DMP. In other cases the counselor will determine that a DMP (and its concessions from creditors) is unnecessary because the client has sufficient income to handle payments on his/her own. But, there could be more driving the observed pattern of DMP offers than just client suitability.

Some critics of the counseling industry have argued that because creditors financially support agencies through payments tied to the amount collected through agency-administered DMPs, it creates a moral hazard problem in which agencies push both over-qualified and under-qualified debtors onto plans. Specifically, counselors may encourage some debtors to enroll in a DMP even when bankruptcy (or some type of less-than-full-balance settlement) would be better for the consumer. Or, agencies may offer DMPs to clients in stronger financial positions who don't really need (but would gladly accept) reduced interest rates and other concessions from creditors.[20]

Table 3 offers interesting evidence on how effectively counselors "diagnose" borrowers and match them to recommended action plans. The top and middle panels of the table provide descriptive data on two groups: the 4,974 clients who were not offered a DMP after counseling (top panel), and the 18,239 clients who were offered a DMP (middle panel). The group not offered a DMP is further subdivided according to the recommended action at the end of the counseling session.[21] The table indicates the proportion in each group for whom a credit report contains a bankruptcy indicator at two points in time, 2003 (around the time of counseling) and 2007. The table also indicates the mean credit score for each group in 2003 and 2007.

Of particular interest are the "risk indicators" of bankruptcy frequency and credit score for each group as of 2007, approximately 4 years after counseling. Not surprisingly, bankruptcy frequency is highest (and shows the largest change from 4 years earlier) for the group referred for legal assistance (nearly 50 percent had filed for bankruptcy by 2007), and next highest for the group referred for "other assistance" (35.2 percent). Bankruptcy frequency in 2007 is lowest for the group labeled "client can handle" (15.8 percent). Credit scores as of 2007 rank order in the same direction: highest for those diagnosed as "client can handle" and lowest for those referred for legal or other assistance. These patterns among those not offered a DMP suggest that counselors are indeed recommending borrowers based on an objective assessment of their circumstances. The recommendations seem appropriate, on average. In particular, clients in relatively strong financial situations were turned away from DMPs, and looked better in 2007 than clients who were recommended for DMPs. In light of the moral hazard risk that creditors assume

Table 3 Proportion of bankruptcies and mean credit scores in 2003 and 2007, by DMP status

	Public record bankruptcies				*Credit score*			
	2003		*2007*		*2003*		*2007*	
	Proportion	*Count*	*Proportion*	*Count*	*Mean*	*Count*	*Mean*	*Count*
DMP not offered								
Client Can Handle	0.055	1,188	0.158	1,150	627.4	1,188	643.2	1,124
Financial counseling only	0.072	222	0.295	217	610.7	222	629.1	211
No information	0.093	832	0.277	794	615.7	832	624.4	763
Referred to legal assistance	0.041	1,126	0.498	1,101	624.6	1,126	621.1	1,052
Referred to other assistance	0.087	1,606	0.352	1,563	605.2	1,606	606.6	1,508
Total	0.069	4,974	0.324	4,825	616.9	4,974	622.7	4,658
DMP offered								
DMP not started	0.079	11,613	0.294	11,214	599.9	11,613	606.2	10,982
DMP started	0.08	6,626	0.222	6,626	598.8	6,626	614.1	6,510
Total	0.079	18,239	0.267	17,840	599.5	18,239	609.1	17,492
DMP started								
DMP still active as of 2007	0.036	1,123	0.019	1,123	634.2	1,123	670.9	1,118
DMP success as of 2007	0.104	998	0.068	998	611.2	998	672.5	986
Self-admin. after three payments	0.087	949	0.154	949	617.2	949	644.6	937
Self-admin. before three payments	0.075	200	0.35	200	597	200	608.9	198
Quit after three payments	0.079	2,244	0.338	2,244	586.4	2,244	573.6	2,184
Quit before three payments	0.101	1,020	0.388	1,020	560.9	1,020	555.8	995
Other status	0.076	92	0.109	92	573.5	92	587.5	92
Total	0.08	6,626	0.222	6,626	598.8	6,626	614.1	6,510

when making deep concessions available through DMPs, these results provide some assurance that counselors are not "giving away the store" to over-qualified borrowers.

The middle panel of Table 3 compares risk indicators in 2003 and 2007 for clients who were offered a DMP and started (i.e., made at least one payment) *vs* clients who were offered a DMP and did not start. Not surprisingly (in light of the evidence above on counselors' diagnostic efficiency), the mean risk scores of the two groups are nearly identical at the time of counseling in 2003. By 2007, non-starters had higher incidence of bankruptcy (29.4 percent *vs* 22.2 percent) relative to starters, and lower risk scores (606 *vs* 614).

The bottom panel of Table 3 suggests that there may be positive benefits to sticking with the repayment plan. Among all DMP starters, clients who dropped off very early (before making three payments) exhibited the highest bankruptcy rates by 2007 (38.8 percent) and the lowest credit scores. This is true even when the reason given for dropping off was that the client intended to "self administer" continued repayment. Furthermore, by 2007, those clients who were still on a DMP or had successfully completed had significantly lower bankruptcy incidence and higher credit scores compared to the rest of the sample. These relationships are only suggestive at this point, and merit further study to determine whether the DMP experience itself is the cause of the improved credit profiles.

The second sample selection issue that seems particularly important for this study revolves around the fact that only one-third of the clients who were offered a DMP actually chose to begin a plan (as evidenced by making at least one payment). After removing outliers and missing observations, 6,065 of the 17,011 clients who were offered a DMP (and had non-zero interest rates) made a payment to initiate the plan.

Selection bias exists if the unobservable factors governing the decision to make the first payment are correlated with the amount of debt that will be repaid. Borrower motivation, perseverance, and "attitude" come to mind as likely to be important determinants of repayment success, especially over the course of a DMP that can last 60 months or more. But, the database lacks explicit measures for these "attitudinal" factors.

To address the problem we employed a maximum likelihood selection correction technique, using the delivery channel through which counseling took place as an instrument in estimating the probability that the client would elect to start a DMP. Clients may receive counseling by means of face-to-face interviews, phone conversations, or by navigating through specially designed, interactive websites. While internet-based counseling was in its infancy in 2003, telephone counseling was well established and widely available, following tremendous growth in the late 1990s [Hunt 2005; Staten 2006]. We hypothesize that clients who go to the trouble of traveling to a face-to-face counseling session will be more inclined to begin a DMP than other clients because their choice of a more effort-intensive delivery channel signals an elevated commitment and desire to take action. Table 4 displays the results of the maximum likelihood estimates of whether a first DMP payment is made and the amount of repayment as of 2007.[22]

As hypothesized, clients counseled via telephone and the internet were significantly less likely to begin the DMP than were clients who received face-to-face counseling. In addition, the estimated correlation between the residuals of the two equations was not statistically different from zero.[23] Furthermore, the estimates of the repayment equation were very near those of Table 2, offering evidence that this form of sample selection is not biasing our estimates.

Interestingly, the weighted average interest rate of debt on the DMP is negatively associated with the probability of starting a plan. The client's existing interest rate (prior to the plan) is positively associated with the decision to start. Both are consistent with expectations, suggesting that the cost of debt (on and off the plan) plays an important role in both the initial appeal of the DMP product and in the completion of a plan. Other factors that relate positively to the decision to accept an offered plan include: being currently employed, monthly income, total assets, age, being female, renting a home, being referred to counseling by family or friends, prior experience on another DMP, the number of bank credit card accounts, and the number of accounts past due at the time of counseling. Factors that relate inversely to the decision to accept a DMP offer include total household liabilities, total expenses, being referred to counseling by a television/radio advertisement.

CONCLUSIONS

This paper has investigated whether or not the amount of debt repaid via a credit counseling DMP can be predicted at the time of origination based on observable client and debt attributes. The project utilized a rich data set that combined

Table 4 Maximum likelihood estimates for sample selection

Variable description	*Repayment*		*First payment made*	
	Coefficient	*Std. err.*	*Coefficient*	*Std. err.*
Weighted average interest rate of debt on DMP	−0.505***	−0.156	−2.963***	−0.31
Weighted average interest rate of debt prior to joining DMP	0.423***	−0.126	3.255***	−0.226
Total assets reported at the time of counseling	5.75e-07***	−1.27E-07	1.18e-06***	−2.38E-07
Total liabilities reported at the time of counseling	−1.29e-06***	−1.49E-07	−1.77e-06***	−2.95E-07
Monthly income at the time of counseling (incl. spousal income)	3.91e-05***	−7.24E-06	0.000130***	−1.29E-05
Monthly expenses on home, automobiles, and utilities	−3.22e-05**	−1.34E-05	−0.000189***	−2.62E-05
Client has previously been on DMP	−0.0104	−0.0377	1.872***	−0.141
Client is employed	−0.00222	−0.0159	0.184***	−0.0314
Marital status is reported to be divorced	−0.00556	−0.0204	−0.107**	−0.0444
Marital status is reported to be single	0.0253	−0.0156	0.00946	−0.0345
Marital status is widowed, other, unreported, or unknown	−0.0174	−0.0214	−0.0473	−0.0469
Client is female	0.00412	−0.0105	0.0545**	−0.023
Client's gender is not reported	0.00884	−0.0182	−0.226***	−0.0385
Age of client	0.00754***	−0.00211	0.00947**	−0.00448
Age of client squared	−5.46e-05**	−2.25E-05	−6.56E-05	−4.76E-05
Client reports two dependents (including self)	0.0362**	−0.0142	0.150***	−0.0299
Client reports three dependents (including self)	0.0101	−0.0153	0.0898***	−0.0327
Client reports four dependents (including self)	−0.0162	−0.0179	0.0342	−0.0384
Client reports five or more dependents (including self)	−0.00784	−0.0174	0.0819**	−0.0375
Client rents or partially rents their home	0.00328	−0.0136	0.0973***	−0.0288
Client is homeless	−0.206	−0.258	1.067	−0.757
Client lives with parents	0.0493	−0.0541	0.892***	−0.164
Client does not report housing status	0.00364	−0.0225	−0.0769*	−0.0457
Client lives in a metropolitan area	−0.0516***	−0.0141	0.0151	−0.03
Percent of state bankruptcy filings declaring Chapter 7 in 2003	−0.00487	−0.0348	0.215***	−0.0752
Percent change in state bankruptcy filings: 2002–2003	−0.191**	−0.0918	0.861***	−0.19
Client was referred by a credit counseling agency	−0.0287	−0.0639	0.066	−0.148
Client was referred by community or employer	−0.071	−0.0539	0.055	−0.126
Client was referred by family or friends	−0.0257*	−0.0149	0.225***	−0.0308
Client was referred by an internet site	−0.0176	−0.0136	−0.0531	−0.0368
Client was referred by legal advice	−0.0806	−0.073	−0.0585	−0.161

Client was referred by other	0.106	−0.148	0.271	−0.329
Client was referred by paid advertisements	−0.0538***	−0.017	0.043	−0.0375
Client was referred by paid leads	−0.0322	−0.0322	−0.211***	−0.0619
Client was referred by public service announcements	−0.0181	−0.0436	0.0368	−0.0986
Client was referred by social work or other government agency	0.193	−0.137	−0.247	−0.279
Client was accompanied with another person in counseling	0.0137	−0.0148	0.0275	−0.0323
Self-reported cause of financial difficulty is deemed situational	−0.0215**	−0.00971	−0.0179	−0.0214
Self-reported cause of financial difficulty is unknown	0.0189	−0.0272	−0.161***	−0.0544
Client's risk score	0.00108***	−9.01E-05	−8.11E-05	−0.000192
Highest delinquency ever on trade	−0.00446**	−0.00192	−0.00937**	−0.00426
Number of currently past due balances	−0.00869***	−0.00301	0.0153**	−0.00674
Number of derogatory public records	−0.0257***	−0.00774	−0.0308*	−0.0161
Client is late on mortgage	−0.0467**	−0.023	−0.0126	−0.05
Number of satisfactory revolving trades	0.00380***	−0.00134	−0.00156	−0.00293
Percent of trades not delinquent	−0.00116***	−0.000313	0.00097	−0.000679
Number of currently active bankcard trades	0.000657	−0.00277	0.0127**	−0.00616
Client was counseled on the telephone	—	—	−0.458***	−0.0278
Client was counseled over the internet	—	—	−0.421***	−0.0443
Constant	−0.265***	−0.101	−1.248***	−0.174
Correlation Coefficient — ρ	−0.0545	−0.0862	—	—
Number of censored/uncensored observations	6,095/17,011			

***$P<0.01$, **$P<0.05$, *$P<0.1$.

interview-based information from more than 17,000 counseling sessions and objective credit bureau measures of each client's credit profile and past payment behavior. The depth of data available on each client also supported empirical techniques to address the technical challenges posed by endogeneity in the variables that influence debt repayment and the potential selection bias present in any study of voluntary credit counseling choices.

From the population of consumers who seek counseling and for whom the counselor recommends the DMP as a viable option, the models described in this paper identify the characteristics of clients who choose to start a DMP, and a variety of observable client and DMP attributes that predict the amount of debt repaid through the DMP. Of particular interest to counseling agencies and creditors is the finding that the magnitude of the interest rate reduction offered by creditors to consumers as a concession within the DMP product has a significant, positive influence on both the probability of accepting a DMP offer, and actual debt repayment once a plan has started. Few economists would express surprise that the price of debt would influence repayment. Nevertheless, the issue of the net value of concessions on DMPs has been hotly debated within the counseling industry for two decades and the magnitude of optimal concessions is a perennial point of contention between agency advocates and creditors. Hopefully, the finding from this large study of clients will move that debate along. We know overall (from Table 3) that clients who both are offered a DMP and start the DMP do better compared to those who do not start. An important tool for encouraging DMP participation is the lender's concession decision, and it is clear that those investments translate into lower bankruptcy incidence, higher credit scores, and clients with better credit profiles over time.

If concessions are effective at encouraging DMP participation, should they be tailored to individual borrowers? Given that creditors have balked at steeper concessions in one-size-for-all programs, perhaps tailoring the concessions according to borrower need would ease their resistance. Toward that end, in the spring of 2009 the NFCC organized a new suite of DMP products under its Call to Action (CTA) program and persuaded leading national creditors to participate [NFCC 2009]. The CTA suite provided for two, deeper levels of creditor concessions beyond the standard concessions offered to traditional DMP clients. Deeper concessions would be offered to consumer clients who could not otherwise qualify for the standard DMP (i.e., insufficient income to amortize 100 percent of total plan debt in 60 months or less). The two additional concession packages called for a monthly payment of 2 percent of outstanding balance per month for the life of the plan, or 1.75 percent in hardship cases (i.e., for those who still don't qualify at 2 percent). The CTA product suite represents a collective attempt to tailor concessions to client need.

By January 2010, 7 of the 10 largest credit card issuers were participating in the CTA program, and well over 100 counseling agencies. As of this writing it is too early to judge the effectiveness of the program in giving consumers a debt-relief alternative that could be less costly than either bankruptcy or debt settlement. Nor is the sustainability of the program clear in terms of creditor willingness to continue participating. But, the program is significant as the most visible, industry-wide attempt to date that would tailor DMP concessions to individual consumer need. And, tailored DMP concessions seem likely to stimulate greater support from creditors already accustomed to tailoring loan product prices and terms to individual borrower characteristics.

Notes

1. Regarding the perils of debt settlement for consumers, a recent study by the US Government Accountability Office (GAO) using secret-shopper methodologies found widespread fraud and abusive practices among prominent debt settlement companies that advertised debt relief to consumers [GAO 2010].
2. Beyond credit card markets, similar problems confront the mortgage industry and mortgage delinquency and foreclosure counseling. Mortgage lenders (including investors in asset backed mortgage securities) are reluctant to make concessions in the form of either interest rate reductions or principal write-downs. Yet, these tools can be useful in keeping borrowers in homes and paying on their mortgage loans. While the models discussed in this paper are built on the experience of consumers struggling with credit card debt repayment, the concept and utility of such a model extends directly to mitigation of mortgage foreclosures.
3. In a workshop on credit counseling sponsored in 2003 by the Federal Reserve Bank of Philadelphia, the managing director of collections for Juniper Bank remarked that credit card issuers were "particularly alarmed by recent trends in (counseling) agency marketing strategies. In addition to targeting 'credit stressed' consumers, some agencies market their services to any consumer who believes he or she is paying too much in finance charges. This makes it difficult for card issuers to know whether consumers who enroll in DMPs are actually trying to avoid bankruptcy or trying to save money in interest and fees" [Furletti 2003].
4. Keep in mind that creditors would always prefer that debtors continue to pay under the original contract interest rate. But, the essence of workout plans for troubled borrowers (whether administered internally by the creditor or externally through a counseling agency) is to provide case-by-base concessions to borrowers who are experiencing financial hardship in exchange for continued payments on the loan.
5. Discussions with executives at several counseling agencies have clarified that while 60 months is the typical maximum length for a DMP (for both regulatory and operational reasons), there are exceptions.
6. This is similar to using IQ scores to control for intelligence in a standard wage equation.
7. Scheduled debt depends on the size of the monthly payments, the plan's original length, and when the plan was initiated. For example, a client who made the first payment in March 2003 is responsible for one additional payment compared to a client who made the first payment in April 2003. In addition, clients with a plan length less than 49 months may have their DMPs scheduled to expire before performance is observed in May of 2007.
8. The authors confirmed this assessment of the environment in 2003 in conversations with representatives from both a major credit card issuer and the National Foundation for Credit Counseling.
9. An analogous situation is the omission of blue and white collar job choice when estimating the returns to education.
10. In 2002 the Federal Financial Institutions Examination Council (FFIEC) restricted the flexibility of accommodating clients who missed DMP payments by limiting the number of "re-ages" (bring to "current" status) on an account to one every 5 years. (*Source*: Letter to the American Bankers Association from the FFIEC dated May 16, 2002, on file with the authors.) This implies that clients who start and fail a DMP are often not eligible to re-age their accounts through a second DMP within 5 years of the initial DMP. This constraint substantially reduces the value of the DMP to the client, because creditors who do not re-age the account will still report the account as delinquent and will continue to make collection calls.
11. Age enters the specification quadratically in order to account for nonlinear effects.
12. Note that some of the variables from the credit profile are not proxy variables, since the unobserved measures of ability likely caused these observed variables (and not the other way around). Including such variables to proxy the unobserved measure of ability could create its own form of endogeneity bias. However, Angrist and Pischke [2009] argue that when the omission of unobserved ability creates a high degree of bias, such controls usually do more good than harm in practice. We adopt this second and more pragmatic approach in our analysis.
13. Of the 4,974 clients who were not offered a DMP, 1,054 were unable to qualify for a DMP, 1,188 were deemed financially able to handle their debt on their own, 1,126 clients were referred for legal assistance (e.g., bankruptcy), and 1,606 clients were referred for other types of assistance.
14. Eliminating these observations did not change the results.
15. It is worth reiterating the previous point that concerns about the potential endogeneity created by inclusion of both the original interest rate and DMP interest rate have been reduced to a large degree

by the richness of the available data. While creditors quite likely relied on the client's risk profile to set the original price of the loan, that event occurred at a point prior to the counseling session and DMP formation. The model's specification contains data directly from the client's credit report at the time of counseling, a more accurate picture of client risk on the payment plan than some earlier credit report. Moreover, information was obtained from the counseling session that even a credit profile is unlikely to capture. And, as noted earlier, the credit card industry was not actively tailoring DMP interest rates to customers in 2003 when our data were gathered. Indeed, if the original interest rate was endogenous due to risk-based pricing, people with higher original interest rates would be likely to repay less debt and one would expect a negative sign on its coefficient. In fact, the sign on *O_IR* is positive in the estimated equation. This is one piece of evidence that endogeneity bias, even if present, may not be severe.

16. Average assets in the sample are $60,770 and average liabilities in this sample are $62,787.
17. The average monthly income is $2,465 and average monthly expenses are $1,089.
18. Mortgage debt is typically not included in debt management plans.
19. The vast majority of credit and budget counseling occurs as a result of consumers voluntarily seeking counseling assistance. Of course, those who take the step of seeking counseling are not necessarily representative of all consumers in financial distress. All of the data utilized in this paper derive from a sample of consumers who did seek counseling, so all of the results are conditional on that decision.
20. We have some doubts as to how serious the latter problem can be in an environment in which creditors are closely monitoring DMP proposals submitted by agencies on behalf of clients — including detailed budget and expense information — as well as client performance on DMPs over time at the agency level.
21. Note that there are 222 clients categorized as financial counseling only and 832 clients with no information about the result of the session. All we really know about these 1,054 clients is that they were not offered a DMP — perhaps because they had insufficient income to fund the plan. Further descriptive statistics in the table suggest these two groups are quite similar in terms of subsequent credit performance.
22. Note that after the initial counseling session has ended, all DMP clients are subject to similar procedures for repayment once a plan is underway. Consequently, other than the channel of counsel, the specification for the first payment equation is the same as in Table 2.
23. The estimated correlation between the residuals in the first payment equation and the residuals in the repayment equation is −0.054. The standard error of this parameter was approximately 0.086, so the null hypothesis that the correlation equals zero cannot be rejected.

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