
THE GEORGE WASHINGTON UNIVERSITY

S C H O O L O F
B U S I N E S S

**AN ANALYSIS OF
WHY DEBT MANAGEMENT PLANS FAIL**

Financial Services Research Program
Working Paper No. 73

August 2007

Michael E. Staten
Financial Services Research Program
The George Washington University School of Business

Charles Link
Department of Economics
University of Delaware

Daniel T. Brown
Department of Economics
University of Delaware

An Analysis of Why Debt Management Plans Fail¹

Prof. Michael E. Staten
The George Washington University

Prof. Charles Link
University of Delaware

Daniel T. Brown
University of Delaware

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 through concessions on finance charges and repayment terms, and a halt to late fees and collection calls. But, most DMPs fail and creditors worry that many borrowers opportunistically enroll just to get a temporarily lower interest rate.

This paper investigates whether probability of success on a DMP can be predicted at the time of counseling based on observable client and debt attributes. A predictive model could help to boost DMP completion rates by giving agencies a tool to make operational adjustments so as to allocate more resources to clients who are likely to need extra help to complete a plan. A predictive model could also be used to move the industry away from the typical one-size-fits-all DMP and toward a system in which creditor concessions are individualized to fit consumer need. We are unaware of any other econometric studies of the determinants of DMP success. Our results provide important information to the counseling and financial services industries as they craft sustainable programs to provide relief for subprime borrowers threatened with mortgage foreclosure and millions more Americans pinched by rising interest rates and falling home prices.

Section 1: Introduction

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 (Staten, 2006). Major national creditors organized a network of non-profit counseling agencies to offer in-person,

¹ The authors thank the MMI Financial Education Foundation for generous financial support of this research.

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 less than 250 agencies operating less than 800 offices in 1992 to over 900 agencies operating as many as 2,000 offices by the end of 2003.² Up to 9 million people sought advice and assistance from a credit counseling organization in 2003.³

A core service of each agency (and the rationale for creditor financial support) is to negotiate with a consumer's creditors to set up voluntary repayment plans, called Debt Management Plans or DMPs. These plans are unique in getting creditors to voluntarily exercise mutual forbearance through concessions on finance charges and repayment terms, and a halt to late fees and collection calls. When successful, these agency-administered DMPs provide a valuable service for consumers by helping them to resolve their debts but avoid the stigma associated with filing for bankruptcy. DMPs also help creditors. 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 ten largest U.S. bank credit card issuers were being serviced through credit counseling debt repayment plans in 2002.⁴ 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.

However, distrust between creditors and counseling agencies grew in the late 1990s as a direct result of the peculiar business model adopted by most counseling agencies. For the typical agency, clients on DMP repayment programs represent less than half of all consumers counseled and assisted. For the remaining majority of counseled clients, the agency provides education, budget analysis, advice, and possible referrals to social service agencies or other institutions to solve specific problems. But, most creditors do not compensate agencies for counseling consumers who do not enroll in DMPs. In fact, creditors generally do not know when one of their accountholders has been counseled, unless that consumer agrees to a DMP. Typically, creditors pay 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

² U.S. Senate (2004) p3.

³ Loonin and Plunkett (2003).

⁴ Furletti (2003), p 2, and author's calculations based on top ten receivables as reported in *Card Industry Directory, 2004 edition*, Thomson Financial Media, New York, NY, 2003.

more and longer on the plan (cherry-picking). 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. Agencies deal directly with consumers, see a fuller picture of their overall debt exposure, and have the benefit of situational information collected at the initial counseling interview. Consequently, they can better assess a consumer’s financial situation than can creditors. 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.⁵ Coupled with the rapid growth in the counseling industry in the late 1990s, the explosion in the number of agencies submitting proposals, differing standards used across agencies and uneven success rates of the resulting plans, the administrative costs to credit card issuers of evaluating DMP proposals soared, as did distrust. Consequently, creditor willingness to continue funding agencies at traditional levels eroded.⁶

Staten (2006) notes that if techniques such as statistical scoring models could be developed that would give both the agency and the creditor a similar indication of who is at greater risk of bankruptcy, and indicate who would be likely candidates for a successful DMP, the cherry-picking problem could be reduced or eliminated. Predictive models could move the industry away from the typical, one-size-fits-all DMP and toward a system in which creditor concessions were individualized to fit consumer need. The same models could be used to help agencies make operational adjustments so as to allocate more resources to clients who seem likely to need extra assistance to complete a plan. And, the models 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. All of these would improve the counseling experience for the consumer and stabilize an industry currently struggling to find a sustainable business model.

The following sections represent a first step toward a model of DMP performance. We empirically examine the factors that determine the “success” of a DMP using a large database of closed DMPs provided by a major national credit counseling agency. Our

⁵ 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), p 3.

⁶ Hunt (2005) reports that by 2003-2004, “creditors began to reduce their fair share payments from the 112 to 15 percent typical of 20 years ago to half this amount, or even lower, today. Among NFCC members, fair share payments currently average about 6 percent of payments made to creditors.. . . In addition, creditors have reduced the concessions (such as lower interest rates) they offer to borrowers enrolled in debt management plans, making them more difficult to complete.” p17.

objectives are two-fold. First, we wish to determine if there are attributes observable at the time of counseling that predict which clients 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. To the extent that readily observable attributes can be shown to influence plan success, they can form the basis of a predictive (scoring) model. Such a model could be built from large samples of client data and used to evaluate (in probabilistic terms) plan suitability and/or viability for particular clients. Second, controlling at the point of initial counseling for these measures of “propensity to do well” on a plan, we wish to identify and quantify the impact of factors that arise after the initial session that appear to contribute to plan success. To the extent that some of these factors can be influenced by the counseling agency, they represent opportunities to manage the DMP process and thus improve the likelihood of plan success for particular clients.

The paper is organized as follows. Section 2 will discuss potential determinants of DMP success. Section 3 will discuss the data and methodological issues associated with reliance on a sample of closed DMP cases. Section 4 presents the results of multinomial logit modeling of DMP success. Section 5 discusses the findings and offers concluding thoughts.

Section 2: Potential Determinants of DMP Success

Since the late 1990s, DMPs have typically been set up as 60-month repayment plans. 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% were due to clients who simply stopped making payments, 21% were attributable to clients choosing to “self-administer” (i.e., take over payments to creditors outside the credit counseling plan), 4% ended in client bankruptcy, and 21% were successful completions.

The literature on factors that influence repayment plan outcomes is sparse. Kim, Garman and Sorhaindo (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 remained active on DMPs after 18 months on the plan. Norberg (1999) and Bermant (2005) report on total amounts paid to creditors through bankruptcy Chapter 13 repayment plans, but do not analyze the factors that contribute to higher payments. Loibl, Hira and Rupured (2006) examined factors that influenced 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. Using objective 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 or had successfully completed after 4 years.

Building on these limited findings from prior research, extensive discussions with credit counselors and counseling industry leaders generated several categories of factors that could influence DMP success. Some factors are inherent in borrowers who agree to enroll in plans as a result of a credit counselor's recommendation. Others factors involve the nature of the plan itself, counseling agency procedures, creditor actions and life events that impact borrowers during the repayment period. Consistent with the objectives outlined earlier, these factors are grouped below into two broad categories: 1) factors that may have observable proxies at the time of the initial counseling interview, and 2) factors that occur and/or become known after the initial interview.

Factors with Attributes Potentially Observable at the Time of Counseling

In essence, these variables serve as proxies for the consumer's willingness and ability to handle a repayment program, and the value that the consumer places on such a program. They also control for the financial "workability" of a proposed DMP, given the client's available resources and existing obligations. Workability refers to the vulnerability of the plan repayment schedule to disruption from unexpected income or expense shocks. Potentially observable attributes include

- credit bureau information reflecting current obligations and past history of opening and handling accounts (signaling borrower reliability and responsibility)
- objective measures of the level of financial distress at the time of counseling (e.g., degree of delinquency and intensity of collection activity; and past or potential foreclosure or repossession)
- survey/interview-based measures of attitudes toward credit usage; familiarity and skill at handling credit obligations and past savings behavior; perceived level of financial distress and other indicators of client willingness to take responsibility for actions and meet obligations
- client demographics and socioeconomic info (e.g., number of dependents, age, marital status, housing status, employment status, income, education, ethnicity, and evidence of illness or disability)
- plan financials (amount of total debt on plan; debt outside plan such as mortgage payments or auto loan payments; number of creditors on the plan; plan payment relative to monthly income and stated expenses; and duration of proposed plan)

Factors that manifest after the initial interview

- agency handling of clients (e.g., frequency and nature of follow-up contacts; educational materials provided during course of plan; and counselor experience)
- creditor concessions (acceptance of DMP proposal for repayment; interest rate reductions and late fee waivers; forbearance from making collection calls; willingness to re-age accounts on plan to give them a "current" payment status)
- exogenous income or expense shocks that have a significant impact on client's budget

Section 3: Data and Methodology

A large national credit counseling firm, Money Management International (MMI), agreed to supply a closed-case sample of depersonalized client counseling data for the project. The sample included all consumers who closed a DMP for any reason during an 8 week period in the first quarter of 2005. The data were archived by MMI (and its affiliated offices) in the normal course of business at the time of the client's initial counseling session, the majority of which occurred between 2001 and 2004. A total of 7,030 client files were available for analysis.

Selection of an appropriate measure of "success" for DMP participants is more complex than it may first appear. One simple definition of success is a plan that pays as agreed until all plan debt is paid off. Historically, this group comprises a small minority of all plans to which clients agree (perhaps 20% - 30%). However, some plans end early (relatively to the scheduled number of payments) because client circumstances improve and it becomes possible for a client to pay off outstanding balances all at once or otherwise assume the responsibility for payment independent of the counseling agency. To the extent that the outstanding debt is actually paid off, these plans could be categorized as successful, even though a substantial portion of the repayment to creditors was not made through the counseling agency. Of course, many more plans end early because a client's financial condition worsens and he/she can no longer maintain plan payments.

The analysis below reports the results for the determinants of DMP success in the closed-case sample, where success is measured in terms of whether a plan was completed. Clients were categorized into four distinct and mutually exclusive categories according to the MMI closed-status code. Clients who repaid 80% or more of their original plan debt were assigned the Success category. Clients that MMI reported as having dropped off a plan because they were handling payments on their own were assigned the Self Administer category.⁷ The remaining clients were categorized as closed for non-payment. Within this large non-payment group, we identified two sub-groups: closed for failure to make first payment (First-deposit Default) and closed after receipt of first payment but prior to completion (Non-payment).⁸ Figure 1 illustrates the timing of closure (measured in months after DMP origination) for the 2,970 cases in the sample that were closed for Non-payment.

⁷ Note that the Self Administer status was determined by MMI, presumably based on information obtained through telephone contact with the clients.

⁸ For one portion of the analysis we developed a third sub-category (to make a total of five distinct outcome groupings) by dividing the "closed for non-payment" group into two additional subgroups based on whether information obtained by MMI about the reasons for closure indicated that it was due to external shocks that elevated the client's expenses or lowered income. However, the resulting partition did not improve the explanatory power of the model beyond what we obtained using the four distinct groups.

The following explanatory variables were obtained directly from MMI's archived records for each closed case. Demographic variables included marital status, gender, age, number of dependents, whether the client or spouse was employed, and occupation. Basic DMP and financial information included whether co-counseling with partner occurred, counseling delivery channel (telephone, in-person, or the Internet), total client assets, total debt, mortgage debt, secured vs. unsecured debt and the number of creditors, monthly income, a detailed breakdown of monthly expenses, the amount of debt on plan, number of payments made, and reason for closure. A variable labeled "Situational Causes for Financial Distress" reflects the counselor's judgment that the cause of the client's underlying problem related to an income or expense shock, rather than primarily "habitual" problems related to poor money management, such as consistent overspending or addictive behaviors. Two variables capture information about the logistics of plan payments. Both indicate whether a client signed up to have their DMP payment directly transferred from their checking account to MMI (designated ACH). One variable indicates whether this ACH transfer is automatic, the other indicates that the client must manually initiate the electronic transfer.

For many cases, MMI was able to provide a calculation of the weighted average interest rate of debt on the plan (across all creditors), a metric that accounts for creditor concessions on finance charge rates. This variable provides an important measure of the gain to a consumer from starting and sticking with a DMP. Higher interest rates on DMP debt (i.e., smaller creditor concessions on finance charges) would negatively impact plan success because higher rates necessitate higher monthly plan payments (relative to the client's monthly income and living expenses) in order to amortize a given amount of debt within the required 60 months. In addition, larger creditor concessions on DMP interest rates give clients more to lose if they should stop making payments on a plan, in which case their finance charge rates would revert to pre-DMP levels and collection calls would resume.

A variable that indicates whether a client had previously been enrolled in a DMP was included to identify consumers with chronic payment problems. It also serves as an additional indicator of the client's gain to sticking with a DMP, once enrolled. Clients who start and fail to complete DMPs are often not eligible to re-age their account by their creditors if the client tries to start a second DMP relatively soon after (within 5 years).⁹ This constraint substantially reduces the value of the DMP to a client because creditors who do not re-age an account to "current" status typically continue to make collection calls and the client's credit report will still reflect such an account as delinquent.

One of the three major U.S. credit reporting agencies supplied credit bureau data for the project. To maintain confidentiality of client data, the credit reporting agency received the client data sample, including personal identification information (name, address, SSN), directly from MMI. Client credit bureau records were appended, including over

⁹ In 2002 the Federal Financial Institutions Examination Council (FFIEC) issued regulations that restricted a credit card issuer's flexibility in accommodating clients who missed payments by limiting the number of "re-ages" on an account in a debt workout program to one every five years. (Source: letter to the American Bankers Association from the FFIEC dated May 16, 2002, on file with the authors.)

150 variables from each of three archived credit report snapshots (March 2002, March 2003 and March 2005). The matched data, stripped of all unique personal identifiers, was provided to the authors for analysis. This important data supplement provided a credit bureau snapshot at approximately the time of the plan closure, as well as at points two years and three years prior to closure.

Two summary measures of creditworthiness were used in the models - the client's credit risk score in March 2003 (two years prior to case closure) and the change in the client's risk score between March 2002 and March 2003. In both cases the risk score was the credit bureau's equivalent of the widely-used FICO risk score which has become familiar to many consumers shopping for home mortgages and other new accounts. The second risk score variable conveys information about the trajectory of the client's credit profile during the period two to three years prior to DMP closure. Five additional credit report variables capture specific information from the client's credit report measured two years prior to DMP closure. These variables indicate the number of accounts with positive balances, the number of active bank credit card accounts (e.g., Visa, MasterCard, Discover accounts), the number of accounts that had never been reported as seriously delinquent (i.e., 60 days or more past due), the client's total dollar amount of revolving debt, and the number of times the client had been reported as 30 days delinquent across all accounts. These variables, along with the credit risk score variables, indicate the severity of the client's credit problems as well as the client's propensity to pay as agreed, based on past payment behavior.¹⁰

Two variables were constructed to capture the client's budget constraint. One variable utilized credit bureau data to calculate the client's total monthly credit obligations (the sum of secured and unsecured debt payments) divided by total monthly income. The second variable was simply the ratio of DMP monthly payment to total monthly income. We would expect the probability of DMP success to fall as either ratio rises, other factors held constant.

Table 1 displays a list of the explanatory variables used in the statistical modeling, along with definitions. Table 2 displays mean values for each variable in the MMI sample and mean values for the variable within each subgroup of cases according to the DMP outcome code. Table 3 displays mean values for the credit variables at three points in time.

¹⁰ While the closed-case sample has the advantage of providing months or years of post-counseling payment experience on plans, it has the disadvantage of having a temporally uneven set of DMP starting dates. So, while the credit report snapshots provide an opportunity to measure the change in each client's credit profile over a three-year period prior to plan closure, the snapshots match the credit bureau profile at the time of DMP origination for only a very few clients. As a result, both the 2002 and 2003 snapshots predate the start of the DMP for a number of clients who started and terminated plans sometime during the 24 months between March 2003 and March 2005. Nevertheless, we shall see that credit bureau data still have significant power in predicting DMP success, even when observed at points in time other than the DMP start date.

Section 4: Multinomial Logit Model Results

Multinomial logit regression techniques were employed to estimate the effects on the four possible DMP outcomes discussed above. Table 4 displays the coefficients that indicate the degree to which each variable contributes to plan outcome (Success, Self Administer, or First Deposit Default) relative to the specific outcome Non Payment. The coefficients in the first column (Success) indicate each variable's effect on the likelihood of the client successfully completing the DMP instead of failing to continue DMP payments. The sign on the coefficients indicate the directional effect of the variable, holding all other explanatory variables constant. Variables having positive coefficients indicate characteristics associated with a greater likelihood of success, relative to closure for non-payment. Variables that exhibit negative coefficients are associated with a smaller likelihood of success, relative to closure for non-payment.

For example, the coefficients of the six variables that indicate one through six or more dependents are statistically significant and negative in the first column of Table 4. In each case, the negative and significant coefficient means that, other factors held constant, clients with one or more dependents are less likely to successfully complete a DMP (more likely to have their status closed due to Non-payment) compared to the omitted reference group of 'no dependents'. Similarly, the first six coefficients in the third column of Table 4 are all significant and positive. This indicates that clients with dependents are more likely than clients without dependents to have their account closed due to failure to make the first payment, rather than having it closed due to a later non-payment.

Because the multinomial logit model's coefficients are derived and interpreted on a logistic scale, they must be converted into percentages for interpretation of the magnitude of the variable's impact.¹¹ Table 5.1 converts selected coefficients from the Number-of-Dependents series into probabilities. Holding all other explanatory variables constant, the probability of Success drops from 42.14% when the client has zero dependents to 27.56% when there is one dependent. It drops still further to 23.37% when there are 2 or more dependents. As one would expect, the likelihood of Non Payment rises from 36% for the case of no dependents to over 50% for the case of two or more dependents.

Marital status affects the probability that a DMP will complete successfully. In particular, the coefficients of the variables representing married, marital status N/A, and divorced are statistically significant at the 10 percent level or higher. The implication is that the clients in these categories are more likely to succeed than clients who have never been married (the reference group). Married clients are also more likely to self administer. Persons who are classified as separated are less likely to succeed and less likely to self administer their program. Table 5.2 indicates the probabilities of the different DMP outcomes by marital status. It is clear that the individuals who are

¹¹ The conversion formula for the nth outcome in k+1 possible outcomes is, $\exp(x \cdot \beta_n) / (1 + \sum_i^k \exp(x \cdot \beta_i))$. See Greene (2003), p 721.

widowed or separated have the lowest probabilities of success. The probability of success for widowed is 21.8% while clients classified as separated have a 10.4% probability of successfully completing their DMP.

Clients for whom the credit counselor identified “situational causes for financial distress” are significantly less likely to succeed (Table 4, first column) and significantly less likely to self administer their debt repayment plan (Table 4, second column), as compared to clients with other causes of financial distress. Situational causes do not appear to impact the ‘first deposit default’ option. As indicated in Table 5.3, the probability of successful completion of the DMP drops from 32% to 24% (other factors held constant) if situational causes are listed as the reason for the client’s distress.

Considering housing status, compared to home owners, clients classified as ‘Renters or Living Status Unknown’ are more likely to succeed in the DMP and are less likely to self administer their debt plan. One result that stands out involves situations where the person on the DMP is living with parents. Living with parents is associated with a large decrease in the likelihood of successfully completing the DMP, relative to being a homeowner. Compared to the mean value of a 28.2% success rate, clients living with their parents have a success rate of 13.38% (Table 5.4). Put another way, clients living with their parents have a probability of failure of 61.16% compared to the average failure rate of 46.54%. Note that about 7% of all DMP clients fall into this category.

The initial counseling session for each client was conducted either by telephone, through the Internet or through a face-to-face meeting. The coefficient on the telephone delivery variable is positive and statistically significant for both the Success and Self Administer outcomes. Persons counseled via the telephone are also less likely to have a first-deposit default. Internet counseling is associated with a lower probability of success of the DMP, relative to face-to-face counseling. Table 5.5 indicates that the probability of success for contact by face-to-face, telephone, and the internet is respectively 25.3%, 32.3%, and 18.14% (compared to the overall mean of 28.2%). Clearly the method of contact is an item of interest given the sizeable variation in the success rate associated with each of the approaches. This result could be attributable to borrower characteristics that led them to select into the respective delivery channels. The face to face, telephone, and internet channels make up, respectively, 24.8%, 60.9%, and 14.3% of the initial counseling sessions delivered to clients in this sample.

Consistent with expectations, the probability of successfully completing the current DMP declines sharply for a client who has had a previous DMP. The probability of success drops from 29.46% to 11.54% for clients who had a previous DMP compared to those who have not (Table 5.6). Given that clients who had DMPs in the past comprise 6% of the sample this is an important result for policy makers to consider, given the federal regulatory agency ban on more than one account re-age in a five-year period.

Some DMP clients participated in an optional program that featured automatic withdrawal of their DMP payments from their bank accounts. Other clients used electronic transfers to make their DMP payments but initiated the transaction manually

each month. The remaining clients made monthly plan payments to the agency through the mail or at the agency office. Two variables in the model identify clients using the two types of electronic withdrawal. The coefficients of both of these variables are statistically significant and positive. For those clients for whom the DMP electronic payment is automatic, the impact on success is quite large. Table 5.7 displays how the probability of success changes when the automatic withdrawals are in effect. Keep in mind that the probability of success is 28.2% when the logit model predictions are evaluated at the means for all the variables. When DMP payments are made electronically and automatically the probability of success rises to 61.5%. There is a more modest increase in success to 32.26% when this automatic withdrawal is initiated by the client. When no such arrangement is in effect, the probability of success dropped to 26.4%.

Credit report information is a statistically significant indicator of DMP success. In the estimated model, the coefficient for the client's credit score in March 2003 (two years prior to DMP closure) is positive and significant, indicating that higher credit scores increase the probability of successfully completing the DMP. The mean credit score for the sample is 629.02. A one standard deviation increase (85 points, or 13.6%) in the credit score is associated with an increase in the probability of DMP success from 28.26% to 32.41%, or a 14.7% increase (Table 5.8). Regarding the variable capturing change in the client's score between 2002 and 2003, a positive change in the credit score increased the probability of DMP success. However, a one-standard deviation increase in the client's credit score between 2002 and 2003 (which would be a change of about 60 points) had only a modest positive effect on the probability of successfully completing the DMP, other things equal. The probability of success rose from 28.2% to 30.45%.

Other credit report variables that captured specific dimensions of the client's credit usage and payment behavior also appeared to be related to DMP success. Five specific credit attribute variables were included in the model: the number of accounts with positive balances, number of active bank card accounts, the total dollar amount of revolving debt, the number of times accounts were 30 days delinquent, and the number of accounts that were never 60 days or more past due. A priori, we would expect that the coefficients on all but the last variable would be negative. That is, higher balances, a larger number of active accounts and a history of delinquency should all be associated with a lower probability of successfully completing a DMP. Indeed, the estimated coefficients were consistent with expectations (and statistically significant) for four of the five variables, as shown in Table 4. The only exception was for the variable indicating the number of times a client was 30 days (or more) delinquent, for which the coefficient was positive and significant. However, calculation of the marginal impact on probability of each outcome revealed that the effects on the probabilities of the DMP outcomes were relatively small.

Two variables are included in the model to measure the financial burden associated with the client's debt. Generally speaking, we expected that a greater percentage of a client's monthly income devoted to debt service (either the DMP payment as a percentage of income or the broader, credit-report-based measure that includes installment payments outside of the DMP on debts such as mortgages and auto loans) would lower the

likelihood of DMP success. In fact, Table 4 shows that the estimated coefficients on both of these measures of payment burden are negative with respect to DMP success, consistent with expectations, but only the variable calculated in terms of total monthly payments (secured plus unsecured) is statistically significant. With respect to the Self Administer outcome, the coefficients on both variables are negative and statistically significant, meaning that greater debt service burden reduces the probability of self administration. However, calculation of the marginal probabilities reveals that the effect on both Success and Self Administration is modest. Table 5.10 displays the results. At the mean value of the ratio of total payments to income, the probability of Success is 28%. If the burden was to rise by 10 percentage points from the mean value to 37.8% (a rise of 36% over the mean value), the probability of Success drops from 28.26% to 27.03%, a decline in probability of only 4.3%.

Finally, we expected that the probability of success would increase and the probability of self-administering would fall as the weighted-average DMP interest rate declined and created a greater incentive to stick with a plan to keep the creditor concessions. The estimated model indicates that, holding debt service burden and other factors constant, a lower DMP interest rate does enhance the likelihood of plan success, as indicated by the negative and significant (at the 5% level) coefficient of this variable in Table 4. Table 5.9 shows the effect of a one standard deviation change in the DMP interest rate on the probability of success and failure. A one standard deviation reduction in the DMP interest rate (about 433 basis points) increases the probability of success by about 6.6% (from 28.26% to 30.15%). The probability of self administering the plan falls by 6.9% (from 22.14% to 20.61%) and the probability of plan failure is basically unaffected. These results clearly establish that the major creditor concession – reductions in interest rates on DMP debt – affect plan outcomes in two ways. Interest rate concessions lower the client’s monthly payment burden and provide a carrot for sticking with the plan payment schedule. Both increase the likelihood of a successful outcome.

Section 5: Summary and Conclusion

This paper has investigated whether or not the outcome of a credit counseling agency Debt Management Plan (DMP) can be predicted at the time of origination based on observable client and debt attributes. We are not aware of any previous study that has estimated the determinants of the success of DMPs or similar debt workout plans with so comprehensive a set of objective variables and using actual plan outcomes. The models described in this paper demonstrate the potential to construct a statistical model for sorting prospective clients according to their likelihood of success, and at a point in time such that the results could shape a counselor’s recommended plan of action.

Based on our analysis of archived data for several thousand cases closed in 2005, it appears that DMP outcomes are related in predictable ways to variables that proxy expected determinants of plan success. The statistical significance of key variables and the fact that these variables indicate behavior in expected directions indicates the potential usefulness of such a model to counseling agencies. Variables including the

weighted average DMP interest rate, client credit score, other credit bureau variables, the number of client dependents, and the ratio of the monthly plan payment to monthly income all had the expected effect on plan success or failure, as did administrative “direct debit” procedures for collecting monthly client payments.

It is important to note that the models were estimated using data archived several years earlier for an entirely different purpose. With more focused selection of variables to be captured, including the gathering of additional data at the time of counseling on the client’s financial behaviors and level of financial distress, it is quite possible that models similar to the one estimated in this paper could be even more predictive. With further refinement, such models can give agencies the basis for making operational adjustments to tailor the structure of plans to fit the needs of particular clients or allocate more resources to clients who seem likely to need extra assistance to complete a plan. In terms of creditor participation, such models could also move the industry away from the typical one-size-fits-all DMP and toward a system in which creditor concessions were individualized to fit consumer need.

References

- Bermant, Gordon. 2005. Bankruptcy by the Numbers: Trends in Chapter 13 Disbursements. *American Bankruptcy Institute Journal*, 24 (February).
- Furletti, Mark 2003. Consumer Credit Counseling: Credit Card Issuers’ Perspectives. *Federal Reserve Bank of Philadelphia Payment Cards Center Discussion Paper*.
- Greene, William, H. 2003. *Econometric Analysis* (5th ed.). Prentice Hall: 720-723.
- Hunt, Robert M. 2005. Whither Consumer Credit Counseling? *Business Review*, Federal Reserve Bank of Philadelphia, Q4.
- Kim, Jinhee, E. Thomas Garman, and Benoit Sorhaindo. 2003. Relationships Among Credit Counseling Clients’ Financial Well-being, Financial Behaviors, Financial Stressor Events, and Health. *Financial Counseling and Planning*, 14 (2): 75-87.
- Kim, Jinhee, E. Thomas Garman, and Benoit Sorhaindo. 2005. Study Finds Positive Financial Behaviors Increased: Credit Counseling and Debt Management Effective. *Journal of Family and Consumer Sciences*, 97 (2): 35-39.
- Loibl, Cazilia, Tahira K. Hira, and Michael Rupured. 2006. First Time Vs. Repeat Filers: The Likelihood of Completing a Chapter 13 Repayment Plan. *Financial Counseling and Planning*, 17 (1): 23-33.
- Loonin, Deanne and Travis Plunkett. 2003. *Credit Counseling in Crisis: The Impact on Consumers of Funding Cuts, Higher Fees and Aggressive New Market Entrants*. Washington, DC: Consumer Federation of America.

Norberg, Scott F. 1999. Consumer Bankruptcy's New Clothes: An Empirical Study of Discharge and Debt Collection in Chapter 13. *American Bankruptcy Institute Law Review*, 7.

Staten, Michael E. 1993. *The Impact of Waiving Finance Charges on Debt Plans at Consumer Credit Counseling Services*. Credit Research Center, Purdue University, Monograph 29.

Staten, Michael E. 2006. The Evolution of the Credit Counseling Industry. *The Economics of Consumer Credit*, edited by Bertola, et al, The MIT Press: 275-300.

U.S. Senate. 2004. *Profiteering in a Non-Profit Industry: Abusive Practices in Credit Counseling*. Staff Report, Permanent Subcommittee on Investigations, March 24.

Figure 1
Number of Months before DMP Terminated for Non Payment
(2,970 cases classified as Nonpayment)

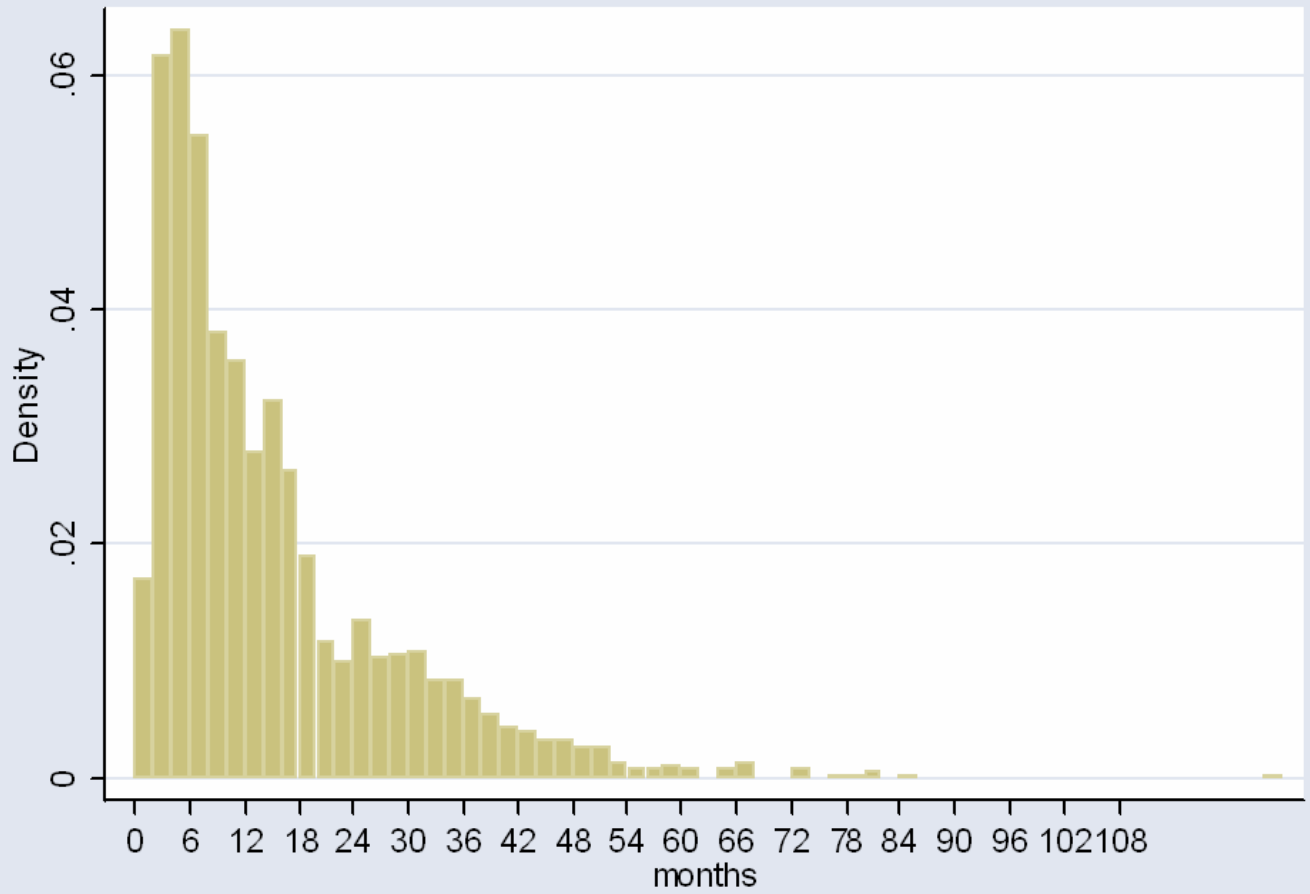


Table 1
Explanatory Variables

Variable	Description
<i>One Dependent</i>	This takes the value of one if the client has one dependent, else zero.
<i>Two Dependents</i>	This takes the value of one if the client has two dependents, else zero.
<i>Three Dependents</i>	This takes the value of one if the client has three dependents, else zero.
<i>Four Dependents</i>	This takes the value of one if the client has four dependents, else zero.
<i>Five Dependents</i>	This takes the value of one if the client has five dependents, else zero.
<i>Six or more Dependents</i>	This takes the value of one if the client has six or more dependents, else zero.
<i>Employed</i>	This takes the value of one if the client is employed, else zero.
<i>Married</i>	This takes the value of one if the client is married, else zero.
<i>Marital Status n/a</i>	This takes the value of one if the client's marital status is unknown, else zero.
<i>Divorced</i>	This takes the value of one if the client is divorced, else zero.
<i>Widowed</i>	This takes the value of one if the client is widowed, else zero.
<i>Other</i>	This takes the value of one if the client's marital status is "Other", else zero.
<i>Separated</i>	This takes the value of one if the client is separated, else zero.
<i>Situational Causes for Financial Distress</i>	This takes the value of one if the client's primary cause for financial distress has been deemed situational (e.g. reduced income, laid-off, divorced, etc.), else zero. See Table A-4 for a full list of situational causes.
<i>Female</i>	This takes the value of one if the client is female, else zero.
<i>Gender n/a</i>	This takes the value of one if the client's sex is unknown, else zero.
<i>Renter or Living Status n/a</i>	This takes the value of one if the client rents their home or if their housing status is unknown, else zero.
<i>Live with Parents</i>	This takes the value of one if the client lives with their parents, else zero.
<i>Partial Renter</i>	This takes the value of one if the client rents their home with others (roommates), else zero.
<i>Contact Channel - Telephone</i>	This takes the value of one if the client made contact with MMI via telephone, else zero.
<i>Contact Channel - Internet</i>	This takes the value of one if the client made contact with MMI via internet, else zero.
<i>Credit Score - 2003</i>	The client's credit score (generic bureau risk score) as of 2003.
<i>Change in Credit Score - 2002 to 2003</i>	This is the change in credit score from 2002 to 2003.
<i>Client Had Previous DMP</i>	This takes the value of one if the client has ever been on a previous DMP, else zero.
<i>Weighted Average DMP Interest Rate</i>	Weighted average of DMP interest rate based on creditors' interest rates and debt level.
<i>Number of Accounts with Positive Balances</i>	The number of accounts with balances greater than zero (credit bureau info).
<i>Number of Active Bankcard Accounts</i>	The number of active bankcard accounts (credit bureau info)
<i>Number of Accounts Never 60 Days Past Due</i>	The number of accounts never 60 or more days past due (credit bureau info)
<i>Total Revolving Debt</i>	The client's total revolving debt (credit bureau info)
<i>Number of Times 30 Days Delinquent</i>	The number of times an account has been 30 or more days delinquent (credit bureau info)

(Table 1 continued)

<i>Total Monthly Payments Divided by Total Monthly Income</i>	Total monthly payments on secured and unsecured debt (credit bureau info) divided by total monthly income.
<i>Total DMP Monthly Payments Divided by Total Monthly Income</i>	Total DMP monthly payments divided by total monthly income.
<i>DMP Payment Drawn Directly From Checking Account</i>	This takes the value of one if the client has payments automatically deducted from a checking account.
<i>DMP Payment Drawn Directly From Checking Account, But Initiated by Client</i>	This takes the value of one if the client has payments deducted directly from a checking account, at the client's initiation (not automatically deducted).

Table 2
Variable Means by DMP Outcome

Variable Description	Success	Self Admin	FDD	Nonpay	Total
<i>One Dependent</i>	0.286	0.306	0.374	0.336	0.32
<i>Two Dependents</i>	0.185	0.230	0.236	0.235	0.22
<i>Three Dependents</i>	0.091	0.127	0.143	0.130	0.12
<i>Four Dependents</i>	0.060	0.110	0.155	0.100	0.09
<i>Five Dependents</i>	0.025	0.040	0.051	0.047	0.04
<i>Six or more Dependents</i>	0.015	0.021	0.023	0.020	0.02
<i>Employed</i>	0.816	0.883	0.889	0.882	0.86
<i>Married</i>	0.423	0.500	0.417	0.423	0.44
<i>Marital Status n/a</i>	0.033	0.003	0.000	0.004	0.01
<i>Divorced</i>	0.120	0.100	0.126	0.106	0.11
<i>Widowed</i>	0.033	0.029	0.021	0.038	0.03
<i>Other</i>	0.014	0.018	0.011	0.020	0.02
<i>Separated</i>	0.005	0.017	0.028	0.033	0.02
<i>Situational Causes for Financial Distress</i>	0.380	0.486	0.598	0.556	0.49
<i>Female</i>	0.453	0.558	0.649	0.587	0.54
<i>Gender n/a</i>	0.163	0.078	0.023	0.061	0.09
<i>Renter or Living Status n/a</i>	0.559	0.385	0.511	0.432	0.47
<i>Live with Parents</i>	0.023	0.061	0.100	0.107	0.07
<i>Partial Renter</i>	0.001	0.004	0.019	0.006	0.00
<i>Contact Channel - Telephone</i>	0.735	0.596	0.421	0.552	0.61
<i>Contact Channel - Internet</i>	0.078	0.176	0.238	0.161	0.14
<i>Credit Score - 2003</i>	639.194	635.212	617.613	620.347	629.02
<i>Change in Credit Score - 2002 to 2003</i>	5.261	-10.660	-1.130	-12.935	-5.94
<i>Client Had Previous DMP</i>	0.022	0.051	0.006	0.090	0.06
<i>Weighted Average DMP Interest Rate</i>	9.514	10.037	9.222	9.609	9.64
<i>Number of Accounts with Positive Balances</i>	1.453	2.305	2.200	2.444	2.09
<i>Number of Active Bankcard Accounts</i>	5.185	6.652	6.038	6.460	6.07
<i>Number of Accounts Never 60 Days Past Due</i>	17.603	20.297	16.104	17.236	17.87
<i>Total Revolving Debt</i>	4915.006	10553.530	8554.826	9853.079	8337.78
<i>Number of Times 30 Days Delinquent</i>	19.407	15.539	13.502	15.854	16.76
<i>Total Monthly Payments Divided by Total Monthly Income</i>	0.206	0.262	0.314	0.335	0.28
<i>Total DMP Monthly Payments Divided by Total Monthly Income</i>	0.184	0.174	0.165	0.192	0.18
<i>DMP Payment Drawn Directly From Checking Account</i>	0.097	0.032	0.030	0.016	0.05
<i>DMP Payment Drawn Directly From Checking Account, But Initiated by Client</i>	0.091	0.078	0.066	0.081	0.08
Count	2227	1363	470	2970	

Table 3
Credit Variable Means by Year

Variable	Nonpay			Success		
	2002	2003	2005	2002	2003	2005
<i>Number of Accounts with Positive Balances</i>	2.46	2.44	1.25	1.68	1.45	1.18
<i>Number of Active Bankcard Accounts</i>	6.44	6.46	4.38	5.77	5.19	4.05
<i>Total Bankcard Utilization Rate</i>	0.69	0.75	0.67	0.65	0.61	0.43
<i>Number of Mortgage Accounts Delinquent in the Past 12 Months</i>	0.21	0.29	0.61	0.26	0.20	0.14
<i>Number of Accounts Ever 60 Days Past Due</i>	2.55	2.97	5.63	3.28	3.46	3.27
<i>Number of Accounts Never 60 Days Past Due</i>	16.47	17.24	15.86	17.59	17.60	18.54
<i>Percent of Accounts Never Delinquent</i>	73.42	69.67	54.63	68.43	67.22	70.99
<i>Total Revolving Debt</i>	8845.86	9853.08	4299.34	6046.99	4915.01	3822.47
<i>At Least One Mortgage Account Currently Past Due</i>	0.02	0.03	0.09	0.02	0.02	0.02
<i>Number of Times 30 Days Delinquent</i>	12.73	15.85	29.66	18.57	19.41	16.91

Variable	Self Administer			FDD		
	2002	2003	2005	2002	2003	2005
<i>Number of Accounts with Positive Balances</i>	2.53	2.31	1.51	2.13	2.20	1.62
<i>Number of Active Bankcard Accounts</i>	6.97	6.65	4.86	5.95	6.04	5.27
<i>Total Bankcard Utilization Rate</i>	0.70	0.72	0.57	0.66	0.70	0.83
<i>Number of Mortgage Accounts Delinquent in the Past 12 Months</i>	0.31	0.35	0.35	0.15	0.23	0.48
<i>Number of Accounts Ever 60 Days Past Due</i>	2.38	2.74	3.65	2.66	2.97	5.55
<i>Number of Accounts Never 60 Days Past Due</i>	19.83	20.30	20.49	15.34	16.10	15.91
<i>Percent of Accounts Never Delinquent</i>	75.73	72.76	67.72	69.11	67.47	55.01
<i>Total Revolving Debt</i>	10733.71	10553.53	6763.12	7403.44	8554.83	7329.41
<i>At Least One Mortgage Account Currently Past Due</i>	0.04	0.04	0.04	0.01	0.03	0.09
<i>Number of Times 30 Days Delinquent</i>	12.86	15.54	23.59	12.13	13.50	22.81

**Table 4
Multinomial Logit Output**

Variable	Success		Self Administer		First Deposit Default		Sample Means
<i>One Dependent</i>	-0.6443	***	-0.1521		2.1001	***	0.32
<i>Two Dependents</i>	-0.8165	***	-0.2848	**	2.1217	***	0.22
<i>Three Dependents</i>	-0.9199	***	-0.3705	***	2.2063	***	0.12
<i>Four Dependents</i>	-1.1175	***	-0.3263	**	2.6314	***	0.09
<i>Five Dependents</i>	-1.2359	***	-0.6108	***	2.2580	***	0.04
<i>Six or more Dependents</i>	-0.8001	***	-0.3609		2.2646	***	0.02
<i>Employed</i>	-0.3486	***	0.0069		-0.1365		0.86
<i>Married</i>	0.1686	*	0.1638	*	-0.1317		0.44
<i>Marital Status n/a</i>	0.8050	**	-0.7400		-29.9920		0.01
<i>Divorced</i>	0.2932	***	-0.0249		0.0377		0.11
<i>Widowed</i>	-0.3580	*	-0.3191		-0.2564		0.03
<i>Other</i>	-0.0994		-0.0179		-0.4899		0.02
<i>Separated</i>	-1.2717	***	-0.4708	*	-0.4351		0.02
<i>Situational Causes for Financial Distress</i>	-0.4338	***	-0.1872	***	0.0872		0.49
<i>Female</i>	-0.2814	***	0.0108		0.2057	*	0.54
<i>Gender n/a</i>	0.1728		0.1076		-0.5825	*	0.09
<i>Renter or Living Status n/a</i>	0.2834	***	-0.1565	*	0.4491	***	0.47
<i>Live with Parents</i>	-0.9640	***	-0.3972	***	0.1628		0.07
<i>Partial Renter</i>	-1.5470	**	-0.3974		1.1124	**	0.00
<i>Contact Channel - Telephone</i>	0.3892	***	0.2280	***	-0.4713	***	0.61
<i>Contact Channel - Internet</i>	-0.3606	***	0.2079	*	0.0589		0.14
<i>Credit Score - 2003</i>	0.0026	***	0.0010	*	-0.0010		629.02
<i>Change in Credit Score - 2002 to 2003</i>	0.0019	***	-0.0003		0.0041	***	-5.94
<i>Client Had Previous DMP</i>	-1.3562	***	-0.5300	***	-2.9228	***	0.06
<i>Weighted Average DMP Interest Rate</i>	-0.0169	**	0.0147	*	-0.0048		9.64
<i>Number of Accounts with Positive Balances</i>	-0.1903	***	-0.0630	***	-0.0510		2.09
<i>Number of Active Bankcard Accounts</i>	-0.0240	*	-0.0231	*	0.0044		6.07
<i>Number of Accounts Never 60 Days Past Due</i>	0.0272	***	0.0270	***	0.0027		17.87
<i>Total Revolving Debt</i>	-0.000032	***	0.000000		0.000002		8337.78
<i>Number of Times 30 Days Delinquent</i>	0.0050	***	-0.0009		-0.0042		16.76
<i>Total Monthly Payments Divided by Total Monthly Income</i>	-0.6959	***	-0.2490	**	-0.0574		0.28
<i>Total DMP Monthly Payments Divided by Total Monthly Income</i>	-0.0868		-0.9546	***	-0.9659	**	0.18
<i>DMP Payment Drawn Directly From Checking Account</i>	1.7599	***	0.6296	***	0.6051	*	0.05
<i>DMP Payment Drawn Directly From Checking Account, But Initiated by Client</i>	0.2452	**	-0.0919		-0.2920		0.08
<i>Constant</i>	-0.5206		-1.2504	***	-2.8276	***	1.00

*** 99% Confidence, ** 95% Confidence, * 90% Confidence

Pseudo R² = 0.124

Table 5.1
DMP Outcome Predictions by Number of Dependents

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated At Means	28.25%	22.10%	3.20%	46.45%	
No Dependents	42.14%	21.27%	0.43%	36.16%	0.196
One Dependent	27.56%	22.79%	4.44%	45.21%	0.317
Two or More Dependents	23.37%	21.04%	5.56%	50.03%	0.487

Table 5.2
DMP Outcome Predictions by Marital Status

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Single	26.49%	21.55%	4.88%	47.08%	0.369
Married	29.00%	23.48%	3.96%	43.55%	0.437
Divorced	32.67%	19.34%	4.67%	43.32%	0.111
Widowed	21.77%	18.42%	4.44%	55.36%	0.033
Separated	10.44%	18.92%	4.44%	66.19%	0.021

Table 5.3
DMP Outcome Predictions by Type of Financial Distress

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Situational Cause for Financial Distress	24.48%	21.76%	3.45%	50.31%	0.490
Other Cause for Financial Distress	32.16%	22.33%	2.69%	42.82%	0.510

Table 5.4
DMP Outcome Predictions by Residential Status

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Live with Parents	13.38%	21.69%	3.76%	61.16%	0.071
Renter or n/a	33.20%	19.66%	3.57%	43.57%	0.468
Own House	26.64%	24.50%	2.42%	46.43%	0.456

Table 5.5
DMP Outcome Predictions by Method of Contact

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Face to Face	25.31%	20.17%	4.35%	50.18%	0.248
Telephone	32.31%	21.92%	2.35%	43.42%	0.609
Internet	18.14%	25.53%	4.74%	51.59%	0.143

Table 5.6
DMP Outcome Predictions by Debt Management History

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Client had a previous DMP	11.54%	19.74%	0.28%	68.44%	0.94
Client did not have a previous DMP	29.46%	22.05%	3.47%	45.01%	0.06

Table 5.7
DMP Outcome Predictions by Type of Payment Withdrawal

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Automatically Withdrawn From Checking Account	61.55%	16.86%	2.31%	19.28%	0.046
Withdrawn From Checking Account at Client's Initiation	32.26%	19.53%	2.24%	45.96%	0.083
DMP Not Directly Drawn From Checking Account	26.40%	22.39%	3.14%	48.07%	0.872

Table 5.8
DMP Outcome Predictions by Credit Score

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Mean and Std. Dev.
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Credit Score + 1 std dev	32.41%	22.14%	2.58%	42.87%	629.017 (+85.773)
Credit Score - 1 std dev	24.42%	21.95%	3.57%	50.06%	629.017 (-85.773)

Table 5.9
DMP Outcome Predictions by Plan Interest Rate

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Change in weighted average DMP interest rate + 1 std dev	26.43%	23.74%	3.01%	46.82%	9.64 (+4.33)
Change in weighted average DMP interest rate - 1 std dev	30.15%	20.61%	3.09%	46.16%	9.64 (-4.33)

Table 5.10
DMP Outcome Predictions by Payment to Income Ratio

	Probability of Success	Probability of Self Administer	Probability of FDD	Probability that DMP Fails	Means
Evaluated at Means	28.26%	22.14%	3.05%	46.54%	
Mean payments divided by monthly income plus 0.10	27.03%	22.15%	3.11%	47.72%	0.278 (+0.100)
Mean payments divided by monthly income minus 0.10	29.53%	22.12%	2.99%	45.36%	0.278 (-0.100)