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Participation in Universal Prevention Programs

Prof. Robert Rosenman,

Washington State University, School of Economic Sciences, Hulbert Hall 101, Pullman,
99164-6210 United States

Mr. Scott Goates, and

Washington State University, School of Economic Sciences, Pullman, United States

Dr. Laura Hill

Washington State University, Human Development, Pullman, United States

Robert Rosenman: yamaka@wsu.edu

Abstract

We analyze family decisions to participate in community-based universal substance-abuse prevention programs through the framework of expected utility theory. Family functioning, which has been shown to be a good indicator of child risk for substance abuse, provides a useful reference point for family decision making. Our results show that well-functioning families (with children at low risk for substance use) should have the lowest incentive to participate, but that high-risk families may also opt out of prevention programs. For programs that are most effective for high-risk youth, this could be a problem. Using data from the Strengthening Families Program and the Washington Healthy Youth Survey, we empirically test the implications of our model and find that at least for one measure of family functioning those families with children most likely to be at risk for substance use are opting out of the program.

Introduction

Early initiation of substance use by adolescents is strongly associated with numerous risk behaviors and negative outcomes, including delinquency, pregnancy, and HIV, poor health and lower educational attainment as well as with long-term substance dependence and abuse (DuRant, et al., 1999; Gil and Molina, 2007). Interventions designed to prevent adolescent substance use are important because of the high personal and societal costs of substance abuse: dollar costs of drug and alcohol abuse and dependence were estimated at \$245.7 billion annually in 1992 and have increased by approximately 5% annually since then (Office of National Drug Control Policy, 2001). Over the past two decades, experimental trials have shown that family-based interventions, which aim to minimize adolescent risk behaviors through strengthening parent-child relationships and improving family management, can reduce rates of adolescent substance use initiation and frequency (Foxcroft, et al., 2003; Hawkins, et al., 1999). In some communities and states, such evidence-based programs are now being implemented on a large-scale as public health interventions.

In the lexicon of public health, “universal” prevention programs or strategies are delivered without any prior screening (e.g. anti-drunk driving campaigns) and are open for all who wish to participate; “selective” prevention programs target those at higher-than-average risk for a problem (e.g. diabetes prevention with overweight individuals); and “indicated”

prevention programs target those who display early signs of a problem (e.g. dropout prevention with students failing classes) (Mrazek and Haggerty, 1994). Most substance abuse prevention programs are designed as universal interventions, usually for young adolescents, either in schools or in community-based family groups. The systematic study of substance abuse intervention effectiveness is relatively recent, and therefore most studies measuring the potential benefits of such programs are based on randomized clinical trials (RCTs). But when universal programs are implemented in a community, participation may be non-random¹, in which case the benefits observed in practice may be appreciably different from those observed in RCTs². More specifically, evaluating community-based prevention programs may be complicated by selective participation. If individual decisions about participation are based on factors that affect the likelihood that the program is successful³, measuring the program's impact becomes problematic. Most importantly, any measurements of benefits and cost must account for an endogenous self-selection bias. Thus, understanding the cause and impacts of self-selection is important in any study of community-based prevention programs.

In this paper we use expected utility theory (EU) to explain self-selection into community-based programs designed to improve how a family functions. High levels of family functioning, as assessed by measures of family management and parent-child relationship, are associated with a lower likelihood of adolescent substance use and misuse (Dakof, 2000; Schmidt, et.al. 1996). Thus we refer to families with high scores on measures of family functioning as “low risk” and those with low scores as “high risk”. Using a model where family functioning influences the propensity of children towards future substance abuse we show that low-risk families would be less likely to participate. Moreover, we also find some evidence that the highest-risk families, by which we mean those with the lowest levels of functioning, may also be less likely to participate in these programs. Since the youth in these families are most needful of the intervention, this is a costly outcome. We test the conjectures from this model with data from one such evidence-based intervention, the Strengthening Families Program for Parents and Youth 10-14 (SFP), in Washington State and find evidence that both very high-functioning families and very low functioning families are less likely to participate.

In the next section we offer further detail of the literature covering selection issues in community-based prevention programs. Following that we develop an EU model which explains family self-selection into such programs in the context of family functionality. We then introduce the analytical techniques we use to test the predictions of the model. Subsequent sections discuss the data we use and our empirical results. We close the paper with conclusions and implications for further research, including briefly describing how self-selection may impact the *apparent* as opposed to real costs and benefit from community-based prevention programs.

Selectivity Issues in Community Based Prevention Programs

A large literature on predictors of prevention program participation has developed in recent years. These studies use constructs derived from the health beliefs model, protection motivation theory, theory of reasoned action, and subjective utility theory to model the decision to attend a prevention program (for a review and comparison of these theories see Weinstein, 1993). Spoth and Redmond (1995) note that “all of these models and theories can

¹For example, it may be that individuals who are least at risk for the behavior and most receptive to the program goals are most likely to attend, while those who are at greater risk and less receptive to the program goals fail to participate.

²Berger and Exner (1999), and Berger and Christophi (2003) discuss how there may be nonrandom participation in RCTs as well.

³For an interesting analysis on what may constitute “success” in the context of substance abuse outcomes, see Brent (1998)

be characterized as value expectancy approaches, incorporating constructs that address the value placed on a specific, health-related outcome and the estimated likelihood that a specific action will achieve that outcome” (p. 295). In a medical application, research on program participation in health interventions has shown selection effects related to value expectancies and demographic characteristics (Murphy, et al., 2010). Other studies have found that families with lower socioeconomic status are more likely to report privacy concerns and logistical barriers (Haggerty et al., 2002; Heinrichs, Bet al., 2005; Spoth, et al., 1995). Orrell-Valente and colleagues (1999) found that parents were more likely to have positive therapeutic alliance and thus to participate when program leaders were of the same race and of similar socioeconomic background. Possibly most relevant to the issue discussed in this paper, some studies have found that parent perception of child behavior problems increases the likelihood of attendance (Haggerty et al., 2002; Heinrichs, et al., 2005), and parents who see potential benefits of a program are also more likely to attend (Spoth, et al., 1996). In addition, several studies have found that positive family attributes, including clear communication patterns and family organizational skills, are positively related to program participation (Bauman, et al., 2001).

Expected Utility and Self-Selection

Community-based universal programs to improve family relationships or prevent substance abuse are open to all. Families choose to participate if their expected gain, in terms of improved family relationships or a lower likelihood of child substance abuse, exceeds the costs of attending. Psychologists have shown measures of parent-child relationship quality and family management practices are good predictors of youth substance abuse, and many programs, like SFP, are designed to improve family functioning and thereby lessen risk for adolescent substance use. In our model we use family functioning as the target of the intervention and demonstrate that the current status of family functioning may affect the decision to attend a universal family preventive intervention.

Let F be a measure of family functioning and $U(F)$ be a family's valuation of this functioning (especially their valuation of the associated likelihood of future drug abuse by children in the family⁴), with $U(F) > 0$, $U'(F) \geq 0$ and $U''(F) < 0$. The program is designed to increase family functioning. Thus, participation in the program can be thought of as “successful” if it increases F and unsuccessful if F does not increase. We assume the program does no harm so F cannot decrease from program participation. The benefit of a successful program to a family is therefore approximated by $\Delta F \times U'(F)$.

Youth who participate in the program incur costs associated with forgone activities, and their willingness to participate is likely to be highly influenced by various social institutions (Leung, 2004). Adults who participate in the program also incur costs, both real dollar costs for such things as transportation, foregone wages⁵ and the loss of leisure time. In addition families face psychological and social costs related to organizing and cajoling the family into participating in the program. For example, families participating in the program may be required to share with strangers matters traditionally considered private to the family, or parents may disagree with each other or with their child about attending a program (Spoth et al., 1996). Public exposure of how the family works may be especially hard for families with lower functioning levels. Some research has shown that youth with problem behaviors are unwilling to attend family programs despite the fact that parents who perceive that their

⁴As discussed in the introduction, higher levels of family functioning have been found to be associated with a lower likelihood of future substance abuse by the children in the family, hence our calling high functioning families “low risk”.

⁵A study by Carlin and Sandy (1990), suggests that families with a higher opportunity cost of time are less likely to engage in the preventative activity of properly installing car seats.

child has a problem or is susceptible to problems are more willing to attend a program (Spath, et al., 1997). In contrast, families with adolescents who feel strongly attached to a parent are more likely to attend a program (Bauman et al., 2001). A decision to attend a family strengthening program may imply that the family is in trouble or that parents are doing a poor job; in this case, participants may face social disapproval, which has been shown to discourage program participation (Gensheimer, Ayers, & Roosa, 1993). It is these psychological and social costs which we expect to be higher for lower functioning families, and which form the basis for our theoretical construct on family costs of attending the program.

Assume that the transportation costs, foregone wages, and lost leisure time are the same for all families but the psychological and social costs differ according to family functioning. Based on the arguments discussed in the previous paragraph we assume that the psychological and social costs decrease as family functioning goes up but all families incur some costs related to transportation and foregone wages. Thus we have $C(F) > C_M > 0$, $C'(F) < 0$ and $C''(F) \geq 0$ where C_M is the minimum costs incurred if a family participates in the program. Hence, C_M is the cost of participation for the most functional families.

The program does not necessarily increase family functioning. We assume initially that the probability of program success, P , is independent of family functioning so $P(F) = P$ for all F . A family participates if the expected value of participation is positive, that is, if

$$EV = [\Delta F \times U'(F) - C(F)] * P + [-C(F)] * [1 - P] > 0 \quad (1)$$

and so families participate only if $\Delta F \times U'(F) * P > C(F)$. For any given ΔF the limit of the left-hand-side of this inequality as $F \rightarrow \infty$ is 0, while the limit of the right-hand-side is C_M . Hence there is some F^* above which families will choose not to attend. Figure 1 shows the case when lower functioning monotonically increases a family's incentive to participate. However, because the psychological and social costs for low-functioning families may be large, it is not clear that families at the very lowest level of functioning will have a positive expected value. Figure 2 shows the case where the very lowest-functioning and the highest-functioning families opt out and only families with levels of functioning, between F_1 and F_2 , participate.⁶

It is likely, however, that the probability of success is not independent of (initial) family functioning, so the probability of success is $P(F)$ with $1 - P(F) \geq 0$. At issue is how $P(F)$ relates to F . We see two possibilities. The first is that lower-functioning families are less likely to have a successful program because they are less likely to follow through on program activities and recommendations, so $P'(F) > 0$. (Spath et al., 1998). The second is that more functional families have "less to fix" and therefore are less likely to find that F improves and so $P'(F) < 0$.⁷ Equation (1) now becomes

$$EV = [\Delta F \times U'(F) - C(F)] * P(F) + [-C(F)] * [1 - P(F)] > 0 \quad (2)$$

and families participate if $\Delta F \times U'(F) * P(F) > C(F)$, or, more conveniently for our purposes, if $\Delta F \times U'(F) > C(F) / P(F)$. Again, for any given ΔF taking the limit of both sides of this inequality as $F \rightarrow \infty$ we find that our previous results still hold. As $F \rightarrow \infty$ the left-hand-side still approaches 0. The right-hand-side approaches C_M if $P'(F) > 0$ (since $P(F) \rightarrow 1$) and

⁶We show $U''(F) = 0$ in this graph. The implications do not change if $U''(F) < 0$.

⁷In neither case does the second derivative of $P(F)$ matter.

it approaches infinity if $P'(F) < 0$ (since $P(F) \rightarrow 0$). Empirically these are observationally equivalent, and the only impact is that families might opt out at lower levels of functionality if $P'(F) < 0$.

One remaining question is if we could ever see higher-functioning families being more likely to opt in when compared to mid-level and low-level functioning families. The answer is yes if $C'(F) \ll 0$ which could be the case if transportation or other costs, especially the opportunity costs of time in terms of foregone wages, is strongly related to family functioning. However, we believe this is unlikely to be sufficiently strong to dominate in the great majority of families.⁸

Data

We test the implications of our theoretical model by examining participation in the Strengthening Families Program (SFP). SFP is a universal program in which families meet once weekly for seven weeks. In each meeting, parents learn effective means of communicating expectations and setting consequences; youth learn peer resistance skills; and parents and youth engage in exercises designed to promote family closeness. The rigorous clinical efficacy trial of SFP has produced solid evidence of long-term effectiveness in delaying onset and frequency of adolescent substance use (Foxcroft, et al., 2003; Spoth, Redmond, & Shin, 2001). In that trial, families were invited to participate in an experiment and then randomized to treatment or control conditions; a telephone survey demonstrated that the trial sample was representative of the local population. In a community-based implementation, however, families self-select into the program. Recruitment techniques vary from community to community: families may hear about the program through friends and neighbors; through a school principal or guidance counselor; through their faith community, or through public advertising.

We use data from multiple sites in a statewide dissemination of SFP. A survey that program participants complete on the first night of the program included questions that assess dimensions of family functioning targeted by SFP, including parent-child involvement, positive reinforcement of children's good behavior, clear communication of rules and consequences, and children's peer-pressure resistance skills. A total of 294 youth from 42 programs in 10 counties participated in the survey.

To perform our analysis, we require a supplementary data set with identical variables to those measured for the SFP participants. The Washington State Healthy Youth Survey (HYS) provides such a data set (Washington State Department of Health, 2008).⁹ The Washington Healthy Youth Survey is conducted biennially in schools statewide in an effort to measure health risk behaviors that contribute to the morbidity, mortality and social problems of youth in Washington State. Demographic items on the HYS are administered to all students in participating schools. Other items and scales are included based on age. Of relevance to this study, 6th graders answered questions on parent-child involvement and positive reinforcement, and did not answer questions regarding peer social skills and family management. Older students answered question of the latter type but not the former.

We used HSY data from grades 6, 8, and 10 (corresponding to the age range in the SFP dataset). School response rates ranged from 80% (6th grade) to 86% (10th grade) and

⁸One alternative theory for decision making under uncertainty is Prospect Theory (PT). A model showing how PT can result in low risk families more likely to opt into the program than high risk families is available from the authors. However, as we show below, our empirical analysis does not support this idea.

⁹To enable comparison of program attendees with non-attendees, the SFP evaluation was specifically designed to include measures assessing risk and protective factors that, besides being targets of the program, are also collected in the Healthy Youth Survey.

individual response rate across grades was 65%.¹⁰ Our dataset included 8294 complete observations for younger children (those that responded to questions regarding parent-child involvement and positive reinforcement) and 4413 complete observations for older children (those that responded to questions regarding family management, peer social skills). Summary statistics for both the SFP dataset and the HYS dataset are given in Table 1. We have indicated in the table significant ($p < .05$) differences in the means for specific variable between the HYS and SFP samples. We note three primary differences. First for both age groups the SFP sample is slightly older than the HYS sample. Second the racial makeups of the samples differ. For the younger age group both whites and Hispanics are over represented compared to the HYS sample. Hispanics are also over represented in the older age group, but whites are underrepresented. Finally, in both age groups there is evidence of lower family functioning on average among the participants in SFP compared to the HYS sample. Younger SFP participants report lower average scores for family involvement compared to the HYS youth of the same age group, while the older SFP participants report lower average peer social skills compared the HYS sample of the same age group.

Analytic Approach

The difficulty in analyzing our choice-restricted (SFP) and supplementary (HYS) data lies in the fact that in our supplementary data set, we are unable to determine which individuals participated in SFP and are therefore included in our data twice (Hill, Goates, and Rosenman, 2010). Steinberg and Cardell (1992) address this issue and develop an appropriate weighting procedure for analyzing this data in a pseudo-logistic regression. As this regression procedure is rarely used, we include details on its implementation in Appendix.

Our dependent variable is participation in the program and our explanatory variables of interest are the various scales that measure family functioning. For the younger children our two measures of family functioning are Positive Reinforcement for Prosocial Behavior (which we term “Reinforcement”) and Opportunities for Prosocial Behavior (which we term “Involvement”). These two measures assess the degree to which parents encourage their children's involvement in family activities and decisions and reward them for doing so. For the older children we have measures of Peer Social Skills (which assesses children's ability to resist peer pressure) and Family Management Skills (which assesses parental monitoring of youth activities and clarity of household rules). All scales have strong psychometric properties and are standard measures of risk and protective factors used in national and state surveys such as the Monitoring the Future survey, supported by the National Institute of Drug Abuse (2010). With both age levels we include as covariates gender, age, race, and for the older group we also include current substance use (this last variable is not available for those in the younger group). Specification tests suggest quadratic terms be used for Reinforcement and Involvement when estimating participation by the younger group, while only linear terms are indicated for the variables of interest in the equation explaining participation by the older group.

Results and Discussion

In Table 2 we present results of a logistic regression using the Steinberg-Cardell technique mentioned earlier. These coefficients can be interpreted the same way a logistic regression from a randomized sample might be interpreted, with each coefficient predicting program participation from each of the risk and protective factor scale scores (both linear and

¹⁰Alternative schools were significantly less likely to participate than regular schools (63% versus 82.7%). However, analysis of survey data patterns showed that school self-selection did not appear to bias survey results.

curvilinear) and controlling for youth race/ethnicity, sex, county, and age. For older youth current substance use (0 or 1) was also included in the regression. Our results show that in the younger group, families with female children and non-minority families were more likely to attend than families without these characteristics. These results are consistent with previous research showing that minority families and those with male children were less likely to attend a family program (Bauman et al., 2001). In the older group, the opposite was true: families with male children were more likely to attend, as were Latino and American Indian families. One possible explanation for this discrepancy is that Latino and American Indian participants were more likely to attend with both older and younger children. Another possibility is that older male children were more likely to be experiencing behavior problems, and their parents were therefore more likely to attend. However, African-American and Asian-American families, and those from other non-White families, were still less likely to attend.

Our main interest here was the effects of family functioning factors on program participation. As noted earlier, preliminary analysis indicated that second-order terms for functioning factors belong in the regression equation for the younger group, but not for the older group. To improve efficiency the reported analysis for the older group reflects this finding and does not include estimates for curvilinear effects. In logit estimation one must be cautious about interpreting the parameter estimates associated with explanatory variables, as they are estimators of the change in the logit caused by a unit change in the independent variable, not the change in the variable itself. The presence of the squared terms in the younger group means this caution is important as one must compute odds ratios using linear, squared and cross-product terms; hence the odds ratios are not constant.

The non-linear terms in the equation for the younger group mean interpretation of the logistic estimates must focus on the total rather than marginal effects. The empirical analysis shows that families reach their highest overall odds ratios of participation with scores of Reinforcement = 4.00 (the highest possible value) and Involvement=1.71, and the odds of participating decrease with movement in any direction from this peak within the range of scale scores. The marginal odds ratios peak at the same values, of course, when computed at the mean of the other variable. However, we note that the estimation results for Reinforcement are not statistically significant even with a p-value of 0.15, hence for the younger group we focus on the results for Involvement. The peak value for this variable (1.71) indicates *for the younger group* those families with a middle level of functioning are most likely to attend, while those at both extremes (low functioning and high functioning) are least likely to attend. This is consistent with figure 2.

Results for the older group are somewhat easier to interpret since the model uses only linear estimation. Odds ratios are much more straightforward; lower scores on Family Management significantly predicted greater participation ($OR = 0.725$, $p < .04$), which is consistent with figure 1. Adolescent substance use was also negatively associated with participation ($OR = 0.654$, $p < .10$). If, after controlling for the other measures of family functioning, we interpret the presence of adolescent substance abuse as lower family functioning our results for the families with older children are also more consistent with figure 2 than with figure 1.

Conclusions and Implications

Using expected utility we explain how a family's functioning affects selection into a universal program to decrease substance abuse. Our theoretical results, supported by our empirical analysis, indicate that high functioning families are less likely to participate. In our view this is not a problem since indications are that youth coming from those families are

less likely to abuse drugs and alcohol in the future. However, also consistent with what our theory showed, our empirical analysis finds that the least functioning families may also decline to participate in programs like SFP. Youth from these families are at relatively high risks of (future) substance abuse, and thus this is a social problem. It may be that social welfare can be increased by targeting lower-functioning families for participation in programs like SFP, perhaps by working to lower the costs of participation, or by subsidizing participation to increase their expected net benefits.

Moreover, our results have implications when analyzing programs using cost-benefit or cost-effectiveness analysis, especially if the probability of program success is correlated with the family functioning of the participants. If a successful program increases functioning equally for all families regardless of the family's initial functioning (i.e., if ΔF is the same for all successful participants) we would still expect that how they value the change (i.e., $\Delta F \times U'(F)$) will differ because of the properties of $U'(F)$. The *economic* valuation of the program then would differ from the valuation coming out of the RCT if the average result of the RCT is used to calculate the program value. Moreover, if the probability of program success and the magnitude of change that results is correlated with family functioning (so $P(F)$ is not constant and ΔF itself is a function of F) then benefit cost estimates for the program will be even more biased if the distribution of family functioning among the participant population is different than that of the RCT population. For example, if lower-functioning families self-select into programs, but the program is more likely to change the risk of substance abuse for these families, then the benefit-cost estimate of the clinical trial would understate the true benefit of application. There is some evidence that the long-term effectiveness of prevention programs does not depend on a family's initial level of functioning (Guyll, et al., 2004) but there is also emerging evidence that prevention efforts are, in fact, disproportionately effective with higher-risk individuals (Griffin, et al., 2003; Spoth, et al., 2008). At the same time, evidence from clinical trials suggests that lower-functioning families are less likely to attend community-based programs (Haggerty et al., 2002), supportive of our finding that the least functioning families are more likely to not participate. Thus, these programs might be missing those families most in need of them, and which would benefit the most from participating, clearly yielding less value than they could.

Appendix: The Steinberg-Cardell Test for Selectivity

Unlike RCTs, real world interventions often have restricted samples that provide information only on participants (i.e. have zero variance in the dependent variable), leaving analysts unable to identify selection using standard techniques such as logit or probit. Ideally, a choice-restricted sample could be augmented with surveys of the general population and estimated as an enriched sample, but such supplementary surveys are often costly and are not always feasible. At the same time, there are many widely available datasets which contain information on the exogenous variables of interest for the general population (e.g. census data, etc.) but fail to contain data on the participation choice of the individual. We will call this second kind of data a supplementary sample.

Several estimators allow us to estimate the parameters of the choice model when appropriate choice restricted and supplementary samples exist (Cosslett, 1981a, 1981b, 2007; Imbens, 1992; Steinberg & Cardell, 1992). The first estimator of this type was developed by Cosslett in 1981. Although Cosslett's 1981 estimator is theoretically appealing, it is extremely difficult to estimate in application. Other estimators in this class are essentially variations of Cosslett's original estimator which allow for easier application.

For reasons of computational simplicity and tractability, we chose to use the Cardell-Steinberg technique. This technique relies on weighting different parts of the classic log-

likelihood function for a logistic regression to produce unbiased estimates of parameters. Because this technique is unfamiliar to many practitioners, we provide a brief description, much of which is taken from Steinberg and Cardell (1992).

The classic log likelihood function for a dichotomous outcome is

$$LL(b) = \sum_{i=1}^N Y_i \log P_i + \sum_{i=1}^N (I - Y_i) \log (I - P_i) \quad (A1)$$

Where P is an appropriate probability model, specifying that $\Pr(Y_i = 1) = h(X_i B)$ for some known function h (in our estimation we use the logit model); β is a column vector of unknown parameters; X_i is a row vector of covariates; $P_i = h(X_i, b)$ and i indexes the observations. Neither the choice-restricted samples nor supplementary samples by themselves can support the estimation of the model in equation (A1). Combined, however, the samples are sufficient to estimate the model. For expository purposes, assume that the entire population is surveyed in the supplementary sample, and all persons that participate in the program are surveyed in the choice restricted sample¹¹. Then the likelihood function in (A1) can be rearranged and rewritten as

$$LL(b) = \sum_{i=1}^N \log(I - P_i) + \sum_{\substack{i=1 \\ \text{i such that } Y_i=1}}^N \log(P_i) - \sum_{\substack{i=1 \\ \text{i such that } Y_i=1}}^N \log(I - P_i) \quad (A2)$$

This likelihood function can be broken up into its separate terms to better understand the Cardell-Steinberg technique. The first term is derived from the entire population (that is, the supplementary sample) and is equivalent to treating every observation as if it had a value of 0 for the response variable, Y . The second term comes from the choice restricted sample, and accumulates the correct $\log P$ term for observations having a value of 1 for the participation variable, Y . The third term is also calculated from the choice restricted sample, and acts as a correction to the first term by subtracting out precisely those values that were misclassified in the first term.

When the sampling rates are less than one, which is almost always the case, a related pseudo-likelihood can be applied to a pooled sample of supplementary and choice-restricted samples:

$$LL(b) = \sum_{i=1}^N \log(I - P_i) + \frac{r_0}{r_1} \sum_{i=N+1}^I \log(P_i) - \frac{r_0}{r_1} \sum_{i=N+1}^I (I - P_i) \quad (A3)$$

where r_0 is the sampling rate of the supplementary sample and r_1 is the sampling rate of the choice restricted sample. N is the size of the supplementary sample, and I is the size of the combined samples. Steinberg-Cardell (1992) show that maximizing this pseudo-likelihood function results in unbiased, though inefficient, estimates of β .¹²

¹¹This assumption is not needed in actual application, but is included here to make the sums in (5) exact.

¹²Cosslett provides an unbiased and efficient estimator of the probability model, but their estimator is notoriously difficult to estimate (Imbens, 1992). In several attempts to use the Cosslett estimator with our data, we found that the estimates were sensitive to initial parameter values. We therefore adopt the theoretically less appealing, but more easily applicable Steinberg-Cardell estimator.

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Figure 1.
The lower the family functionality the greater the incentive to join SEP.

Figure 2.
Only families in the midrange of functionality join SEP.

Table 1
Summary statistics for the younger children (n_{HYS}=8041, n_{SFP}=200) and the older children (n_{HYS}=4413, n_{SFP}=94)

Variable	Range	Ages (11-12) ^a				Ages (13-16) ^b			
		HYS		SFP		HYS		SFP	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Male	0,1	.48	.0056	.46	.035	.47	.50	.56	.50
Age (A,B)	11-16	11.28	.0050	11.42	.035	13.29	.48	13.57	.74
White (A,B)	0,1	.522	.0056	.635	.034	.645	.48	.468	.50
Black	0,1	.020	.0016	.025	.011	.027	.16	.012	.10
Asian/Pacific (A)	0,1	.048	.0024	.025	.011	.050	.22	.032	.18
Hispanic (B)	0,1	.167	.0042	.195	.028	.169	.37	.340	.47
Native (B)	0,1	.096	.0033	.065	.017	.056	.23	.106	.11
Other (A,B)	0,1	.21	.0045	.055	.016	.093	.29	.050	.20
Reinforcement	1-4	3.42	.0072	3.37	.045	n/a	n/a	n/a	n/a
Involvement (A)	1-4	3.19	.0079	2.89	.049	n/a	n/a	n/a	n/a
Family Mgmt Skills	1-4	n/a	n/a	n/a	n/a	3.10	.73	2.86	.78
Peer Social Skills (B)	1-4	n/a	n/a	n/a	n/a	3.31	.64	3.21	.61
Substance Use	0,1	n/a	n/a	n/a	n/a	.209	.41	.234	.43

A implies a significant ($p < .05$) difference in the mean for the younger group

B implies a significant ($p < .05$) difference in the mean for the older group

Table 2
Summary of Steinberg-Cardell Pseudo- Logistic Regression Analysis for Variables Predicting Decisions to participate in the program for children age 11-12 and children age 13-16, Controlling for Background Variables

Predictor	Ages 11-12			Ages 13-16		
	B	SE B	OR	B	SE B	OR
Male	-.14	.15	.87	.12	.22	1.12
Hispanic	-.34**	.20	.71	.75***	.27	2.11
Native American	-.88***	.30	.42	.57*	.38	1.76
Asian/Pacific Islander	-.70*	.46	.50	-.10	.57	.91
Black	-.29	.46	1.33	-.63	.96	.53
Other	-1.80***	.33	.17	-1.11**	.61	.33
Reinforcement	.54	1.03	n/a	n/a	n/a	n/a
Involvement	1.36	.80	n/a	n/a	n/a	n/a
Reinforcement Squared	-.02	.21	n/a	n/a	n/a	n/a
Involvement Squared	-.45	.17	n/a	n/a	n/a	n/a
Reinforcement*Involvement	.05	.28	n/a	n/a	n/a	n/a
Peer Social Skills	n/a	n/a	n/a	-.04	.18	.96
Family Management Skills	n/a	n/a	n/a	-.32**	.18	.73
Substance Use	n/a	n/a	n/a	-.42*	.32	.65

* $p < .10$.

** $p < .05$.

*** $p < .01$.