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PARTICIPATION IN UNIVERSAL PREVENTION PROGRAMS

By

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Abstract

We analyze the decision to participate in community-based universal prevention programs through the framework of prospect theory, with family functionality, and related risk status, providing the reference point. We find that participation probability depends on the relative ratios of the weighting and valuation functions. Using data from the Strengthening Families Program and the Washington Healthy Youth Survey, we empirically test the implications of our model. We find that family functionality affects the participation decision in complex and, in some cases, non-linear ways. We discuss the implication of these findings for cost-effectiveness analysis, and suggest directions for further research.

Introduction

Most studies measuring the potential benefits of drug abuse prevention programs are based on randomized clinical trials (RCTs). But when universal programs are implemented in a community, participation may be non-random[1], in which case the benefits observed in practice may be appreciably different from those observed in RCTs[2]. 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 successful, 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 prospect theory (PT) to explain self-selection into community-based substance abuse prevention programs. We predict that risk status, which is related to initial family functionality, will have a significant impact on family decisions to participate in such programs. In the context of PT we argue that a family's functionality gives it a reference point that skews both the valuation of any gain from participating in a program and the perceived probability of program success. Thus we are able to explain the likelihood of participating in a program based on a family's characteristics, including measures of functionality. We test the conjectures from this model with data from the Strengthening Families Program for Parents and Youth 10-14 (SFP) in Washington State.

In the next section we offer further detail of the literature covering selectivity issues in community-based prevention programs. Following that we develop a PT 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

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[1] For 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.

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

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 usually deal with constructs derived from the health belief model, protection motivation theory, theory of reasoned action, and subjective utility theory (for a review and comparison of these theories see Weinstein (1993)). Spoth and Redmond (1995) note that "all of these models and theories can 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). These studies have found that families with lower socioeconomic status are more likely to report privacy concerns and logistical barriers (Haggerty et al., 2002; Heinrichs, Bertram, Kuschel, & Hahlweg, 2005; Spoth, Redmond, Haggerty, & Ward, 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, Redmond, Hockaday, & Shin, 1996). In addition, several studies have found that positive family functionalities, including clear communication patterns, and family organizational skills, are positively related to program participation (Bauman, Ennett, Foshee, Pemberton, & Hicks, 2001).

Prospect Theory and Self-Selection

Prospect theory was first introduced by Kahneman and Tversky (1979) as an alternative to expected utility theory for modeling decisions under risk. The primary difference between prospect theory and expected utility theory is that in the former individuals make decisions under uncertainty based on marginal effects while in the latter decisions under uncertainty are made based on final outcomes. So in PT individuals assign values to gains and losses relative to a *reference point*. This is in contrast to expected utility theory where values are placed on final states and the alternative with the largest overall value is then chosen. Moreover, prospect theory assumes that people assign subjective probabilities to specific outcomes. As a result the overall value of a given prospect is measured by:

$$V(x, p, y, q) = \pi(p)v(x) + \pi(q)v(y) \quad (1)$$

where x and y are potential outcomes that occur with probabilities p and q respectively. The decision weights, $\pi(\cdot)$, measure not only the impact of the perceived probabilities on the overall value of the prospect, but also the influence of event ambiguity. Most empirical evidence suggests that $\pi(p) < p$, and $\pi(p) + \pi(1-p) < 1$ (Camerer, 1998; Kahneman & Tversky, 1979, 2000). However, often small probabilities tend to be over weighted, in which case $\pi(p) > p$. The value functions, $v(\cdot)$, measure the value of gains and losses relative to the reference point. This function is believed to be concave for gains and convex for losses, giving it an S-shape (see examples in Figure 1). The function passes through the reference point, and it is normally assumed to be steeper for losses than gains, indicating risk aversion. However, decision weights that overweight low probability events and underweight high probability events can cause some people to be risk seeking for potential losses and risk averse for potential gains (Camerer, 1998; Kahneman & Tversky, 1979, 2000).

The application of PT to preventive health behavior is well established, though studies that particularly address family participation in prevention programs are rare. One such study by McDermott (1998) compares PT to the health beliefs model, the theory of reasoned action and self-efficacy theory as explanatory theories for participation in AIDS prevention. McDermott notes that, because of its emphasis on the context of the decision-making situation, “prospect theory provides an alternative and useful model for understanding adolescent risk behavior.” Other applications of PT in preventive health include Meyerowitz and Chaiken (1987), who found that negatively framed information led to increased breast self-examination. It has also been shown that negative framing may be more persuasive when the perceived efficacy of a solution is low (Block & Keller, 1995). This might be the case, for example, when trying to promote preventive measures for diseases. Bleichrodt and Pinto (2000) stress the importance of probability weighting in medical decisions after finding significant evidence of its existence. The importance of evaluating outcomes relative to a reference point has been empirically observed in health by several studies (McNeil, Pauker, Sox, & Tversky, 1982; van Osch, van den Hout, & Stiggelbout, 2006) .

Prospect theory can be easily adapted to the decision to participate in a universal prevention program. Adapt equation (1) to expresses a family's perceived value of participating in a prevention program against not participating. A family chooses to participate only if the prospect of participating in the program is greater than the prospect of not participating (which we scale to zero), hence

$$V(x, y, p, q) = \pi(p)v(x) + \pi(q)v(y) > 0 . \qquad (2)$$

In equation (2), p is the probability of the program being a success, x represents a successful outcome and v(x) is the net value of the successful outcome, which we characterize as a marginal decrease in the risk of substance abuse. The argument q is the probability that the program is not successful, y represents an unsuccessful outcome and v(y)<0 represents the net value of an unsuccessful outcome. We assume that participation in the program will not make substance abuse more likely so y is equal to the costs (both direct and indirect) of participating in the prevention program.[3] The left hand side of the inequality is the prospect value of participating in the program while the right hand side is the value of not participating, which, as noted, we set equal to 0 since nonparticipation means there is no change in the probability of substance abuse. Rearranging (2) we can see that a family will participate in the program if

$$\frac{-v(x)}{v(y)} > \frac{\pi(q)}{\pi(p)} > 0 . \qquad (3)$$

Analysis of this inequality suggests that family functionality will impact the decision to participate in prevention programs.

First, assume that the right hand side of the inequality is the same for both more and less functional families. Differences in participation across family types would then be the result of their relative valuation of program success and failure. Recall that y [and in a simple case v(y)] is equal to the costs of program participation, with no program benefit. It is likely that this cost will be higher for less functional families because of their lack of family management skills (e.g. convincing and organizing the family to attend the program may entail higher costs). This suggests that higher functioning families would be more likely to attend the program.

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[3] Our discussion implies that if y is the outcome there is no decrease in the risk of substance abuse. It is easily generalized, with no change in the results, to the case where the risk of substance abuse drops but the costs of participation are sufficiently large so that v(y)<0.

Alternatively, it may be that less functional families recognize that they are in trouble and thus have a higher v(x) than higher functioning families. More precisely, compare a less functional family to a more functional family. *Assuming* children in a less functional family are more prone to substance abuse, then given the current level of risk the less functional family should value a 10% reduction in the risk of substance abuse more than a highly functional family because of diminishing marginal utility. If this is the case, we would expect less functional families to be more likely to participate.

Both these possibilities, the costs (and valuations thereof) of participation being higher for less functional families and the valuation of a marginal decrement in the risk of substance abuse being higher for less functional families are illustrated in Figure 1. The bold curve represents the more functional family and the thinner curve represents the less functional family. The valuations are on the *change* in the risk of substance abuse minus the cost of the program; hence, since we are talking about change from their respective status quo, both curves go through the origin.

Now assume that the left hand side of the inequality is the same for both higher- and lower-functioning families. Differences in participation across family types are now the result of the families' relative subjective probability of success and failure. If less functional families have lower perceived expectations that the program will have a positive outcome, perhaps because of problems in family functionality, then higher-functioning families are more likely to participate in the program.

Given our assumptions regarding valuations and perceived probabilities we now have a testable hypothesis. If less functional families are more likely to participate in the program, then, under our assumptions on costs of participation and perceived program success, we know that family functionality strongly affects the relative valuation of a positive outcome since the value of a positive outcome relative to the costs is higher for the less functional family than for the more functional family. In fact, it would argue that less functional families place very large values on a marginal decrease in the risk of substance abuse (large enough to overcome potentially greater costs of participation). On the other hand if more functional families are more likely to participate in the program, then we know that an alternative explanation holds[4].

Our prospect theory model can be viewed as an extension of previous work which uses value expectancy approaches to model program participation. The advantage of incorporating prospect theory is that it accounts for the fact that value expectations are often systematically biased in predictable ways. If we treat logistical barriers, privacy concerns, positive family interaction and family communication skills as factors which increase or decrease the costs of the program, these predictors become easily incorporated into our model. We can incorporate other predictors from the literature, such as parental perception of program benefits and positive therapeutic alliance as arguments affecting the probability weights of our model. Our model then analyzes the role of family functionality *given* these other predictors.

In the next few sections of this paper we discuss an empirical analysis to establish whether a reference point related to family functionality affects the likelihood that a family will participate in a community-based prevention program, and if so, how. The analysis offers an empirical test of our hypothesis.[5] Given our findings we discuss the implications for cost-benefit analysis of community-based programs.

Data

We test the implications of our theoretical model by examining participation in the Strengthening Families Program (SFP). The rigorous clinical efficacy trial of SFP, a universal seven-week program for parents and youth aged 10-14, has produced solid evidence of long-term effectiveness in delaying onset and frequency of adolescent substance use (Foxcroft, Ireland, Lister-Sharp, Lowe, & Breen, 2003; Spoth, Redmond, & Shin, 2001).

We use data from multiple sites in a statewide dissemination of SFP. A survey that program participants were asked to complete included questions that assess family functionality

[4] Such alternatives include that the relative valuation of outcomes is higher for more functional families, or that the relative valuation is indeed higher for less functional families, but this effect is dominated by greater participation costs or pessimistic probability weightings.

[5] A complete description of the data and empirical approach is given in XXX (2008) (suppressed for anonymity).

dimensions targeted by SFP[6]. The collected data assessed opportunities for prosocial involvement, rewards for prosocial involvement, family management and peer social 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). 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 opportunities and rewards for prosocial involvement, 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 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 individual response rate across grades was 65%. Our dataset included 8294 complete observations for younger children (those that responded to questions regarding rewards and opportunities for prosocial involvement) 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.

Analytic Approach

The difficulty in analyzing choice-restricted and supplementary 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. Steinberg and Cardell (1992) address this issue and develop an appropriate weighting procedure for analyzing this data in a pseudo-logistic regression. As

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[6] To enable comparison of program attendees with non-attendees, the SFP evaluation include measures assessing risk and protective factors that, besides being targets of the program, are also collected in a biennial statewide school survey known as the Healthy Youth Survey, which serves as our supplemental data set.

this regression procedure is rarely used, we include details on its implementation in the Appendix.

Our dependent variable is participation in the program and our variables of interest are the various scales that measure family functionality. We include as covariates gender, age, race, and substance use (this last variable is only available for those in 8th and 10th grade). Specification tests suggest quadratic terms be used for two variables of interest (rewards for prosocial involvement and opportunities for prosocial involvement), while linear terms are indicated for the other variables of interest.

Results and Discussion

In Table 2 we present results of the Steinberg-Cardell regression using the logistic probability function. 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 curvilinear; see Table 3 for non-linear coefficients) and controlling for youth race/ethnicity, sex, county, and age. For older youth the substance use index 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. In the older group, the opposite was true: families with male children were more likely to attend, as were Latino and Pacific Islander and Native American families. 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 to test for the effects of family functionality factors on program participation. Preliminary analysis indicated that second-order terms for functionality 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 (see Table 1b). The presence of the squared terms in the younger group means this caution is even more important, as one must compute odds ratios using linear, squared and cross-product terms; hence the odds ratios are not constant. Figure 2 and Figure 3 show how the overall odds ratio (Figure 3) and marginal odds ratios (Figure 2) change with the indicated values for Rewards for Prosocial Involvement (Rewards) and Opportunities for Prosocial Involvement (Opportunities). Figure shows that families with scores of Rewards = 4.00 and Opportunities=1.71 have the highest odds ratio, which decreases with movement in any direction from that peak within the range of scale scores, while Figure shows the maximum marginal odds ratios occur at Reward=4.00 and Opportunities=1.70. Both these are computed at the mean of the other variable. Since the model for the older group uses only linear estimation, odds ratios are much more straightforward; lower scores on Family Management significantly predicted participation (OR = 0.725, $p < .04$), and drug use was negatively associated with program attendance (OR = 0.654, $p < .10$).

Our results provide evidence that family functionality affects the decision to participate in prevention programs. Lower scores on family management were a significant predictor of program participation, indicating that families with poor family management (those we might characterize as less functional) are more likely to participate. The coefficients on the terms for opportunities for prosocial involvement indicate that the probability of participation is maximized when the family is relatively high risk on this measure. Functionality measures for peer management skills and rewards for prosocial involvement, however, failed to have a significant impact on program participation.

If our prospect theory model is correct, the empirical results (that less functional families are more likely to participate) are consistent with the idea that family functionality is reflected more in the value function than in the perceived probability that the program will be successful or not in changing the child's risk of substance abuse.

Conclusions and Implications

Using Prospect Theory we explain selectivity in a universal program to decrease substance abuse. Moreover, we empirically test how a family's functionality, which we use to define the reference point for prospect analysis, affects the relative valuation of positive or negative outcomes of the program compared to the relative perceived probability of success or failure. Our results are consistent with less functional families placing greater value on a positive outcome relative to the costs of participation.

These results have significant implications for targeting programs designed to reduce the risk of substance abuse. If, as our findings suggest, less functional families value a marginal decrease in substance abuse risk more than higher functioning families, then social welfare may be increased by ensuring these programs are known and available primarily to families with functional problems.

Moreover, our results have implications when analyzing programs using cost-benefit or cost-effectiveness analysis. It is possible that the success of the program is correlated with the family functionality of the participants. If the program decreases the risk of substance use equally for all participants regardless of family functionality, *and* they value that risk reduction the same, then there is no reason to believe that benefit cost outcomes from RCT are incorrect. However, if the benefit of the program is correlated with family functionality or the valuation of the risk reduction is correlated with functionality then benefit cost estimates for the program will be biased if the distribution of family functionality among the participant population is different than that of the RCT population. For example, if lower-functioning families self-select into programs, and the program is more likely to change the risk of substance abuse for these families or they value the marginal increase more, then the benefit-cost estimate of the clinical trial would understate the true benefit of application. There is emerging evidence that prevention efforts are, in fact, disproportionately effective with higher-risk families and individuals (Spoth, Guyll, & Day, 2002; Spoth, Trudeau, Shin, & Redmond, 2008). On the other hand, evidence from clinical trials, unlike the evidence from our community-based program, suggests that lower-functioning families are less likely to attend community-based programs (Haggerty et al., 2002).To further understand the implication of our results, we must learn more about the relationship between program success and family functionality, and the valuation of program success. We see this as a direction for future research.

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 which 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 essentially 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

$$LL(b) = \sum_{i=1}^{N} Y_i \log P_i + \sum_{i=1}^{N} (1-Y_i)\log(1-P_i) \tag{4}$$

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 (5). 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 sample[7]. Then the likelihood function in (5) can be rewritten as

$$LL(b) = \sum_{i=1}^{N} \log(1-P_i) + \sum_{\substack{i=1 \\ i \text{ such that } Y_i=1}}^{N} \log(P_i) - \sum_{\substack{i=1 \\ i \text{ such that } Y_i=1}}^{N} \log(1-P_i) \tag{5}$$

[7] This assumption is note needed for application, but is included to make the sums in (5) exact.

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, or the supplementary sample, and is equivalent to erroneously treating every observation in the sample 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 response 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:

$$LL(b) = \sum_{i=1}^{N} \log(1-P_i) + \frac{r_0}{r_1} \sum_{i=N+1}^{I} \log(P_i) - \frac{r_0}{r_1} \sum_{i=N+1}^{I} (1-P_i) \qquad (6)$$

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 beta[8].

[8] Cosslett (1981a, 1981b) 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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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)$^{\alpha}$				Ages (13-16)$^{\beta}$			
		HYS		SFP		HYS		SFP	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Male	0,1	.48	.0056	.46	.035	.47	.50	.56	.50
Age	11-16	11.28	0050	11.42	.035	13.29	.48	13.57	.74
White	0,1	.522	.0056	.635	.034	.645	.48	.468	.50
Black	0,1	.020	.0016	.025	.011	.027	.16	.012	.10
Asian/Pacific Island	0,1	.048	.0024	.025	.011	.050	.22	.032	.18
Hispanic	0,1	.167	.0042	.195	.028	.169	.37	.340	.47
Native	0,1	.096	.0033	.065	.017	.056	.23	.106	.11
Other	0,1	.21	.0045	.055	.016	.093	.29	.050	.20
Reward$^{\alpha}$/ Fam. Mgmt$^{\beta}$	1-4	3.42	.0072	3.37	.045	3.31	.64	3.21	.61
Involve$^{\alpha}$/Peer Skills$^{\beta}$	1-4	3.19	.0079	2.89	.049	3.10	.73	2.86	.78
Substance Use	0,1	n/a	n/a	n/a	n/a	.209	.41	.234	.43

Table 2: *Summary of Steinberg-Cardell Psuedo- 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*

	Ages 11-12			Ages 13-16		
Predictor	*B*	*SE B*	e^B	*B*	*SE B*	e^B
Male	-.137	.147	.872	.116	.224	1.12
Hispanic	-.342**	.203	.710	.748***	.271	2.11
Native American	-.875***	.304	.417	.566*	.383	1.76
Asian/Pacific Islander	-.698*	.459	.498	-.0969	.574	.908
Black	-.287	.463	1.33	-.634	.962	.531
Other	-1.80***	.330	.165	-1.11**	.612	.330
Rewards for Involvement$^{\Psi}$			1.75	n/a	n/a	n/a
Opportunities for Involvement$^{\Psi}$			.167***	n/a	n/a	n/a
Peer Social Skills	n/a	n/a	n/a	-.0369	.184	.964
Family Management Skills	n/a	n/a	n/a	-.321**	.176	.725
Substance Use	n/a	n/a	n/a	-.424*	.321	.654

*$p < .10$. **$p < .05$. ***$p < .01$.

$^{\Psi}$*The marginal odds ratio for these variables is calculated at the mean for the HYS participants. Because these variables enter the equation in a nonlinear way, the beta estimates and standard errors cannot be interpreted in the classical way. Beta estimates and standard errors for these non-linear terms are given below. Significance results are reported using the delta method.*

Table 3: *Summary of non-linear terms in Steinberg-Cardell Psuedo-Logistic Regression*

Age 11-12

Variable	*B*	*SE B*	e^B
Reward	.538	1.03	1.71
Involve	1.36	.801	3.88
Reward Squared	-.0188	.214	0.981
Involve Squared	-.449	.167	.636
Reward*Involve	.0500	.275	1.05

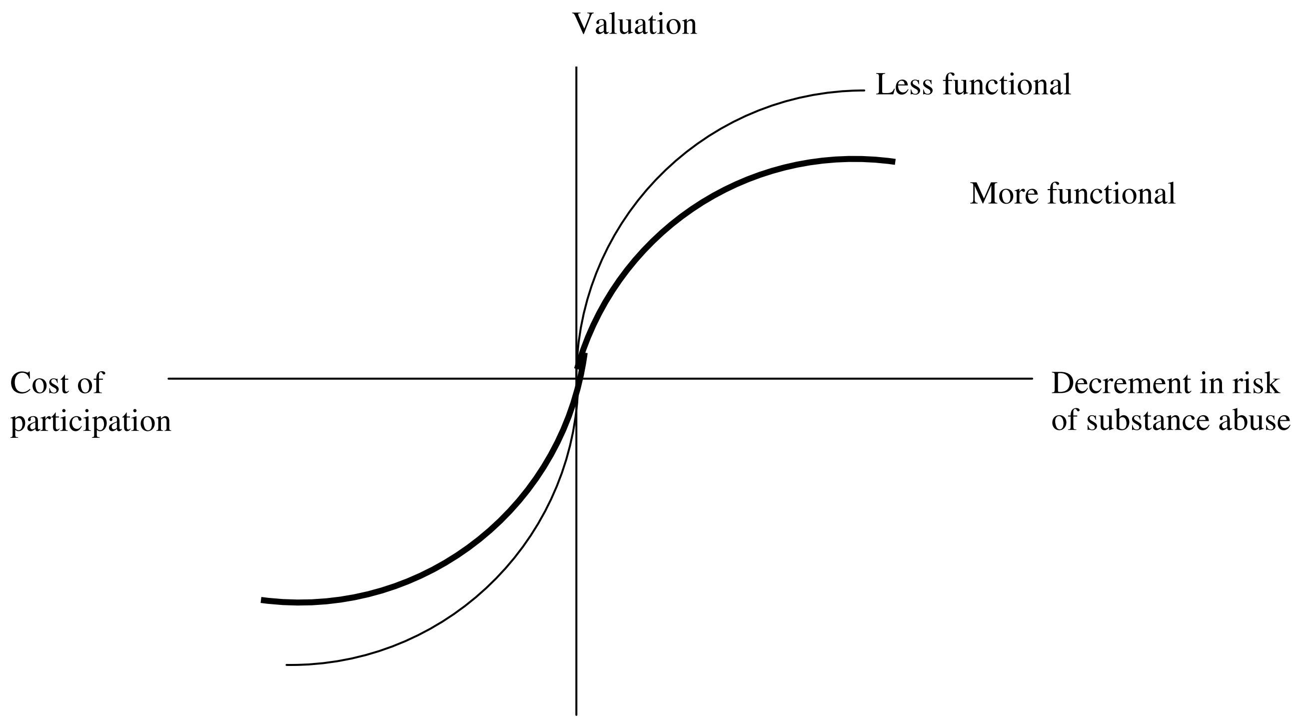

Figure 1: Prospect Valuations of Less and More Functional Families

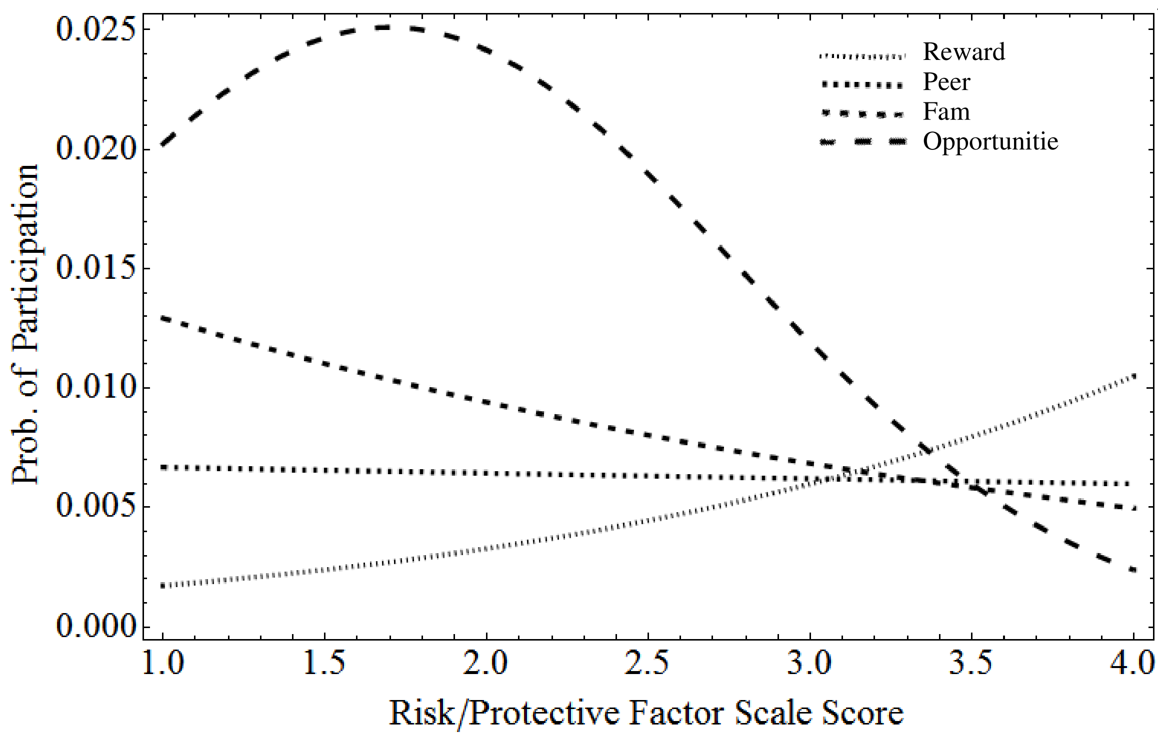

Figure 2

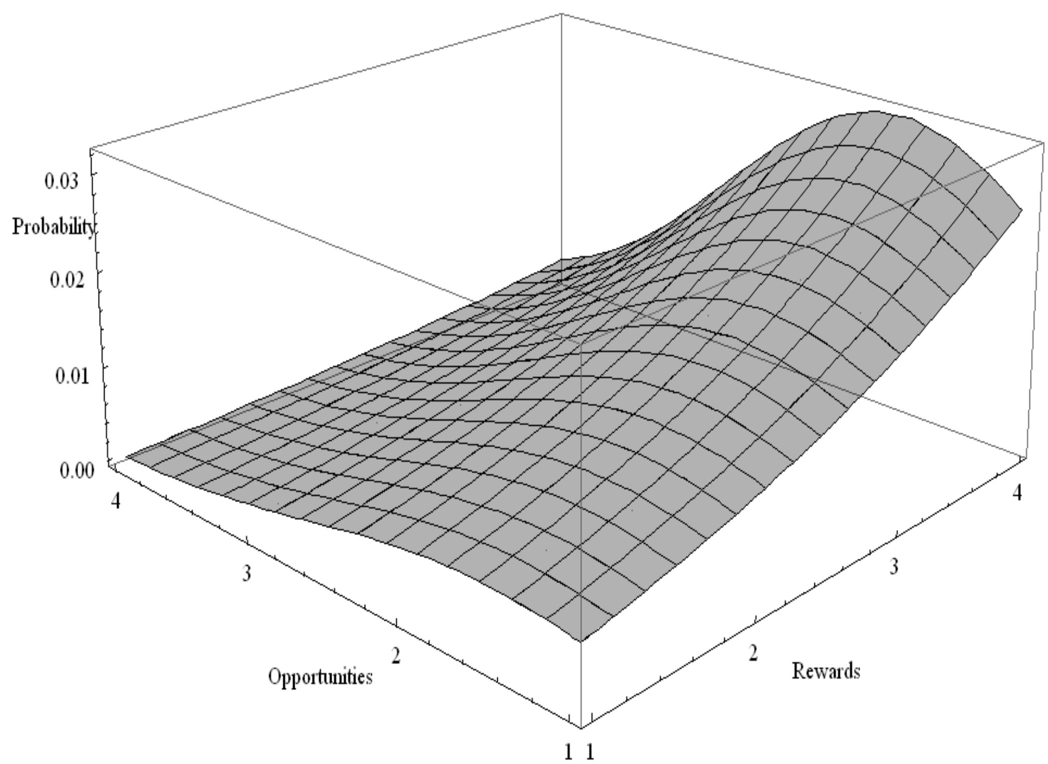

Figure 3