Parental Learning and Teenagers' Risky Behavior

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Extended Abstract
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1 Introduction

It is well documented that teenagers engage in risky behaviors at high rates. Usually these behaviors occur without parental consent and teens invest resources to preclude parents from knowing whether and to what extent they engage in such behaviors. This may give rise to parental incentives to learn about their children by paying close attention to observable "signals" of the underlying risky behavior. Moreover, parents can set up parenting rules which are contingent upon the realization of these signals in an effort to control their children's behavior. We explore a game theoretic model of parent-child interactions and propose an empirical strategy to identify the equilibrium reaction functions that determine teenagers' risky behavior and parenting rules. In preliminary work, we estimate approximations to these reaction functions using data on teen risky behavior and stringency of parental rules from the National Longitudinal Survey - Young Adults (NLS-YA)

2 The Model

Parents cannot observe their child's risky behavior a. However, parents observe a vector of indicators b of their child's risk-taking behavior. We refer to b as the signal and let

$$b = B(a, \varepsilon) \tag{1}$$

where ε is random noise with variance σ_ε and it is uncorrelated with a. Parents and children play repeated rounds so behaviors and signals may vary over time. Parents may attempt to limit the ability of their children to engage in risky behaviors by establishing parental rules whose stringency we denote by r. We assume that these rules are effective in limiting the child's risky behavior possibilities to a set $\{a : a \in A(r)\}$, but can only be enforced and monitored at a cost $C^p(r)$ to the parent. Moreover, these rules inflict a static utility cost $C^C(r)$ on the child (e.g. loss of privileges or autonomy). It is is instructive to think about $C^C(r)$ as the difference between a constrained and an unconstrained static utility maximization problem. Let ω denote a parameter characterizing the teenager's

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preferences for risky behavior. Then, $C^C(r) = \max_a \{u_c(a;\omega)\} - \max_{a\in A(r)} \{u_c(a;\omega)\}$. Note that $C^C(r)$ would be zero for those teens who dislike risky behavior. However, is it likely that this kids will face a utility cost if their social life gets limited by some very stringent parental rule (e.g. in the event of an unlucky draw from $f(\varepsilon)$). Therefore, while it is conceptually important to treat r as a constraint, it is more general to allow for it to have a direct impact on utility, above and beyond the disutility that potentially arises from limited opportunities for risky behavior.

We assume that parents are not perfectly informed about their own child's preferences for risky behavior ω but they start the game holding a prior about it, denoted by $G_0(\omega)$.[1] Based upon this prior, parents set an initial parenting rule r_0. At the beginning of the first period, the child chooses an initial risky behavior a_0 from the set given by $A(r_0)$ in order to maximize expected utility. After that, Nature draws noise ε so that by the end of the period, the signal b has been realized. Then parents can act upon b when setting the parental stringency that will prevail in the next round of the game. The child's optimal initial reaction function is given by

$$a_0^* = c_0(\omega, r_0, G_0) = \arg\max_{a_0\in A(r_0)} \left\{u_c(a_0;\omega) + \beta E\left[V^C(G_1;\omega)|a_0;G_0\right]\right\} \tag{2}$$

with

$$V^C(G_1;\omega) = \max_{a_1\in A\left(r_1^*(G_1)\right)} \left\{u_c(a_1;\omega) + \beta E\left[V^C(G_2;\omega)|a_1,G_1\right]\right\} \tag{3}$$

Note that the expectation in (2) is taken over the distribution of ε_0, the noise in the signal function for the first period. Intuitively, for a given risky behavior a_0, different realizations of ε_0 will give rise to different observable signals b_0, which will lead parents to differentially update their prior (from G_0 to G_1) and set next period's parenting rule $r_1^*(G_1)$ accordingly.

In general, for any $t = 1, ...T$ we have

$$a_t^* = c_t(\omega, r_t, G_t) = \arg\max_{a_t\in A(r_t)} \left\{u_c(a_t;\omega) + \beta E\left[V^C(G_{t+1};\omega)|a_t;G_t\right]\right\} \tag{4}$$

with

$$V^C(G_{t+1},\omega) = \max_{a_{t+1}\in A\left(r_{t+1}^*(G_{t+1})\right)} \{u_c(a_{t+1};\omega) + \beta E[V(G_{t+2};\omega)|a_{t+1},G_{t+1}]\} \tag{5}$$

Parents derive disutility $u_p(a)$ from their child's engagement in the risky behavior or lack thereof. They also face the above mentioned costs $C^p(r)$ of enforcing and monitoring a given parental stringency level r. Let parental utility at stage t be given by $W_p = u_p(a) - C^p(r)$. Then, with the initial prior in hand, parents set the initial rule optimally using

$$\begin{aligned} r_0^* &= \arg\max_{r_0} \left\{E\left[u_p(a) - C^p(r_0) + \beta V^P(G_1)|G_0, r_0\right]\right\} && (6)\\ r_0^* &= \arg\max_{r_0} \left\{E\left[u_p(c_0(\omega, r_0, G_0)) - C^p(r_0) + \beta V^P(G_1)|G_0, r_0\right]\right\} \\ r_0^* &= r(G_0) && (7) \end{aligned}$$

with

$$V^P(G_1) = \max_{r_1} \left\{E\left[u_p(a_1) - C^p(r_1) + \beta V^P(G_2)|G_1, r_1\right]\right\} \tag{8}$$

In each subsequent round of the game, $t = 1, ..., T$ parents update their beliefs $G_{t-1}(\omega)$ using an updating rule based upon the last period signal b_{t-1}, as well as on the degree of information contained in the signal, $\frac{1}{\sigma_\varepsilon}$, and the current duration of the learning game t. We denote this updating rule by Ω,

$$G_t = \Omega\left(G_{t-1}, b_{t-1}, \frac{1}{\sigma_\varepsilon}, t\right) \tag{9}$$

[1] For example, if G_0 is normal, the parameters characterizing the prior would be $\mu_\omega = E[\omega]$ and $\sigma_\omega = Var[\omega]$. These paramters would then be sequentially updated trough the rounds of the game.

Further, denote by H the inverse mapping from signals b to risky behaviors a,

$$a = H(b, \varepsilon) = B^{-1}(b, \varepsilon) \tag{10}$$

Each round t, armed with the updated prior G_t, parents set a rule r_t to maximize their remaining expected utility,

$$r_t^* = \arg\max_{r_t} \left\{ E\left[u_p(a_t) - C^p(r_t) + \beta V^P(G_{t+1}) | G_t, r_t \right] \right\} \tag{11}$$

but

$$\begin{aligned} u_p(a_t) &= u_p(H(b_t, \varepsilon_t)) \\ &= u_p(H(B(a_t, \varepsilon_t), \varepsilon_t)) \\ &= u_p(H(B(c_t(\omega, r_t, G_t), \varepsilon_t), \varepsilon_t)) \end{aligned} \tag{12}$$

so we get

$$r_t^* = p_t(G_t) = \arg\max_{r_t} \left\{ E\left[u_p(H(B(c_t(\omega, r_t, G_t), \varepsilon_t), \varepsilon_t)) - C^p(r_t) + \beta V^P(G_{t+1}) | G_t, r_t \right] \right\} \tag{13}$$

where now the expectation is taken over both the distribution of ω and the distribution of ε_i and

$$V^P(G_{t+1}) = \max_{r_{t+1}} \left\{ E\left[u_p(a_{t+1}) - C^p(r_{t+1}) + \beta V^P(G_{t+2}) | G_{t+1}, r_{t+1} \right] \right\} \tag{14}$$

3 Empirical Specifications

Instead of structurally estimating the above dynamic game, here we estimate approximations to the optimal decision rules or "reaction functions" for the teenager and the parent. Assume the parenting policy for stringency level r is specified as a linear function of the mean $\mu_{\omega_{it}} = E_t[\omega_i]$ in the prior that parents hold at time t. If for simplicity we ignore the role of the current prior's variance we get,

$$r_{it} = \alpha_i + \beta_1 E_t[\omega_i] + \beta_2 Z_{it}^c + \beta_3 Z_{it}^p + \beta_4 I_{it}^p + \varepsilon_{it} \tag{15}$$

where we allow for additional determinants of parental rule setting given by $(Z_{it}^c, Z_{it}^P, I_{it}^p)$, with (Z_{it}^c, Z_{it}^p) a vector of time-varying common knowledge characteristics of the children Z_{it}^c and the parents Z_{it}^p and with I_{it}^p a vector of rule setting determinants which are only known to the parents.

Note that $\mu_{\omega_{it}}$ depend on $\mu_{\omega_{i0}}$ and on the information gathered in previous rounds of play. Now, the prior is not observable but we have some information about its determinants. For the moment, we can simplify things substantially, if we proxy the current prior's mean with the signal, b_{it}.

$$r_{it} = \alpha_i + \beta_1 b_{it} + \beta_2 Z_{it}^c + \beta_3 Z_{it}^p + \beta_4 I_{it}^p + \varepsilon_{it} \tag{16}$$

Note that b_{it} is likely to be endogenous in (16) because the risky behavior a_{it}, and thus the signal b_{it}, will be responsive to r_{it}. This induces correlation between b_{it} and ε_{it} that prevents straightforward estimation of β_1. However, we can exploit an instrumental variable I_{it}^c that influences teen's risky behavior a_{it} (and therefore the signal b_{it}) but is unknown to the parents, and so it cannot be conditioned upon when deciding on stringency level r_{it}.

Turning to the specification of $a_t = c(\omega, r_t, G_t)$, the teenagers's policy function regarding engagement in risky behaviors, we let

$$a_{it} = \gamma_i + \theta r_{it} + \gamma I_{it}^c + \delta(Z_{it}^c, Z_{it}^p) + \varphi_{it} \tag{17}$$

Note that the risky behavior decision depends on the stringency of parental rules, r_{it} and on the child's information set, which includes two types of child attributes: those that parents know Z_{it}^{c}, and those they don't know, I_{it}^{c}. Risky behavior also depends on one type of parental characteristics that are known to both, parent and child, Z_{it}^{p}.

Again, the game theoretic nature of the model implies that r_{it} is endogenous in (17) rendering OLS estimation of θ inconsistent. Here we rely on I_{it}^{p}, the time-varying and privately-known-to-parents drivers of parental stringency, as instrumental variables for r_{it}

We also specify an ordered probit models for the signal function (1) using a latent construct behind the discrete grade classification.

$$b_{it}^{*} = a_{it} + X_{it}\beta + \varepsilon_{it} \tag{18}$$

We also present a linear probability model for "good grades" (B or better)

4 The Data

To estimate the model, we exploit data from NLS-YA, a set of surveys administered to children of the original NLSY-79 female respondents, once they grew into late adolescence and early adulthood. The NLS-YA offers a unique opportunity to estimate this model because we are able to observe several measures of teenage risky behavior (including, drinking, smoking and drug use). More importantly, we are able to observe a measure of parental stringency that summarizes the degree of control that parents exert over the teenager. Finally, we are able to observe potentially valid signals of underlying risky behavior,(e.g. school performance). Also important, note that we are able to observe all these variables at least twice for each teenager.

As discussed in the previous section, the timing of the behavior and stringency observations may generate endogeneity in both estimating equations. Consistent estimation requires the existence of variables I_{it}^{p} to instrument for parental rule stringency in the teenager's behavior policy function, and variables I_{it}^{c} to instrument for the endogenous signal in the parental rule setting equation. To that end we note that NLS-YA provides detailed self-reports of respondents' subjective feelings of pressure exerted by her peers to engage in each of the risky behaviors of interest. These variables could be conveniently used for I_{it}^{c}, as parents are not likely to know the existence, let alone the intensity of such pressure, but may be considered important determinants of behavior. Regarding I_{it}^{p}, we are able to exploit the abundant information that we can observe about the parents in the NLSY-79 surveys. In particular, we can observe many things that the children are unlikely to know about their mothers, but that may explain parental rule setting. For example, we can recover the age (if any) at which the mother started engaging in each of the same risky behaviors we are analyzing for the children. This information is arguably unknown to children but may drive parental rule setting if parents refer to their own youthful experience with these behaviors as benchmark.

5 Preliminary Results

Table 1 presents preliminary estimates of the signal function. As we can see in both, Ordered Probit and Linear Probability Models, engaging in risky behaviors is shown to be correlated with lower grades. Moreover, the more intense or frequent is the risky behavior, the lower the grades.

Table 1 : Low Grades as A Signal of Risky Behavior

	Dependent Variable: School Grades							
	Ordered Probit	OLS	Ordered Probit	OLS	Ordered Probit	OLS	Ordered Probit	OLS
How often smoked cigs or used marijuana during the last30 days?								
	Tobbaco		Marijuana					
Less than once p/week	-0.279***	-0.120**	-0.107	-0.048				
	[0.103]	[0.047]	[0.106]	[0.049]				
1 to 2 p/week	-0.156	-0.108*	-0.303**	-0.065				
	[0.128]	[0.058]	[0.127]	[0.058]				
3 to 4 p/week	-0.714***	-0.187**	-0.442***	-0.135*				
	[0.160]	[0.073]	[0.162]	[0.075]				
5 to 6 p/week	-0.344**	-0.085	-0.906***	-0.282***				
	[0.166]	[0.076]	[0.226]	[0.102]				
Every Day	-0.626***	-0.220***	-0.550***	-0.198***				
	[0.055]	[0.025]	[0.137]	[0.063]				
# Drinks per day in the last 30 days					-0.024***	-0.010***		
					[0.006]	[0.003]		
How often drank last year?								
1 to 2 days							-0.108**	-0.015
							[0.047]	[0.022]
3 to 5 days							-0.120*	-0.028
							[0.066]	[0.030]
Every other month							-0.182***	-0.029
							[0.068]	[0.031]
1 to 2 times a month							-0.206***	-0.026
							[0.058]	[0.027]
Several times a month							-0.275***	-0.082**
							[0.081]	[0.037]
1 or 2 days a week							-0.393***	-0.159***
							[0.081]	[0.037]
Almost daily							-0.435***	-0.136**
							[0.144]	[0.067]
Daily							-0.618**	-0.219*
							[0.282]	[0.128]

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Ommited categories include "Didn't Drink" for how often drank in the past year? and "Didn't do it at all" for tobbaco and marijuana . For the ordered dependent variable the higher the category number the better the grade (i.e. category 1 is "less than C", category 2 is C, ….., category 7 is A- and category 8 is A)