



ELSEVIER

Available online at www.sciencedirect.com

SCIENCE @ DIRECT®

Journal of Economic Psychology xxx (2005) xxx–xxx

JOURNAL OF
**Economic
Psychology**www.elsevier.com/locate/joep

2 Preference formation, school dissatisfaction 3 and risky behavior of adolescents

4 Louis Lévy-Garboua *, Youenn Lohéac, Bertrand Fayolle

5 *TEAM (CNRS), Université de Paris I-Panthéon Sorbonne,*
6 *Maison des Sciences économiques, 106-112 Boulevard de l'Hôpital, 75647 Paris Cedex 13, France*

8 Abstract

9 School dissatisfaction is an important component of the subjective well-being of adoles-
10 cents associated with “risky behavior” like drug use, unprotected sex, norm violations and ille-
11 gal behavior. We extend the standard human capital model to joint human investment
12 (education) and disinvestment (risky behavior). Based on this model, we develop a general
13 dynamic framework to analyze the preference formation of children and behavioral change
14 at school. Once an educational norm is set by adults, children can rationally deviate from this
15 norm, while staying at school, after experiencing bad surprises like a school failure. The same
16 type of dynamic equation can be used in a sequence to predict education, satisfaction with
17 school, and a host of risky behavior. We test these assumptions with a unique panel data
18 set on American adolescents attending middle or high school. School dissatisfaction is found
19 to have a significant positive effect upon nine different types of risky behavior.

20 © 2005 Published by Elsevier B.V.

21 *JEL classification:* D12; D83; I12; I21; I31; Z13

22 *PsycINFO classification:* 2820; 3230; 3233; 3236; 3920

23 *Keywords:* Education; Satisfaction; Risky behavior; Preference formation; Economic behavior of children

* Corresponding author. Tel.: +33 1 44 07 82 45/48; fax: +33 1 44 07 82 47.
E-mail address: louis.levy-garboua@univ-paris1.fr (L. Lévy-Garboua).

25 1. Introduction

26 Children's behavior has received little attention in economic studies, partly be-
27 cause it does not fit with basic assumptions of the economic theory of choice. Chil-
28 dren have been implicitly described as "decision-takers" whom their parents can
29 control, manipulate or make decisions for, having no budget constraint and no pref-
30 erence of their own. Given the central place of children in many human investments
31 and consumer expenditures, and the growing prevalence among adolescents of "ris-
32 ky behavior" like drug use, unprotected sex, norm violations and illegal behavior,
33 the neglect of children's behavior does not seem to be warranted. Teenagers have
34 some control of their own time and effort and make decisions within bounds set
35 by adults. For example, parents may impose school enrollment and the postpone-
36 ment of regular legal work upon their children, but the latter are able to skip classes,
37 choose their friends and in-groups, have sex, smoke cigarettes or marijuana, steal in
38 supermarkets, etc. While adults set and inculcate the norms and sanctions, adoles-
39 cents make decisions of their own and may rationally choose to deviate from these
40 norms. However, their rationality is moderated by the fact that children do have
41 malleable preferences, discovering their unknown tastes and forming their future
42 habits through their own contingent experiences and exposure to other information.
43 Therefore, the conventional economic assumption of given and known preferences
44 would lead to extreme and unacceptable conclusions in the context of children's
45 behavior. Few would accept the claim that a child will base her behavior once and
46 for all over an extended period of schooling on the expectations that she formed
47 upon entering school without ever wanting to revise the latter. And equally few
48 would accept the alternative conclusion that a child will adopt the highly unstable
49 point expectations and behavior which would closely reflect her contingent percep-
50 tions at any moment in time. It is certainly more reasonable to believe that the child,
51 submitted to a sequence of dissonant cognitions, will feel uncertain of her own true
52 preference and revise her expectations and preference consistently conditional on
53 personal experience and other information (Lévy-Garboua & Montmarquette,
54 1996).

55 We develop a general dynamic framework to analyze the preference formation of
56 children and behavioral change at school. This theory is applied here to model the
57 interaction between education and risky behavior and show the causality exerted
58 by school disorders on risky behavior. In order to examine the trade-off between edu-
59 cation and risky behavior of adolescents, we posit these terms in the standard human
60 capital framework. Risky behavior is defined as any potential human disinvestment
61 as opposed to education which is what parents, teachers and legislators alike norma-
62 tively view as human investment. Risky behavior brings utility to an adolescent while
63 at school at the cost of depreciating her stock of human capital in the future. The
64 main prediction of our model of preference formation is that children, on experienc-
65 ing bad surprises like a school failure, may rationally deviate from the educational
66 norm set by adults while staying at school by substituting risky behavior for
67 education.

68 However, testing the latter prediction directly is not an easy task because many
69 surprises experienced by children at school and in other activities are not usually ob-
70 served in surveys. We propose to use self-reported school satisfaction as a convenient
71 variable for predicting changes in schooling and risky behavior of adolescents. This
72 follows Lévy-Garboua and Montmarquette's (2004) interpretation of job satisfaction
73 as the worker's experienced or post-decisional preference for her job in comparison
74 with alternatives. By a straightforward adaptation to children's behavior, we claim
75 that the child who reports her satisfaction or dissatisfaction with school manifests
76 her intention to either respect the current educational norm or deviate from it in
77 the near future in specified directions. Moreover, as the intention and subsequent
78 behavior reveal successive states of the child's preference, *the same type of equations*
79 can be used *in a sequence* to predict both school satisfaction and future risky behav-
80 ior. This is implemented with unique panel data (*Add Health* survey) on the health-
81 related behaviors of US adolescents attending middle or high school. School dissat-
82 isfaction is found to have a significant positive effect upon nine different types of
83 risky behavior.

84 The theoretical foundations of the paper are provided in Sections 2 and 3. We ex-
85 tend the standard human capital model to joint human investment (education) and
86 disinvestment (risky behavior). Based on this model, we develop a general dynamic
87 framework to analyze the preference formation of children and behavioral change at
88 school. Data and empirical strategy are described in Section 4. Then the main results
89 are presented and discussed in Sections 5 and 6. Section 7 concludes.

90 2. A dynamic model of education and risky behavior of adolescents

91 2.1. A human capital model of investment in education and disinvestment in risky 92 behavior

93 We describe the rational behavior of adolescents who should normally attend
94 middle or high school. It is assumed that they are conscious of the investment value
95 of schooling and devote time and effort to their own education in relation with the
96 returns that they expect to derive from the latter in their future working life. How-
97 ever, in contrast with older students and adult workers, they depend materially and
98 financially on one parent or tutor at least, and are unwilling or unable to work for
99 their living.¹ The child lives $T + 1$ periods. Schooling is the current period followed
100 by T periods of working life. In order to examine the trade-off between education
101 and risky behavior of adolescents, we posit these terms in the standard human cap-
102 ital framework. "Education" is taken in the broad sense of human capital, which
103 includes schooling, a healthy lifestyle and all leisure activities (e.g., sports, piano
104 lessons) that parents and teachers normally consider as investments in health,

¹ Summer and occasional work is allowed insofar it does not prevent the adolescent from performing any of her school duties.

105 education and cultivation of taste. Symmetrically, activities which do not fit into this
 106 normative definition are “risky behavior” that parents and teachers view, from their
 107 own perspective, as a potential *human disinvestment*. This meaning of risky behavior
 108 is much broader than the economic usage of risk-taking activities like gambling as it
 109 applies to a variety of activities that bear a deferred risk of capital loss or social sanc-
 110 tion, like drug use, unprotected sex, norm violations and illegal behavior. However,
 111 the explicit treatment of risk would not change our main conclusions, and will not be
 112 pursued here for expositional convenience. Consequently, the trade-off between edu-
 113 cation and “risky behavior” can be studied very simply with a human capital model
 114 by allowing for the possibility of both investing *and* disinvesting in human capital.
 115 The future returns to human disinvestments are negative, and can be viewed as po-
 116 sitive depreciation of the stock of human capital.

117 Let e denote the time devoted to education and l the time devoted to risky behav-
 118 ior by an adolescent attending school, with

$$e + l = 1, \quad 0 \leq e, l \leq 1. \quad (1)$$

122 The normative expectation of child’s behavior is

$$l^* = 0. \quad (2)$$

126 However, parents and teachers are unable to monitor the child in such a way that she
 127 educates full time. They merely see to her attending school and not working (even
 128 beyond the age of compulsory education). The child remains free to allocate her
 129 own time between education and risky behavior under the constraint: $e > 0, l < 1$.
 130 Her utility function can be described by the expected present value of school

$$V = v(l) + \frac{y}{i} \quad (v' > 0, v'' < 0). \quad (3)$$

134 In Eq. (3), y designates the expected permanent earnings of the child in her working
 135 life, i the child’s positive discount rate (corrected for the finiteness of life) and $v(l)$ the
 136 utility that the child derives from time devoted to risky behavior during the schooling
 137 period. Future earnings of the child are produced by the initial stock of human cap-
 138 ital and ability, denoted h , as well as by further investments in education and disin-
 139 vestments in risky behavior:

$$y = h(1 + re - al). \quad (4)$$

143 The rate of return to education r is assumed to be positive, and the rate of depreci-
 144 ation due to risky behavior a is typically positive but might be negative for illegal
 145 behavior. The maximization problem which conditions the child’s allocation of time
 146 is easily derived from Eqs. (1), (3), (4) and $l < 1$

$$\begin{aligned} \text{Max}_l \quad & V(l) \equiv v(l) + \frac{h(1 + r - (r + a)l)}{i} \\ \text{s.t.} \quad & l \geq 0. \end{aligned} \quad (5)$$

150 It does not follow from (5) that the child’s optimum must coincide with the educa-
 151 tional norm (2) prescribed by her parents and teachers. This would only happen if

$$h \frac{r+a}{i} \geq v'(0). \quad (6)$$

155 For adolescents who adhere to the educational norm set by parents, teachers and leg-
 156 islators, the present value of education outweighs the marginal present value of risky
 157 activities net of future depreciation of human capital. The depreciation of human
 158 capital caused by risky behavior facilitates the child's compliance with the educa-
 159 tional norm. Eq. (6) allows us to define the latent *decision variable of the child* which
 160 conditions her education and risky behavior within the schooling period as

$$S^* \equiv h \frac{r+a}{i} - v'(0). \quad (7)$$

164 This latent variable is unobservable, but adherence to the educational norm (and
 165 risky behavior) is captured by a variable S which takes a discrete number of values.
 166 With just two values for instance

$$\begin{cases} S = 1 & \text{if } S^* \geq 0, \\ S = 0 & \text{if } S^* < 0. \end{cases} \quad (8)$$

170 2.2. A dynamic model of behavioral change at school

171 The new important point we wish to make at this stage is that all the parameters
 172 entering the child's latent decision variable (7) and conditioning the discrete choice
 173 (8) are revisable cognitions conditional on personal experience and other informa-
 174 tion. The static model of investment/disinvestment presented in the last sub-section
 175 would obtain if the latter were known with certainty at any moment in time. How-
 176 ever, given the great amount of experience that a child may encounter over her ex-
 177 tended period of schooling and the contingent nature of perception, it is more
 178 reasonable to believe that the child has no given preferences and feels uncertain of
 179 her own true preference. This general assumption is introduced by treating the child's
 180 expectation $\tilde{E}S^*$ as *stochastic* (Lévy-Garboua & Montmarquette, 1996). Thus, sur-
 181 prises experienced by an adolescent at school may lead to revised expectations and
 182 behavioral change within the boundaries of schooling.²

183 To model this, we divide the schooling period into a number of sub-periods which
 184 usually coincide with grades and school years. The decision process is illustrated by
 185 Fig. 1. The child makes a decision of education and risky behavior at the beginning
 186 of sub-period t ($1 \leq t \leq n$) which is dictated by ES_{t-1}^* , then experiences a contingent
 187 value of the decision variable $S^*(t)$ during sub-period t , revises her expectation into
 188 ES_t^* in the light of this new information, makes a new decision at the beginning of
 189 sub-period $t+1$ and so on. For a quadratic cost of error, the rational expectation
 190 at the beginning of any sub-period is also the mean value at this date. It will be

² Lévy-Garboua (1976) has used a similar argument to explain the anomalous behavior of French students in the 1970s, confronted with an unexpected decline in the rate of return to education (a bad surprise) at the upsurge of mass universities. Students reacted by diminishing their education time and effort while staying at university.

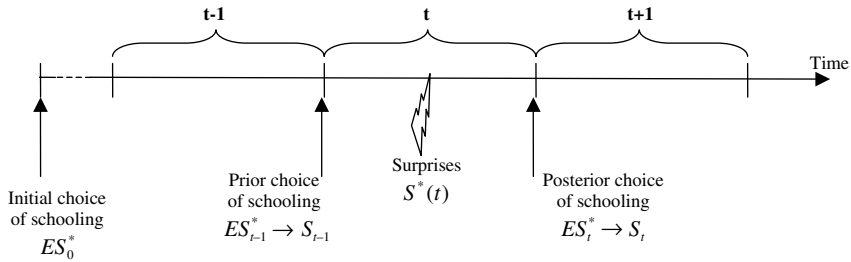


Fig. 1. The child's decision process.

191 assumed that the sequence $S^*(1), \dots, S^*(n)$ is a random sample from a stable normal
 192 distribution \tilde{S}^* with an unknown value of the mean ES^* and precision (inverse of var-
 193 iance) $\tilde{\theta}$. Suppose also that the prior joint distribution of ES^* and $\tilde{\theta}$ is as follows: the
 194 conditional distribution of ES^* when $\tilde{\theta} = \theta$ ($\theta > 0$) is a normal distribution with a
 195 finite mean ES_0^* and precision $\tau\theta$ ($\tau > 0$) and the marginal distribution of $\tilde{\theta}$ is a
 196 gamma distribution with parameters α and β ($\alpha, \beta > 0$). Given the ordinal nature
 197 of the decision variable, we choose a monotonic transformation of (7) such that
 198 the prior mean can be assumed to be normal

$$ES_0^* = \log h_0 + \log(r_0 + a_0) - \log i_0 - \log v_0'.$$

201 Then, assuming a Bayesian revision of the probability distribution (see, for instance,
 202 DeGroot, 1970, chap. 9), the posterior conditional distribution of ES^* after t random
 203 *i.i.d.* experiences is also a normal distribution with mean:

$$ES_t^* = \frac{\tau + (t - 1)}{\tau + t} ES_{t-1}^* + \frac{1}{\tau + t} S^*(t), \quad (9)$$

207 and precision: $(\tau + t)\theta$. This can also be written³:

$$ES_t^* - ES_{t-1}^* = \frac{1}{\tau + t} (S^*(t) - ES_{t-1}^*) = \frac{\varepsilon_t}{\tau + t}, \quad (10)$$

211 with $\varepsilon_t \equiv S^*(t) - ES_{t-1}^*$ designating the surprise experienced by the individual during
 212 her t th experience. Eq. (10) depicts how the latent decision variable of a rational
 213 child confronted with dynamic uncertainty (surprises) changes with her experience
 214 of school and risky behavior. Behavioral change is *caused*, literally speaking (see
 215 Granger's Nobel lecture, 2004), by the experienced surprises in the short run, and
 216 behavior converges to a stable habit in the long run when surprises are serially inde-
 217 pendent. For instance, a school failure is a bad surprise that diminishes expectations
 218 of ability and educational returns. Bad surprises will drive the child to reduce the
 219 time and effort devoted to education and to increase the time and effort devoted
 220 to risky behavior. By iteration of Eq. (10), we get

³ The marginal distribution of $\tilde{\theta}$ is a gamma distribution with an experience-dependent mean value of the posterior distribution which increases indefinitely with experience.

$$ES_t^* = ES_0^* + \frac{1}{\tau + 1} \varepsilon_1 + \dots + \frac{1}{\tau + t} \varepsilon_t. \quad (11)$$

224 This last formulation of the decision process shows that an accumulation of bad sur-
 225 prises (for instance $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_t < 0$) may eventually lead ES_t^* to become negative even
 226 when ES_0^* was not. The adolescent is driven by the succession of bad experiences to
 227 breach the educational norm and indulge in risky behavior.

228 3. School dissatisfaction as a predictor of risky behavior

229 Since the decision variables ES_t^* are unobservable, a convenient variable for pre-
 230 dicting schooling and risky behavior of adolescents has to be found. A few psycho-
 231 logical studies have shown a significant positive relationship between life
 232 dissatisfaction of adolescents attending high school and their use of drugs (Zullig,
 233 Vallois, Huebner, Oeltmann, & Drane, 2001) and alcohol (Clark & Kirisci, 1996;
 234 Newcomb, Bentler, & Collins, 1986). Zullig et al. (2001) also suggest that risky
 235 behavior forms a bundle of correlated activities such that dissatisfaction with life
 236 might be related to other kinds of risky behavior as well. The results of Coker
 237 et al. (2000) from the same data set support the view that the causality runs from
 238 satisfaction to behavior but this causal link has not been firmly established by lack
 239 of a proper theory of risky behavior. Previous studies have generally taken a broad
 240 view of satisfaction and quality of life while they focused on a single aspect of risky
 241 behavior like alcohol and substance abuse. In contrast with earlier studies, we adopt
 242 here a narrower view of satisfaction with school but we examine its full impact on a
 243 very wide spectrum of risky behavior. By narrowing the scope of satisfaction to
 244 school, we gain insight on the interaction between education and risky behavior;
 245 by broadening the scope of risky behavior, we capture the multi-faceted nature of
 246 the latter. If risky behavior is a substitute for education, school satisfaction will be
 247 a more specific predictor for the risky behavior of adolescents than is life satisfaction.

248 The reason why dissatisfaction with school should *predict* risky behavior is simply
 249 that it reveals the child's *intention* to deviate from the current educational norm in
 250 the near future. This statement follows from a new interpretation of satisfaction
 251 judgments with respect to an individual experience (Lévy-Garboua & Montmar-
 252 quette, 2004). Self-reported satisfaction is identified to the discrete variable (S
 253 Eq. (8)) which relates to the decision of repeating the experience in the near future.
 254 For instance, job satisfaction expresses a worker's experienced or post-decisional
 255 preference for her job in comparison with alternatives. The model presented in Sec-
 256 tion 2 posits that such preference is known imperfectly and subject to changes caused
 257 by the surprises that were experienced in the past. Thus *the same* equations (8) and
 258 (9) can be used *in a sequence* to predict prior school choices (just before t), school
 259 satisfaction (between t and $t + 1$), and future school choices or risky behavior (just
 260 before $t + 1$). Panel data are especially appropriate for this purpose.

261 Since this is perhaps the first economic investigation of school satisfaction
 262 whereas job satisfaction has been extensively studied by economists in recent years

263 under the impetus of Clark and Oswald (1996), it can be useful to draw the parallel
264 between education and jobs in order to distinguish the specificities of school satisfac-
265 tion and school choices. The main similarity is that school choices and job choices
266 are decisions to invest in the future which can both be described in a human capital
267 framework. However, the returns to schooling lie essentially in the future since
268 investment in schooling is made early in life, while a 40-year old worker would have
269 already experienced a great part of the returns from her job decisions in the past.
270 School satisfaction is prospective whereas job satisfaction is partly retrospective.
271 As a result, school satisfaction should be a more accurate predictor of future educa-
272 tion behavior than is job satisfaction with respect to job mobility (Lévy-Garboua,
273 Montmarquette, & Simonnet, 2004). Another important difference between educa-
274 tion and jobs which is perhaps less visible is the following: a child who feels unhappy
275 at school will typically have fewer schooling alternatives than a worker who can turn
276 to the job market. A dissatisfied adolescent unable to shift from school to work is
277 almost inevitably confronted with risky alternatives, all the more so as people who
278 face the risk of a large loss become risk-seeking (Kahneman & Tversky, 1979).
279 Lastly, risky behavior breaking the educational norm is by nature more hidden
280 and diffuse than the simple exit-voice alternative to a bad job postulated by Hirsh-
281 man (1970). Our data set enables us to observe many types of risky behavior which
282 correlate with school dissatisfaction.

283 4. Data and empirical strategy

284 We used a unique large-scale survey, the National Longitudinal Survey of Ado-
285 lescent Health (*Add Health*, contractual data; Udry, 2003), which was carefully de-
286 signed to explore the causes of health-related behaviors of US adolescents
287 attending middle or high school (grades 7 to 12). Schools and students were drawn
288 from the US population with unequal probabilities in order to over-represent small
289 categories and obtain unbiased estimates by region, urbanization, school type,
290 school size, and ethnic origin (Harris et al., 2003). The same questionnaire was
291 administered in-home to a large sample of adolescents clustered in 52 middle schools
292 and 80 high schools. On the same occasion, another questionnaire was administered
293 to parents. The children who responded to the in-home questionnaire were observed
294 in two waves, in 1995 and 1996,⁴ with 14 738 adolescents still present in the second
295 wave out of 20 745 who had been participating to the first wave. Their educational
296 status and school satisfaction is described from the first wave of in-home interviews.
297 Eighteen manifestations of risky behavior (aggregated in eleven categories) are then
298 described from the second wave of in-home interviews.

299 Survey administrators took several steps to secure confidentiality of the data and
300 minimize biases from self-reporting. Respondents were not provided with any

⁴ A shorter questionnaire was administered in-school to 90 118 adolescents drawn from the same sample of schools about six months before the first in-home questionnaire. This questionnaire will not be used here.

301 printed questionnaire. The interviewer read the questions aloud and entered the
302 respondent's answers on a laptop computer. For sensitive topics like sexual and ille-
303 gal behavior or substance use, the adolescents even listened to pre-recorded ques-
304 tions through earphones and entered their answers directly on the laptops.

305 Since we interpret adolescents' satisfaction with school as their experienced pref-
306 erence for education versus risky behavior at the date of the first in-home survey, we
307 can use Eq. (11) of the theoretical model to predict school satisfaction. The latter is
308 explained by the prior value of this variable and by the sum of school surprises. The
309 prior schooling decision variable can be related to the child's background (sex, ethnic
310 origin). The sum of school surprises is partly captured by the gap between the child's
311 current school status and her normative expectation, which we call the "education
312 gap", and unexpected family events (absent father, absent mother). In addition,
313 school fixed-effects control for the child's specific school environment; and satisfac-
314 tion with health, parents, friends and neighborhood all together control for unob-
315 servable personality traits of the child and for her specific non-school environment.

316 We first estimate the education level and take the regression's residual to measure
317 the education gap. The latter is then incorporated in the school satisfaction equation
318 along with the other explanatory variables. It should have a positive effect on school
319 satisfaction. Testing the satisfaction equation permits to validate the suggested inter-
320 pretation of satisfaction judgments in a new domain. Finally, a wide spectrum of ris-
321 ky behavior can be predicted one period ahead by the dynamic equation (9). Each
322 form of risky behavior is explained by the same one-year lagged variable which de-
323 fines the child's prior state, school satisfaction one year back that captures the child's
324 intention to deviate from this prior state after experiencing surprises at school and in
325 other activities, and individual characteristics (age, grade, sex, ethnic origin, health
326 and family status) which may have a differential effect on each specific risky
327 behavior.

328 5. Education and school satisfaction

329 Table 1 shows the education equation and summary statistics. The dependent var-
330 iable of the education equation is the school grade that children had reached at the
331 time of the in-home survey. The education level of children is estimated by an or-
332 dered Probit since we observe six education grades (from 7 to 12) and the latter
333 are not entirely determined by age in the American educational system (20.10% of
334 the sample have repeated or been held back one grade, and 2.37% have skipped
335 one grade). After controlling for children's age, the results are in line with those
336 which have been commonly found in the economic literature. The role of differences
337 in economic opportunities across families is attested by the significant effect of paren-
338 tal income (with a positive sign) and number of siblings (with a negative sign), school
339 size and region (South). The role of differences in school choices and norms is also
340 present through the strong positive coefficients of parents' education, suburban resi-
341 dence and private school. The child's health captures an important aspect of ability.

Table 1

Estimation of school grade: Ordered Probit (6 levels) analysis (Add Health, In-Home I)

Variable	Description mean (%)	Estimation	
		Coefficient	(Standard error)
Female	50.03	0.304***	(0.021)
White	56.30	<i>Reference</i>	
Black	18.97	0.021	(0.029)
Hispanic	13.72	0.184***	(0.036)
Asian	4.66	0.156***	(0.053)
Other origin	6.35	0.041	(0.044)
Good general health	68.80	0.120***	(0.023)
Cohort: 11–13 years	12.33	<i>Reference</i>	
Cohort: 14 years	13.90	2.098***	(0.051)
Cohort: 15 years	18.21	3.788***	(0.060)
Cohort: 16 years	20.31	5.495***	(0.067)
Cohort: 17 years	19.18	7.148***	(0.073)
Cohort: 18–21 years	16.07	8.852***	(0.079)
Parents: education 1 ^a	11.68	<i>Reference</i>	
Parents: education 2 ^a	29.16	0.167***	(0.037)
Parents: education 3 ^a	22.13	0.319***	(0.040)
Parents: education 4 ^a	24.26	0.329***	(0.041)
Parents: education 5 ^a	12.77	0.376***	(0.047)
Parents: income 1 ^b	20.81	<i>Reference</i>	
Parents: income 2 ^b	28.61	0.204***	(0.031)
Parents: income 3 ^b	24.37	0.307***	(0.033)
Parents: income 4 ^b	26.21	0.336***	(0.035)
No brother neither sister	20.41	<i>Reference</i>	
One brother or sister	39.21	−0.04	(0.028)
Two brothers or sisters	25.21	−0.11***	(0.031)
More than 2 brothers or sisters	15.17	−0.23***	(0.035)
Region: North-East	14.77	<i>Reference</i>	
Region: West	22.88	0.074**	(0.036)
Region: Middle-West	25.91	−0.02	(0.034)
Region: South	36.44	−0.17***	(0.033)
School: small	14.56	−0.12***	(0.035)
School: medium	37.64	<i>Reference</i>	
School: big	47.80	0.310***	(0.026)
Rural area	17.25	0.021	(0.035)
Suburban area	53.73	0.154***	(0.026)
Urban area	29.02	<i>Reference</i>	
Private school	7.48	0.356***	(0.045)
Level 1		1.968***	(0.070)
Level 2		3.789***	(0.079)
Level 3		5.675***	(0.087)
Level 4		7.380***	(0.092)
Level 5		9.051***	(0.097)
<i>N</i>			13626
Log-likelihood			−11081.079
$\chi^2_{(29)}$			26382.424

Significance levels: * = 10%; ** = 5%; *** = 1%.

^a Highest school level of parents: 1 = more than 8th but not graduated from high school, 2 = high school graduate, 3 = went to college or other school, 4 = graduated from college or university, 5 = professional training beyond a 4 year college or university.

^b Parents' disposable income in 1994 (thousand US dollars): 1 = less than 20, 2 = between 20 and 40, 3 = between 40 and 60, 4 = more than 60.

342 Finally, the higher education level of girls, *ceteris paribus*, may be the consequence of
 343 girls' human capital being more severely depreciated than boys' by risky behavior
 344 like substance use, unprotected sex and violent behavior.

345 The education equation will now be used to calculate the education gap as the
 346 estimated residual. The predicted level of education for one adolescent i (\hat{s}_i) is defined
 347 as her *expected* grade among six possible grades:

$$\hat{s}_i = \sum_{k=7}^{12} k \cdot P \quad (s = k/i). \quad (12)$$

350 Probabilities of being in each grade k are computed from Table 1 given the observa-
 351 ble characteristics of adolescent i . This is more robust than the simple linear estima-
 352 tor (see Choi, Laibson, Madrian, & Metrick, 2003, for a recent application). The
 353 education gap is a continuous variable measured by the difference between the ob-
 354 served grade of adolescent (s_i) and her predicted level of education (\hat{s}_i).

355 In order to study school satisfaction, we use the following question from the *Add*
 356 *Health In-Home I* survey: "How do you agree or disagree with the following: You
 357 are happy to be at your school". Five ordinal answers are allowed: "strongly dis-
 358 agree", "disagree", "neither agree nor disagree", "agree", and "strongly agree".
 359 Two-thirds of the respondents were unambiguously "satisfied" as they agreed or
 360 strongly agreed with this statement. In Table 2, two decompositions of school satis-
 361 faction, which both respect the ordinal nature of the dependent variable, are intro-
 362 duced. The more detailed variable (5 levels) is estimated by an ordered Probit in the
 363 first two columns, and a simple dummy variable (satisfied/not satisfied) is estimated
 364 by a Probit in the next three columns. Including satisfaction as a dummy makes the
 365 presentation and interpretation of marginal effects of the explanatory variables very
 366 straightforward. It is reassuring to verify that these two regressions yield similar re-
 367 sults. Since reporting one's satisfaction with school is like repeating one's prior deci-
 368 sion of schooling in the light of additional experience, the satisfaction equation at
 369 date $t + 1$ is basically like the education equation at date t plus the additional effect
 370 of relevant surprises that occurred in the meantime. The addition of these contem-
 371 poraneous surprises and other variables in the regression permits the identification
 372 of all coefficients.

373 As predicted by Eq. (11), the education gap has a positive effect on 5-level school
 374 satisfaction which is significant at the 1% threshold (5% only for 2-level satisfaction).
 375 Since the education gap is uncorrelated with the education level, this result shows
 376 that satisfaction is caused by surprises, i.e., unexpected deviations from one's norma-
 377 tive expectation. Moreover, since two-thirds of adolescents are satisfied with their
 378 school, the average positive effect of good surprises on the satisfaction variable
 379 should be less than the average negative effect of bad surprises. We tested this con-
 380 jecture by splitting the education gap into two continuous variables, one for a posi-
 381 tive gap and another for a negative gap (regression not shown). Indeed, a positive
 382 gap had no effect on school satisfaction while a negative gap had a strong negative
 383 effect (significant at the 1% level). Adolescents should be more vulnerable to unob-
 384 servable negative shocks on their expected returns to education as the latter get smal-

Table 2

School Satisfaction equation: Ordered Probit (5 levels) and Probit analysis (Add Health, In-Home I)

Variables	5 level-school satisfaction		School satisfaction dummy		
	Coefficient	(Standard error)	Coefficient	(Standard error)	Marginal effect
Education gap	0.085***	(0.031)	0.083**	(0.038)	0.0300**
Female	-0.041	(0.019)	-0.036	(0.024)	-0.0131
White	<i>Reference</i>				
African-American	-0.071**	(0.033)	-0.089**	(0.041)	-0.0324**
Hispanic	0.006	(0.036)	0.039	(0.045)	0.0140
Asian	0.043	(0.052)	0.019	(0.065)	0.0070
Other origin	-0.042	(0.041)	-0.062	(0.051)	-0.0225
Education: grade 7	<i>Reference</i>				
Education: grade 8	-0.138***	(0.052)	-0.186***	(0.066)	-0.0688***
Education: grade 9	-0.205***	(0.080)	-0.266***	(0.100)	-0.0985***
Education: grade 10	-0.331***	(0.100)	-0.376***	(0.125)	-0.1404***
Education: grade 11	-0.403***	(0.122)	-0.461***	(0.153)	-0.1735***
Education: grade 12	-0.469***	(0.147)	-0.568***	(0.183)	-0.2160***
Age: between 11 and 13	<i>Reference</i>				
Age: 14	0.001	(0.051)	0.004	(0.064)	0.0016
Age: 15	0.040	(0.071)	0.051	(0.089)	0.0184
Age: 16	0.115	(0.091)	0.122	(0.113)	0.0430
Age: 17	0.150	(0.112)	0.164	(0.139)	0.0573
Age: between 18 and 21	0.154	(0.131)	0.189	(0.163)	0.0654
Satisfaction: parents ^a	0.232***	(0.027)	0.263***	(0.032)	0.0980***
Satisfaction: friends ^b	0.148***	(0.019)	0.141***	(0.024)	0.0503***
Satisfaction: neighborhood ^c	0.449***	(0.021)	0.467***	(0.026)	0.1599***
Good general health	0.286***	(0.020)	0.318***	(0.025)	0.1165***
Religion: attend services	0.146***	(0.020)	0.169***	(0.024)	0.0612***
No father	-0.067***	(0.019)	-0.096***	(0.024)	-0.0346***
No mother	-0.011	(0.028)	-0.014	(0.035)	-0.0052
(131 School dummies)					
Constant			0.035	(0.087)	
Level 1	-1.344***	(0.071)			
Level 2	-0.691***	(0.070)			
Level 3	-0.051	(0.070)			
Level 4	1.144***	(0.071)			
<i>N</i>		13 545		13 545	
Log-likelihood		-18173.14		-7977.70	
$\chi^2_{(154)}$		1767.95		1335.87	

Significance levels: * = 10%; ** = 5%; *** = 1%.

Note: For each of these three variables, there are five response options: “not at all”, “very little”, “somewhat”, “quite a bit”, “very much”. We dichotomized the scores as “satisfied” (“very much”) versus “dissatisfied” (other responses) based on subjects’ item responses.

^a “How much do you feel that your parents care about you?” (satisfied = 85.50%).

^b “How much do you feel that your friends care about you?” (satisfied = 43.23%).

^c “On the whole, how happy are you with living in your neighborhood?” (satisfied = 33.14%).

385 ler. Since the marginal rate of return to education is steadily decreasing with the edu-
 386 cation level (Becker, 1993), children become increasingly vulnerable to bad surprises

387 as they reach higher grades. Thus, in Table 2, school satisfaction is found consis-
388 tently to correlate negatively and strongly with education levels. The cumulated ef-
389 fect of climbing from grade 7 to grade 12 is to diminish the probability of being
390 satisfied with school by as much as 21.60%.

391 Additional variables were introduced in the regression to capture the effect of con-
392 temporaneous surprises and personality. First of all, 131 dummy variables were in-
393 cluded to control for the fixed effect of the child's school on her satisfaction with
394 school. A likelihood ratio test ($\chi^2(131) = 345.60$) validates the specific role of school.
395 The fixed effect of school aggregates factors not accounted for by the education gap
396 or level, like school quality and peer group effects (e.g., Gaviria & Raphael, 2001;
397 Hanushek, Kain, Markman, & Rivkin, 2003). Other variables were included to grasp
398 the specific non-school environment of the child. Four school-related satisfaction
399 variables are highly significant with the expected sign: satisfaction with parents, sat-
400 isfaction with friends, satisfaction with neighborhood, and self-reported health. They
401 describe the preference for present non-pecuniary components of education at large
402 over risky behavior and may also capture the effect of unobservable personality traits
403 on reported satisfaction (Diener, Suh, Lucas, & Smith, 1999). All of these "environ-
404 mental" variables have large marginal effects on how the child feels at school. As
405 does religion, measured by attendance to church (at least once a month), which is
406 consistent with many other studies. Lastly, the absence of father (but marginally
407 so the absence of mother) can be seen as another bad surprise that diminishes the
408 child's satisfaction with school.

409 6. School satisfaction and risky behavior

410 In this section, we demonstrate empirically that the risky behavior of adolescents
411 can be statistically predicted *in all domains* by their dissatisfaction with school. The
412 problem of endogeneity is addressed by taking school satisfaction from the first in-
413 home survey and risky behavior from the second, one year later. The problem of
414 causality is solved because the school satisfaction variable contains information
415 about current surprises at school and in school-related activities that is unique,
416 and in no other variable (Eq. (10)), so that school satisfaction truly causes risky
417 behavior.

418 The Add Health survey enabled us to observe 18 types of risky behavior which we
419 aggregated in 11 categories: school absenteeism, cigarette smoking (over the last 30
420 days), alcohol drinking (over the last year), drunkenness (over the last year), mari-
421 juana (over the last 30 days), other drugs, drug selling, illegal or violent behavior
422 (tagging, vandalism, running away from home, driving without license, group fight-
423 ing, and making a din), stealing (shoplifting, stealing private property, and armed
424 robbery), unprotected sex, and suicide attempt. Since alcohol drinking and drunken-
425 ness are highly correlated, we decided to consider them as a single behavior and re-
426 tain only alcohol drinking. This leaves us finally with 10 categories.

427 Table 3 shows that the prevalence of risky behavior is quite substantial among
 428 adolescents attending middle or high school. For instance, 30% of these adolescents
 429 did not attend courses, 32% smoked cigarettes and 16% smoked marijuana, 53% had
 430 some kind of illegal or violent behavior, 24% stole something and 27% of those who
 431 reported a sexual relationship had unprotected sex. 76% of adolescents had one risky
 432 behavior at least (excluding unprotected sex). Indeed, many adolescents break the
 433 educational norm in one way or another. Moreover, as suggested by Zullig et al.
 434 (2001), different types of risky behavior correlate with each other. However, these
 435 correlations follow a distinctive pattern. Table 4 shows the correlation matrix for
 436 nine types of risky behavior (excluding unprotected sex). Substantial correlations
 437 can be seen within three groups of risky behavior: (i) cigarette, alcohol, marijuana;
 438 (ii) marijuana, other drugs, selling drugs; (iii) selling drugs, illegal or violent behav-
 439 ior. School absenteeism, stealing, and suicide attempts are more loosely related to
 440 other types of risky behavior.

Table 3
Effect of school satisfaction and risky behavior in year t on the proportion adopting risky behavior in year $t + 1$ (Add Health)

Risky behavior in $t + 1$	Satisfaction and behavior in t (proportions in %)				All sample	N
	Satisfied No risk	Dissatisfied No risk	Dissatisfied Risk	Satisfied Risk		
School absenteeism	17.29	23.95	64.69	61.34	29.52	9232
Cigarette (30 days)	16.55	20.75	78.55	74.23	32.33	9788
Alcohol (365 days)	19.79	23.05	64.40	64.67	37.89	9864
Marijuana (30 days)	8.57	13.18	56.61	57.48	16.02	9663
Other drugs	4.37	9.97	18.85	9.73	7.91	9686
Selling drugs	3.55	6.71	52.22	41.64	7.46	9684
Illegal, violent behavior	27.91	33.33	70.43	66.05	52.54	9678
Stealing	11.92	14.51	52.85	49.20	24.23	9686
Unprotected sex	18.99	24.74	44.30	37.40	27.32	2207
Suicide attempt	1.98	3.03	31.41	28.22	3.32	9665
All behaviors (except sex)	40.22	45.43	89.68	85.34	75.85	8722

Table 4
Correlation between nine types of risky behavior at time $t + 1$ (Add Health, In-Home II) ($n = 8810$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
School absenteeism (1)	1								
Cigarette (2)	0.205	1							
Alcohol (3)	0.201	0.373	1						
Marijuana (4)	0.235	0.389	0.320	1					
Other drugs (5)	0.137	0.243	0.234	0.354	1				
Selling drugs (6)	0.163	0.222	0.190	0.419	0.322	1			
Illegal, violent behavior (7)	0.132	0.186	0.219	0.192	0.141	0.331	1		
Stealing (8)	0.156	0.205	0.226	0.236	0.202	0.264	0.186	1	
Suicide attempt (9)	0.040	0.099	0.078	0.114	0.140	0.087	0.097	0.086	1

441 Table 3 indicates that school satisfaction in period t has a clear influence on adop-
 442 tion of a risky behavior in $t + 1$, whatever was the child's behavior in t . This is true
 443 for all types of risky behavior with the exception of alcohol drinking. Among those
 444 who had not adopted a given risky behavior in t , school dissatisfaction markedly in-
 445 creases the likelihood of adopting this behavior one year later (columns 1 and 2);
 446 and, among those adopting a given risky behavior in t , school satisfaction markedly
 447 decreases the likelihood of adoption of this behavior one year later (columns 3 and
 448 4). To go further, let $R_{ij,t+1}^*$ denote the adolescent (i)'s latent decision variable for
 449 adopting risky behavior j in sub-period $t + 1$, R_{ijt} her observable discrete analog in
 450 t (defined as (8)), S_{it} school satisfaction, $X_{i,t+1}$ a vector of individual variables in
 451 $t + 1$, $u_{ij,t+1}$ an error term and α_j , β_j , ρ_j constant risk-specific (vector of) coefficients.
 452 Since all risky behaviors are measured with dummy variables, and school satisfaction
 453 is supposed to indicate a general aversion toward risky behaviors, we chose to mea-
 454 sure also school satisfaction in binary form in these regressions (after checking that
 455 the main results were virtually identical when a 5-level satisfaction index was in-
 456 cluded in the regressions). We estimate the following adaptation of Eq. (10) for 10
 457 types of risky behavior in sub-period $t + 1$:

$$R_{ij,t+1}^* = \beta_j R_{ijt} + \rho_j S_{it} + \alpha_j X_{i,t+1} + u_{ij,t+1}. \quad (13)$$

460 In Table 5, based on a Probit estimation of $R_{ij,t+1}^*$, we report only the two coeffi-
 461 cients β_j and ρ_j which describe the respective effects of habit and school satisfaction
 462 on a specific risky behavior. The regression results confirm the indications of Table 3.
 463 With the exception of alcohol drinking, school dissatisfaction predicts risky behavior
 464 in all domains one year ahead (the same result held when risky behavior was disag-
 465 gregated in 18 categories). The coefficients are usually statistically significant at the
 466 1% level (at the 5% level only for unprotected sex). In conformity with Eq. (10) that
 467 predicts a dampening effect of surprises with the duration of habit, it is worth noting
 468 that the higher coefficients of school satisfaction obtain for the low-frequency types
 469 of behavior (other drugs and drug selling). A strong prediction of Eq. (10) is that the
 470 habit coefficient should be equal to 1 in the long run, holding surprises experienced in
 471 the last year constant through the school satisfaction variable (the precise timing of
 472 effects is described in Fig. 1). This conclusion would hold if all risk-specific experi-
 473 ences were stochastically independent. Thus, habit coefficients which significantly
 474 differ from one indicate that experiences are serially correlated, positively when
 475 the coefficient exceeds one and negatively when the coefficient is below one. Interest-
 476 ingly, the habit coefficient is much greater than one for cigarettes, marijuana, other
 477 drugs, and drug selling, which are clearly addictive behaviors. Suicidal experiences
 478 also correlate positively, but unprotected sex exhibits strong negative serial correla-
 479 tion which indicates fast learning. The assumption of serial independence of experi-
 480 ences applies essentially to school absenteeism, stealing and illegal or violent
 481 behavior. These results make a lot of sense, thereby suggesting that the assumptions
 482 of rational expectations and Bayesian updating are not grossly inadequate. Thus a
 483 future extension of the stochastic model of preference formation presented here
 484 should allow for serial dependence of surprises in order to accommodate addictive
 485 behavior as one particular kind of risky behavior.

Table 5

Coefficients (satisfaction and habit) of behavioral equations: Probit (Add Health, In-Home II)

Behavior ($t + 1$)	Satisfaction coefficient (t)	Habit coefficient (t)	N	Log-likelihood	$\chi^2_{(39)}$
School absenteeism	−0.140*** (0.036) [−0.046]	1.006*** (0.038) [0.362]	7392	−3685.80	1381.35
Cigarette smoking	−0.134*** (0.036) [−0.046]	1.502*** (0.038) [0.540]	7700	−3582.74	2137.85
Alcohol drinking	−0.048 (0.034) [−0.018]	1.090*** (0.033) [0.408]	7765	−4275.69	1608.68
Marijuana	−0.119*** (0.040) [−0.025]	1.331*** (0.048) [0.410]	7610	−2671.23	1137.84
Other drugs	−0.311*** (0.047) [−0.036]	1.189*** (0.052) [0.243]	7747	−1735.10	765.61
Selling drugs	−0.294*** (0.048) [−0.032]	1.378*** (0.064) [0.309]	7795	−1617.90	822.22
Illegal, violent behavior	−0.122*** (0.032) [−0.048]	0.955*** (0.031) [0.366]	7787	−4754.47	1197.85
Stealing	−0.115*** (0.036) [−0.033]	1.091*** (0.034) [0.353]	7780	−3635.05	1255.60
Unprotected Sex	−0.137*** (0.066) [−0.045]	0.510*** (0.068) [0.174]	1823	−1006.09	123.12
Suicide attempt	−0.186*** (0.061) [−0.010]	1.331*** (0.087) [0.211]	7781	−965.76	382.58

Robust standard error in parentheses (Huber–White–Sandwich).

Marginal effect in brackets.

Significance levels: * = 10%; ** = 5%; *** = 1%.

Other variables: Female, Black, Hispanic, Asian, Other origin, Age, Education, Good health, One parent, weekly earnings; PARENTS: Age, Born in USA, Public assistance, Work outside home, Unemployed, Full-time work, PTA member, Choice of neighborhood for less delinquency, Choice of neighborhood for better school, Disposable income, No money problems, Tobacco, Alcohol; SCHOOL: Private, Rural, Urban, Small, Medium, West, Middle-West, North-East.

486 Many controls were introduced in the regressions to account for additional fac-
 487 tors which favor or impede the adoption of specific risky behavior. For instance, par-
 488 ents' smoking and drinking indicates a lenient educational norm, which facilitates the
 489 similar attitude of their children. And girls would be less prone to adopt some risky
 490 behaviors (and more eager to study) if they suffered from a higher depreciation of
 491 their human capital than boys. However, additional effects of this kind might as well
 492 reflect spurious correlations. A given control may be significant if it correlates with

493 unobservable surprises. Only are (norm-dependent) surprises the true causes of the
494 revealed preference at a given moment in time.

495 7. Conclusion

496 Even though children's behavior is often constrained by adults, there remains con-
497 siderable degrees of freedom and scope for rational behavior which deserve system-
498 atic exploration. The behavioral model of choice and school satisfaction of children
499 presented here yields a joint prediction of education and risky behavior. School
500 (dis)satisfaction expresses an experienced or post-decisional preference for education
501 (risky behavior), that is an intention to respect (deviate from) the educational norm
502 in the near future. Thus educational choices, school satisfaction, and risky behavior
503 share the same dynamics which can be recovered on panel data as successive revealed
504 preferences of children.

505 The preference formation process that we described is remarkably simple: all pref-
506 erence and behavioral changes are caused in the short run by unexpected deviations
507 from one's current normative expectations (surprises, or stress). Bad surprises imme-
508 diately drive the child away from the educational norm and toward risky behavior.
509 However, since this causal effect fades away with experience, rational behavior will
510 converge to a stable habit in the long run if surprises occur independently over time.
511 A specific behavioral episode would turn into an addiction (e.g., drug use) if sur-
512 prises were serially positively correlated and into a "durable" experience which
513 should not be repeated (e.g., unprotected sex) if surprises were negatively correlated.

514 This model of behavioral change is an economic model, building on human cap-
515 ital theory and assuming rational behavior, with a psychological twist, uncertain and
516 constructed preferences. A major implication of this theory is that rational persons
517 with uncertain preferences will behave in ways which are not consistent in general
518 with constrained maximization of a given utility function. The dynamic uncertainty
519 which results from the continual occurrence of surprises generates apparent time
520 inconsistencies which are particularly salient in children's and addictive behavior.

521 Our analysis of school satisfaction offers another instance of the duality between
522 economics and psychology by reconciling the affective (hot) and cognitive (cold) na-
523 ture of satisfaction and choice. Satisfaction is the affect caused by the disclosure of
524 unexpected information which drives individuals into an immediate preference
525 change, as noted by Zajonc (1980).

526 The fact that our interpretation of school satisfaction judgments was empirically
527 validated is an example of the fruit borne by this duality. For predictive and policy
528 purposes, it may be valuable to rely on the child-specific and easy-to-collect judg-
529 ment of school satisfaction for predicting a general propensity to risky behavior.
530 Lastly, as a theoretical note, the dynamic approach to preference formation and sat-
531 isfaction which has been developed here can be applied generally to other contexts,
532 and we hope that it will prove useful in future behavioral research.

533 Acknowledgements

534 We are grateful to Andrew Clark, Fabrice Étilé, François Gardes, Harold Hoch-
535 man, Sylvaine Poret, Catherine Sofer, Antoine Terracol, Fabienne Tournadre, two
536 anonymous referees and participants at XX^{èmes} JMA (Montpellier, 2003), XIII^{èmes}
537 Journées SESAME (Caen, 2003) and the 24th Arne Ryde Symposium on Substance
538 Use (Lund, 2004) for very helpful discussions. We are indebted to MILDT and IN-
539 SERM for financial support.

540 This research uses data from Add Health, a program project designed by J. Rich-
541 ard Udry, Peter S. Bearman, and Kathleen Mullan Harris, and funded by a grant
542 P01-HD31921 from the National Institute of Child Health and Human Develop-
543 ment, with cooperative funding from 17 other agencies. Special acknowledgment
544 is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design.
545 Persons interested in obtaining data files from Add Health should contact Add
546 Health, Carolina Population Center, 123W. Franklin Street, Chapel Hill, NC
547 27516-2524 (www.cpc.unc.edu/addhealth/contract.html).

548 References

- 549 Becker, G. S. (1993). *Human capital* (3rd ed.). New York: National Bureau of Economic Research [1st ed.,
550 1964].
- 551 Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2003). Optimal defaults. *American Economic*
552 *Review*, 93(2), 180–185.
- 553 Clark, A. E., & Oswald, A. J. (1996). Satisfaction and comparison income. *Journal of Public Economics*,
554 61(3), 359–381.
- 555 Clark, D. B., & Kirisci, L. (1996). Posttraumatic stress disorder, depression, alcohol use disorders and
556 quality of life in adolescents. *Anxiety*, 2(5), 226–233.
- 557 Coker, A. L., McKeown, R. E., Sanderson, M., Davis, K. E., Valois, R. F., & Huebner, E. S. (2000).
558 Severe dating violence and quality of life among South Carolina high school students. *American*
559 *Journal of Preventive Medicine*, 19(4), 220–227.
- 560 DeGroot, M. H. (1970). *Optimal statistical decisions*. New York: McGraw-Hill.
- 561 Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of
562 progress. *Psychological Bulletin*, 125(2), 276–303.
- 563 Gaviria, A., & Raphael, S. (2001). School-based peer effects and juvenile behavior. *Review of Economics*
564 *and Statistics*, 83(2), 257–268.
- 565 Granger, C. W. J. (2004). Times series analysis, cointegration, and applications. *American Economic*
566 *Review*, 94(3), 421–425.
- 567 Hanushak, E. A., Kain, J. F., Markman, J. M., & Rivkin, S. G. (2003). Does peer ability affect student
568 achievement? *Journal of Applied Econometrics*, 18(5), 527–544.
- 569 Harris, K. M., Florey, F., Tabor, J., Bearman, P. S., Jones, J., & Udry, J.R., (2003). *The National*
570 *longitudinal study of adolescent health: Research design*. Available from [http://www.cpc.unc.edu/](http://www.cpc.unc.edu/projects/addhealth/design)
571 [projects/addhealth/design](http://www.cpc.unc.edu/projects/addhealth/design).
- 572 Hirshman, A. O. (1970). *Exit, voice and loyalty: Responses to decline in firms, organizations and states*.
573 Cambridge, MA: Harvard University Press.
- 574 Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrica*,
575 47(2), 263–291.
- 576 Lévy-Garboua, L. (1976). Les demandes de l'étudiant ou les contradictions de l'université de masse. *Revue*
577 *Française de Sociologie*, 17(1), 53–80.

- 578 Lévy-Garboua, L., & Montmarquette, C. (1996). Cognition in seemingly riskless choices and judgments.
579 *Rationality and Society*, 8(2), 167–185.
- 580 Lévy-Garboua, L., & Montmarquette, C. (2004). Reported job satisfaction: What does it mean? *Journal of*
581 *Socio-Economics*, 33(2), 135–151.
- 582 Lévy-Garboua, L., Montmarquette, C., & Simonnet, V. (2004). Job satisfaction and quits. Mimeo,
583 TEAM, Université Paris I.
- 584 Newcomb, M. D., Bentler, P. M., & Collins, C. (1986). Alcohol use and dissatisfaction with self and life: A
585 longitudinal analysis of young adults. *Journal of Drug Issues*, 63, 479–494.
- 586 Udry, J. R. (2003). The National Longitudinal study of adolescent health (Add Health), Waves I & II,
587 1994–1996; Wave III, 2001–2002 [machine-readable data file and documentation]. Chapel Hill, NC:
588 Carolina Population Center, University of North Carolina at Chapel Hill.
- 589 Zajonc, R. B. (1980). Feeling and thinking: Preferences need no inferences. *American Psychologist*, 35,
590 151–175.
- 591 Zullig, K. J., Vallois, R. F., Huebner, E. S., Oeltmann, J. E., & Drane, J. W. (2001). Relationship between
592 perceived life satisfaction and adolescents' substance abuse. *Journal of Adolescent Health*, 29(4),
593 279–288.
594