Marijuana Use and High School Drop Out: The Influence of Unobservables

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MARIJUANA USE AND HIGH SCHOOL DROPOUT: THE INFLUENCE OF UNOBSERVABLES

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SUMMARY

In this study, we reconsider the relationship between heavy and persistent marijuana use and high school dropout status. Using a unique prospective panel study of over 4500 7th grade students from South Dakota who are followed through high school, we developed propensity score weights to adjust for baseline differences found to exist before marijuana initiation occurs for most students (7th grade). We then used weighted logistic regression that incorporates these propensity score weights to examine the extent to which time-varying factors, including substance use, also influence the likelihood of dropping out of school. We found a positive association between marijuana use and dropping out (OR \(= 5.6\), RR \(= 3.8\)), over half of which was explained by prior differences in observational characteristics and behaviors. The remaining association (OR \(= 2.4\), RR \(= 1.7\)) became statistically insignificant when measures of cigarette smoking were included in the analysis. Because cigarette smoking is unlikely to seriously impair cognition, we interpret this result as evidence that the association between marijuana use and high school dropout is unlikely to be due to its adverse effects on cognition. We then explored which constructs drive this result, determining that they are time-varying parental and peer influences. Copyright \(\odot\) 2009 John Wiley & Sons, Ltd.

1. INTRODUCTION

Considerable research has demonstrated a positive association between early marijuana use and low educational attainment as measured by both years of education and high school dropout status (Chatterji, 2006; Bray et al., 2000; Ellickson et al., 1998; Schulenberg et al., 1994; Mensch and Kandel, 1988; Newcomb and Bentler, 1986). This finding has frequently been interpreted as evidence that marijuana use interferes with learning by impairing memory, attention or other cognitive functioning and/or motivation, any of which could translate into poor schooling outcomes. However, evidence supporting alternative explanations for the negative association challenges this causal interpretation. For example, some studies show that poor schooling outcomes actually precede regular and heavy marijuana use (Fergusson and Horwood, 1997; Hawkins et al., 1992; Newcomb and Bentler, 1988). Other research suggests that the relationship between marijuana use and low educational attainment is explained by a common third variable (Barnes et al., 2005; Kumar et al., 2002; Sander, 1998; Schulenberg et al., 1994; Farrell and Fuchs, 1982) or that marijuana use influences other factors such as peer associations and attitudes toward schooling (Brook et al., 1989; Brook et al., 2002; Friedman et al., 1994) which serve as an alternative pathway to affecting school completion.

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Separating any causal effects of marijuana use on educational attainment from the effects of other factors is complicated by the sheer number of potential confounders and the presence of selection biases in observational data. In addition, adolescence is a period of development and marked change in the child’s environment; hence accounting for third variables at one point in time may miss relevant changes that have occurred earlier or later. Instrumental variables and techniques usually employed to overcome these sorts of problems have been less useful in the case of illicit drugs, as models testing what are typically weak state-level instruments generally reject the assumption of endogeneity (Chatterji, 2006; Bray et al., 2000).

This study revisits the question of how and why marijuana use and schooling are related. In particular, it explores the conjecture that the relationship reflects a causal effect of marijuana on student cognitive functioning and, in so doing, improves upon previous studies in two important ways. First, it minimizes the effects of selection bias by using propensity score methods, which create observationally equivalent groups of marijuana users and nonusers who are matched on a rich set of constructs and observable characteristics at baseline. A new longitudinal data source allows us to control for a wide variety of alternative factors that have been used to explain the association between marijuana and high school dropout, including one’s predisposition toward problem behavior, use of substances other than marijuana, peer and family social influences, attachment to conventional institutions such as family, school and religion, emotional distress and time preference. Second, we evaluate whether changes in these constructs between early and middle adolescence help explain the association rather than assume that the measurement or influence of a particular construct is stable over time.

As in previous studies, we find a positive association between marijuana use and high school dropout status (OR = 5.6, RR = 3.8), but we show that over half of the association can be explained by prior differences in observational characteristics and behaviors (i.e. selection bias). The remaining association (OR = 2.4, RR = 1.7) becomes statistically insignificant after measures of cigarette smoking are included in the analysis, a variable that is not systematically included in economic analyses. Because we are aware of no physiological justification for why controlling for cigarette smoking should account for marijuana’s cognitive effects on learning, we interpret this as indicating that the negative relationship between marijuana use and high school completion is unlikely to be due to adverse effects on cognition and more likely to be the result of omitted variable bias or the effects of peer associations or other factors. We then explore the source of this bias using the rich panel data.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of the literature indicating the importance of alternative constructs frequently ignored in the economics literature. Section 3 describes our propensity score methods and the data used to construct these weights. Section 4 presents the empirical model used to evaluate the impact of persistent and heavy marijuana use on schooling. Results are presented in Section 5. Section 6 summarizes the implications for future work by economists interested in examining the causal association between marijuana use and high school outcomes.

2. LITERATURE REVIEW

2.1. Literature on mechanisms through which marijuana might influence schooling

Three explanations have been put forth for the association between marijuana use and low educational attainment: (1) marijuana use causes poor schooling outcomes; (2) marijuana use is a consequence of poor school performance; and (3) marijuana use and low educational attainment are not directly related but share a common underlying cause, such as deviant behavior, peers, family dysfunction, or rates of time preference. Evidence supporting each of these explanations comes from studies informed by a variety of disciplines.
The basic sciences provide the main rationale for believing that marijuana use causes low educational attainment. Neuroscientists have shown that marijuana use interrupts normal cognitive functioning and memory by activating cannabinoid receptor sites in the part of the brain that controls memory (Matsuda et al., 1993; Heyser et al., 1993). What remains debated is whether the detrimental effect on memory and cognitive functioning is short-lived, sustained for a period of time past intoxication, or cumulative in terms of its total detrimental effect on cognitive functioning. Although a few economic studies provide support for the cognitive detriment explanation, none have satisfactorily dealt with the issue of endogeneity (Chatterji, 2006; Roebuck et al., 2004; Bray et al., 2000; Yamada et al., 1996).

Economics and psychology provide explanations for why poor schooling could precede marijuana use. The economic theory of health production (Grossman, 1972) suggests that schooling will be positively associated with healthy behavior and negatively associated with unhealthy behaviors, as an individual’s ability to understand how particular behaviors affect health improves with schooling and hence makes individuals better producers of health. The psychological literature postulates that use of marijuana and other substances is a coping mechanism for students who struggle in school (Newcomb and Bentler, 1986; Wills and Shiffman, 1985). Empirically, a substantial literature outside of economics supports the notion that poor school performance precedes marijuana use (Hawkins et al., 1992; Fergusson et al., 1996; Duncan et al., 1998). However, evidence showing that poor school performance may precede marijuana use does not rule out the possibility that marijuana use leads to poor (or worse) schooling outcomes. The association may run both ways.

The third variable explanation is supported by several theories. Problem behavior theory postulates that individuals with a predisposition toward nonconformity and deviance are more likely to engage in multiple unconventional behaviors that reciprocally influence one another (Jessor and Jessor, 1977; Donovan and Jessor, 1985). Social attachment theory argues that it is weak bonds with family, school, religion, or other conventional institutions that lead to general problem behaviors (Hawkins and Weis, 1985; Simmons and Blyth, 1987; Sommer, 1985). Social learning theory (Bandura, 1977, 1985) stresses the influence of exposure to deviant peers or family members who act as role models for specific actions through their approval of them. Finally, health economists postulate that a positive association between poor schooling outcomes and substance use could also result because of their association with a high discount rate or rate of time preference (Fuchs, 1982; Farrell and Fuchs, 1982). Individuals with high rates of time preference place greater value (or ‘utility’) on rewards and punishments that happen immediately and less value on rewards and punishments that happen in the future. Substantial empirical evidence supports each of these ‘third factor’ theories (Roebuck et al., 2004; Brook et al., 1999; Sander, 1998; Fergusson et al., 2002; Schulenberg et al., 1994).

2.2. Prior studies attempting to investigate the role of selection bias and other unobservables

Economic analyses have attempted to determine the causal association between marijuana use and educational attainment by using two-stage least squares, instrumental variables techniques, or fixed-effects modeling to disentangle the influence of selection bias and the other unobserved factors mentioned above. The findings from this literature support a negative association between marijuana and schooling outcomes, but the causal interpretation remains elusive due to limitations of each study.

Bray et al. (2000) examine the relationship between marijuana initiation and the age-specific probability of dropping out of high school for a sample of 1392 students who participated in a longitudinal study in a Southeastern US school system. Early marijuana initiation is used as an instrument for current marijuana involvement, which is supported by research identifying a strong association between the two (Perkonigg et al., 2007; van Ours, 2006). Empirical tests were done to evaluate the exogenous treatment of age of initiation and the hypothesis of exogeneity could not be rejected, although the authors do not report information on identifying variables used to generate the test results. In their models they find that early marijuana initiation (prior to the age of dropout) has a
positive and statistically significant effect on the probability of dropping out at ages 16 and 18. They estimate that early marijuana initiators are 2.3 times more likely to subsequently drop out of high school than nonusers.

In a similar study using a nationally representative sample, Register, et al. (2001) examine the impact of early marijuana use on subsequent educational attainment (i.e. years of schooling) using young males from the 1992 NLSY. The authors defined ‘early’ marijuana use as use prior to age 18. They employed a two-stage regression technique to deal with the structural endogeneity of marijuana use. In the first set of regressions they predicted separate likelihood functions for the probability of using any illicit drug, any hard drug, or any marijuana use prior to age 18, with the primary identifying instrument in the first stage for marijuana use being whether the person lived in a decriminalized state at age 14. They then constructed predicted probabilities for each of these measures and evaluated their effects on subsequent total educational attainment in 1992, when the respondents were between the ages of 27 and 34 years of age. They found that any use of marijuana prior to age 18 had a negative and statistically significant effect on educational attainment in the full sample, but the result was generally driven by their sample of whites, for whom they found an average reduction of 1.187 years of education among early marijuana users.

While studies support the high correlation between early marijuana initiation and subsequent use, Chatterji (2006) and other social scientists point out that it may also be the case that adolescents who are able to initiate at a young age have environmental or personal factors that may make them less likely to complete high school independent of their later marijuana use, such as less parental supervision, bad peer group, ADHD, general antisocial behavior, or other mental health problems. In her study of the effect of marijuana on educational attainment at age 26 using the National Education Longitudinal Survey (NELS), Chatterji (2006) shows that including school environmental factors in an examination of the effect of 10th grade marijuana use on final educational attainment reduces the association between marijuana use and schooling by 69%, and the additional inclusion of 8th grade risk factors reduces the association of marijuana use and schooling even further by another 14%. The negative association between marijuana use and educational attainment remained statistically significant in the final specification, but it was dramatically smaller than in models that excluded these additional factors, suggesting that selection into marijuana use based on environmental and personal risk factors could be extremely important.

Chatterji (2006) also presents estimates from IV models that attempt to purge the potentially endogenous drug use measure of its correlation with the error term, under the assumption that even with her rich data set unobservable factors may still bias results. What is most compelling in her IV analysis is that standard state policy instruments and individual-level variables that have been used in previous studies to predict marijuana use (e.g. state decriminalization status) did not generate F-test statistics above a value of 4. When additional controls capturing 8th grade risk factors were also included in the first stage, the F-statistics rose but only one test exceeded 8 (reaching a value of 8.51). Chatterji herself concludes from this result and the fact that the estimated effect on marijuana use in the IV model was larger than that for the OLS model, that the instruments used to generate the IV estimates in the case of marijuana were fairly weak.

In light of the results presented by Chatterji (2006) and concerns raised in the alcohol literature regarding the use of weak instruments to assess the causal effect of alcohol on educational attainment and other outcomes (Dee and Evans 2003; Koch and Ribar, 2001), it seems reasonable to question whether current attempts to assess a causal association between marijuana use and schooling using IV or two-stage estimation techniques are indeed reliable. Another method to account for unobserved factors that might influence both the selection to use drugs as well as lower educational attainment is through fixed-effect methods. We are aware of only one study that employs individual fixed-effects methods. Using repeated observational data from the Persistent Effects of Treatment Study – Adolescent (PETS-A), Engberg and Morral (2006) examine the impact of reducing marijuana use (as
well as other substance use) on schooling attendance during 3-month intervals over the course of a year. Random and fixed-effects models were estimated and controls for baseline (pre-treatment) differences in the sample were included. The results for marijuana showed that any use was negatively associated with the probability of attending school, whereas the findings for other substances (alcohol, stimulants, hallucinogens, and other drugs) showed that their effects were specific to the quantity consumed and their use was not statistically associated with lower probabilities of attending school.

Because the association between marijuana use and poor schooling outcomes persists even after econometric techniques are applied to deal with selection bias and unobservables, the hypothesis that marijuana use is causally associated with poor schooling outcomes remains viable. The mechanism through which this association operates, however, remains highly questionable.

In this paper, we revisit the question of the causal association between marijuana use and schooling using propensity score methods as an alternative strategy to reduce the influence of selection bias. Taking the analysis a step farther, we also test the assumption of stable unobserved influences. After adjusting for pre-existing differences in user groups, we control for additional variables that change over time when assessing the relationship between marijuana and high school dropout status. Thus, we can assess whether factors shown to influence these associations change over time, as suggested by developmental theorists (LaGrange and White, 1985; Bailey and Hubbard, 1990).

3. STRUCTURAL MODEL AND DATA

3.1. Economic theory on the causes of dropping out

In his seminal work on the economics of schooling, Gary Becker described education as a form of ‘human capital’ that raises the skill set and hence the productive capacity of a worker (Becker, 1964). Hence, schooling became viewed as a form of investment, with higher wages being the return on that investment. Huge literatures have evolved examining both the returns to schooling (Card, 1999; Willis, 1987) as well as the productive inputs that lead to improved human capital formation in school (Becker 1993; Willis and Rosen, 1979; Schultz, 1961). Based on these literatures, standard economic theory models the decision to leave school early as a function of individual achievement, family resources and personal characteristics. Within this construct, marijuana use could positively influence one’s willingness to leave school by reducing his or her general achievement (through reduced cognitive ability, school attendance, or willingness to work hard and get good grades). Alternatively, marijuana use may simply be highly correlated with specific personal characteristics that make it more likely for the individual to decide to drop out of school, such as anti-social disorder, weak social bonds with formal institutions, high discount rates, and other behavioral factors described in the previous section.

3.2. Causal model and propensity score approach

Our empirical model is based on the linear latent variable model in which the net benefits of schooling, \( Y^* \), are a function of a vector of individual characteristics, \( x_i \), and, assuming a causal influence of marijuana on schooling, the decision to be a heavy and persistent marijuana user (HPMU), or:

\[
Y_i^* = \beta x_i + \gamma \text{HPMU}_i + \epsilon_i
\]  

We cannot observe the net benefits of schooling, but we do observe whether an individual continues schooling or not: \( Y_i = 1 \) if \( Y_i^* > 0 \) and the person does not drop out of high school (DO, = 0).

\( Y_i = 0 \) if \( Y_i^* < 0 \) and the person does drop out of high school (DO, = 1).

Let DO, denote dropout status (1 if dropout; 0 otherwise) if a chosen student with characteristics \( x \) is a HPMU. Similarly, let DO, denote dropout status if the chosen student was not a HPMU. Assuming a logistic specification, we can then denote the probability of a HPMU dropping out and a non-HPMU
dropping out, respectively, as:

\[
P(DO_1 = 1) = e^{\alpha + \beta x + \gamma}/(1 + e^{\alpha + \beta x + \gamma})
\]

\[
P(DO_0 = 1) = e^{\alpha + \beta x}/(1 + e^{\alpha + \beta x})
\]

The parameter \( \gamma \) determines the ratio of the odds of dropout for the counterfactual outcomes and is the causal effect parameter of interest. We can observe only a single counterfactual outcome on each student and cannot directly estimate \( \gamma \). However, as discussed in Bang and Robins (2005), the probability of being a HPMU, also referred to as the propensity score (Rosenbaum and Rubin, 1983), can be used to weight the data and obtain consistent estimates of causal effects provided the model for the propensity score or the structural model is correct and strong ignorability holds.

Strong ignorability requires that there are no unobserved variables that predict both the probability of dropping out and the probability of HPMU by the 10th grade (the point at which school is no longer mandatory). To ensure strong ignorability, we need to construct propensity score weights that can account for an array of constructs that the literature suggests are correlated with both behaviors of interest, including early use of alcohol and cigarettes, deviance, time preference, family influence, peer substance use, religiosity, social bonds, school bonds, parental bonds and emotional distress.

Given a vector of such pre-existing variables, \( W \), we estimate the propensity score \( p_w = \Pr(\text{HPMU} = 1|W) \) using generalized boosting methods (GBM), a flexible nonparametric approach to modeling the \( \log(p_w/(1-p_w)) \). GBM-based propensity scores provide a flexible model for the propensity score equation, handle a large number of variables in an automated and systematic manner, and have been shown to provide estimated propensity scores that yield better estimates of effects than do other approaches (Ridgeway and McCaffrey, 2007).1 Because we are interested in estimating the effects of being a HPMU on users, we weight each HPMU by a weight of one and every student who was not a HPMU by \( p_w/(1-p_w) \), the odds of being a HPMU, to obtain an estimate of the average effect of being a HPMU on the users (Wooldridge, 2002).

3.3. ALERT plus data

We use data from the field trial evaluation of the ALERT and ALERT Plus drug prevention programs, which were administered to seventh-grade students in 61 middle schools drawn from 48 school clusters in South Dakota in 1997. Schools in the study were randomly assigned to one of the two treatment conditions or a control group condition (see Ellickson et al., 2003 for details on the experimental trial). Students completed annual paper-and-pencil surveys in school at Grades 7–11. Study participants also completed a mail or web survey during the summer and fall of 2004, when they were about 14–20 months post their expected high school graduation date. The baseline survey, administered to 5857 students, collected detailed background information including age, gender, race/ethnicity, family structure, and parental education, as well as information regarding school performance, deviant behavior, attitudes toward school and family, family influences, peer influences, and substance use. Many of the same questions were included in follow-up surveys each year. Extensive tracking procedures to survey students who left the study schools were employed. Follow-up response rates in 8th, 9th, and 10th grade were 91, 87, and 83%, respectively.

The dependent variable, high school dropout status, was collected through both school staff reports and student self-reports.2 School-reported graduation data are missing for 301 students who moved

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1We also explored models with fixed effects for the high schools the students attended in 9th grade. The models provided qualitatively similar results to models without fixed effects and are not reported here.

2The student survey asked ‘What is the HIGHEST LEVEL of education you completed?’ Response choices included: less than high school, GED, high graduate or college attendance. The school survey was administered about a year after the student’s scheduled graduation date and provided schools with a list of students’ names and a box to check if the student was a ‘High School Graduate.’
from South Dakota before completing high school and for another 387 students for whom the South Dakota high schools’ reported graduation status was unknown. Self-reported graduation status is missing for 2560 participants who failed to complete the post-high school follow-up and 29 who completed the survey but failed to report high school graduation status. The two data sources disagree with each other for some students. In particular, of the students the school data reported as dropouts, 40% of those who also provided self-reported status reported graduating. Hence, as discussed in the next section, we develop a model for the joint distribution of student and school-reported graduation status that allows for measurement error in both.

Building on previous work demonstrating the importance of differentiating light and heavy marijuana use (Chatterji, 2006; Roebuck et al., 2004; Ellickson et al., 1998; Yamada et al., 1996), we construct a dichotomous measure of heavy and persistent marijuana use that equals one if the student reports using marijuana in the past month on both the 9th and 10th grade surveys and three or more times in that period on at least one survey and zero otherwise. This measure has the advantage of capturing relatively extreme use, as only about 30% of past year marijuana users are heavy and persistent users. In addition, it predicts drug dependence and alcohol abuse at ages 19 and 21 for our sample and explains more of the variance in these outcomes than daily use of marijuana (as defined by use on 20 or more days in the past month at the tenth grade survey administration).

The following background, attitudinal and behavioral Grade 7 control variables capture the constructs represented in $W$: student demographics; family characteristics; school grades and academic expectations; impulsivity; beliefs about the health consequences of alcohol, cigarette, and marijuana use; parental monitoring; deviance; rates of time preference; religiosity; school bonds; parental bonds; emotional distress; family (parent/sibling) substance use; and alcohol, cigarette, and marijuana use in Grade 7. We also control for peer effects for alcohol and cigarette use, school size, region of the state, and the school’s experimental condition for the drug prevention trial. Next, we discuss how these constructs are measured. Unless otherwise noted, measures are created at Grades 7–10 using parallel items; the Grade 7 measures are included in the propensity score weights and measures from later grades are used in sensitivity analyses.

Cigarette use is the logarithm of the 30-day average of one plus an overall frequency index combining lifetime, past year, and past month frequency of use scaled by the student’s quantity of use. Alcohol use is represented by categorical indicators measuring the number of days of alcohol use in the past month, with levels of use indicated by none, 1, 2–4 days, 5–8 days, and 9 or more days (the reference group). Deviance is the average frequency of six items tapping various deviant behaviors in each grade (e.g. skipped school or breaking into houses, schools or places of business). To accommodate developmental change in the forms of deviant behavior, we added additional items to the Grade 10 deviance index.

To address this question, we used a seven-item drug dependence sum based on items chosen to meet DSM-IV criteria (D’Amico et al., 2005) and the AUDIT for alcohol (Babor et al., 1992; Bohn et al., 1995).

Models with daily use also showed the same pattern of results as our models with heavy and persistent use: marijuana use is a significant predictor of dropout out even accounting for baseline variables, but the effect is greatly reduced and not significant when we control for cigarette smoking or smoking and peer effects. Results are available from the authors upon request.

Research suggests that by including all of these variables we risk potentially introducing greater variance into our estimate (and hence are more likely to reject the finding of significance), but the alternative is introducing bias caused by omitting relevant variables and violating the assumption of strong ignorability by failing to control for variables related to HPMU and dropout (Rubin, 1997; Rubin and Thomas, 1996).

The measure can be negative or positive (the minimum value is $\ln(1/30) = -3.4$), because it uses the logarithm of index values that are both less than or greater than 1.

An alternative specification using binge drinking (days of 3 or more drinks in the past month) was also considered for the sensitivity analyses. The results using this measure were qualitatively similar to those presented here and did not change the estimated relationship between marijuana use and drop out status.

Additional items are questions regarding how often during the past year the student: ran away from home for a night or more; stole or tried to steal items worth $50 or more; sold marijuana; sold other drugs; took a vehicle for a joyride without the owner’s permission; drove a car, motorcycle or other vehicle after drinking alcohol; used strong-arm force to get money or things from people; attacked someone with the idea of seriously hurting or killing that person; purposely set fire or tried to set fire to a building, car, or other property; got into trouble with the police because of something s/he did.
The student’s rate of time preference is measured in Grades 7 and 9 as the sum of two items: How much of the time do you do or feel the following things: you do what feels good now without thinking about the future, and you focus on the short run instead of the long run (range = 0 (never) – 5 (almost always)).

Grade-specific measures of family influences on student behavior are based on two items: whether the respondent perceives the adult they are closest to has a drinking habit and the extent to which their parents would disapprove of them smoking or using marijuana. Grade-specific measures of peer effects are tapped through self-reports by the students regarding the frequency with which they are with marijuana-using peers and whether they think their best friend uses marijuana.9

Student attitudes and beliefs about alcohol, cigarettes, and marijuana are based on three positive and three negative items for each substance, with a higher score on either scale indicating more pro-drug attitudes. Indicators of bonds with conventional institutions are captured through a measure of religiosity, school bonds, and parental bonds.10 Details regarding the constructs of each of these can be found in Ellickson et al. (2003). Finally, we measured emotional distress with the six-item mental health inventory index (MHI-6) that equals the MHI-5 (Wells et al., 1996) plus an additional item on the frequency of feeling downhearted and blue in the past month. See Table I for descriptive statistics on the baseline (Grade 7 or Grade 8 when Grade 7 data do not exist) values of variables for all students and by HPMU status. As shown in the table, there are large differences between the groups on cigarette use, grades, deviance, attitudes about substance use, and parental approval of substance use; however, these differences are greatly reduced by weighting.

3.3.1. Attrition and missing data. The data set includes 4375 students with both marijuana use and high school dropout data, which excludes 718 cases without graduation information from either source, and 656 students who failed to respond to either or both of the Grades 9 and 10 surveys, and 108 students who completed both surveys but did not provide information about marijuana on at least one of them. To account for attrition, we weighted the observations using propensity score-based nonresponse weights (Little and Rubin, 2002). In this case the propensity score represents the probability that a student with a given set of baseline covariate values answered the 9th and 10th grade survey questions on past month marijuana use and had data on graduation status. Nonresponse weights equal the inverse of this probability for responding students. Missing data for baseline covariates are imputed using a Bayesian model for the joint distribution of all baseline and 8th grade follow-up variables.11 For data from the 9th and 10th grade follow-ups, missing values of independent variables other than marijuana use are also imputed using a Bayesian model for the joint distribution of all analysis variables.

4. EMPIRICAL SPECIFICATION

As shown in Table II, graduation information collected through self-reports did not always match school administrator reports. To account for potential errors in reported graduation status and make

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9Because the original scales for the two items in the peer measures differ, we standardized the items to mean zero and standard deviation one prior to being averaged for the index. Hence the index takes on both positive and negative values, with higher values on this index indicating more exposure to peer-using friends.

10Religiosity was not measured at grade 7.

11The Bayesian imputation model uses a multivariate Gaussian distribution to approximate the joint distribution for the variables conditional on the unobserved parameter values. The imputed values are a random sample from the posterior distribution of the missing data and conditional on the observed data and the model. Using the NORM software (Schafer, 1999), we sampled five sets of imputed values. Imputed values have been found to be robust to model misspecifications (Schafer, 1997).
Table I. Summary statistics and standard bias for baseline variables

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<tr>
<th></th>
<th>All</th>
<th>HPMU</th>
<th>Comparison</th>
<th>Comparison</th>
<th>Std. bias</th>
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<td>Std. dev.</td>
<td>Mean</td>
<td>Std. dev.</td>
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<tr>
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<td>Father's education</td>
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<td>Mother's education</td>
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<td>1.88</td>
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<td>Nuclear family</td>
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<td>Experimental condition: ALERT only</td>
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<td>0.54</td>
<td>0.35</td>
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<tr>
<td>Experimental condition: control</td>
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<td>Days alone after school</td>
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<td>3.17</td>
<td>2.23</td>
<td>2.69</td>
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</tr>
<tr>
<td>Used alcohol 1 day in past month</td>
<td>0.01</td>
<td>0.13</td>
<td>0.02</td>
<td>0.18</td>
<td>0.01</td>
</tr>
<tr>
<td>Used alcohol 2–4 days in past month</td>
<td>0.00</td>
<td>0.07</td>
<td>0.00</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Used alcohol 5–8 days in past month</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Freq. of cig. use</td>
<td>−3.18</td>
<td>0.89</td>
<td>−2.69</td>
<td>1.64</td>
<td>−3.24</td>
</tr>
<tr>
<td>Grades</td>
<td>1.92</td>
<td>1.03</td>
<td>2.27</td>
<td>1.27</td>
<td>1.88</td>
</tr>
<tr>
<td>Deviance</td>
<td>0.27</td>
<td>0.57</td>
<td>0.55</td>
<td>0.83</td>
<td>0.24</td>
</tr>
<tr>
<td>Religiousity</td>
<td>2.40</td>
<td>1.18</td>
<td>2.85</td>
<td>1.33</td>
<td>2.35</td>
</tr>
<tr>
<td>School bonds</td>
<td>2.29</td>
<td>0.73</td>
<td>2.60</td>
<td>0.89</td>
<td>2.25</td>
</tr>
<tr>
<td>Family bonds</td>
<td>1.84</td>
<td>0.86</td>
<td>2.09</td>
<td>0.99</td>
<td>1.81</td>
</tr>
<tr>
<td>Emotional distress</td>
<td>1.24</td>
<td>0.94</td>
<td>1.40</td>
<td>1.13</td>
<td>1.22</td>
</tr>
<tr>
<td>Positive attitudes,</td>
<td>1.40</td>
<td>0.84</td>
<td>1.80</td>
<td>1.30</td>
<td>1.35</td>
</tr>
<tr>
<td>Negative Attitudes,</td>
<td>1.56</td>
<td>1.01</td>
<td>1.90</td>
<td>1.32</td>
<td>1.52</td>
</tr>
<tr>
<td>Adult use cig.</td>
<td>1.08</td>
<td>1.56</td>
<td>1.68</td>
<td>1.78</td>
<td>1.01</td>
</tr>
<tr>
<td>Parental approval cig.</td>
<td>1.40</td>
<td>0.83</td>
<td>1.90</td>
<td>1.24</td>
<td>1.34</td>
</tr>
<tr>
<td>Parental approval marijuana</td>
<td>1.13</td>
<td>0.53</td>
<td>1.46</td>
<td>1.03</td>
<td>1.10</td>
</tr>
<tr>
<td>Peer effects</td>
<td>0.18</td>
<td>0.50</td>
<td>0.16</td>
<td>0.53</td>
<td>0.18</td>
</tr>
</tbody>
</table>

All values are weighted for nonresponse and where noted the comparison group is weighted by propensity score weights. All covariates are measured at grade 7 unless otherwise noted. Standardized bias equals the difference in HPMU and comparison group means divided by the standard deviation for the HPMU.

a Other race is the reference category for ethnicity.

b ALERT Plus is the reference group for the treatment condition.
c No use is the reference category for alcohol use.
d Grade 8 measures because variable was not collected at grade 7.

Table II. Summary of graduation status data as reported by schools and participants

<table>
<thead>
<tr>
<th>School Reports</th>
<th>Graduate</th>
<th>Dropout</th>
<th>Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graduate</td>
<td>2657</td>
<td>15</td>
<td>1490</td>
</tr>
<tr>
<td>Dropout</td>
<td>101</td>
<td>149</td>
<td>377</td>
</tr>
<tr>
<td>Don’t Know</td>
<td>121</td>
<td>53</td>
<td>213</td>
</tr>
<tr>
<td>Not collected</td>
<td>132</td>
<td>40</td>
<td>509</td>
</tr>
</tbody>
</table>
DO = DO₀HPMU + DO₀(1 − HPMU),

\[
P(\text{DO} = 1|x, \text{HPMU}) = \frac{e^{\beta x + \gamma \text{HPMU}}}{1 + e^{\beta x + \gamma \text{HPMU}}} \quad (4)
\]

The model also assumes that both school and student reports of graduation status might contain errors. The error rates were specified through the conditional distribution of self-reported status, \(U\), given the true status, \(DO\), and the conditional distribution of the school reported status, \(Z\), given \(DO\). These were

\[
P(U = 1|DO = 1) = 1 - \epsilon_1 \quad (5)
\]

\[
P(U = 1|DO = 0) = 0 \quad (6)
\]

\[
P(Z = 1|DO = 1) = 1 - \epsilon_2 \quad (7)
\]

\[
P(Z = 1|DO = 0) = \epsilon_2 \quad (8)
\]

Equation (5) states that dropouts might self-report graduating with an error rate of \(\epsilon_1\). Equation (6) assumes that high school graduates never incorrectly reported dropping out. Equations (7) and (8) allow for errors in school reports and assume that false reports of dropout for graduates and false reports of graduation for dropouts are equal.\(^{12}\)

Limited write-in data suggest that some students who had completed alternative education programs mistakenly reported graduating from high school. We assumed that students who had truly graduated from high school provided the correct information because there is no obvious potential source of confusion that would result in misreporting graduation when it truly occurred. We also assumed that students who reported dropping out provided the correct information because there is no clear motivation for students to purposely misreport dropping out (such as avoiding stigma or providing a socially desirable outcome) and because many students who reported dropping out supplied reasons. Equations (7) and (8) are consistent with the assumption that errors in school reporting are due to clerical mistakes, so that errors in either direction have an equal probability of occurring.

The model also assumes that \(U\) and \(Z\) are independent conditional on \(DO\), which implies that the errors made by schools are independent of errors by students. Given that the likely sources of error in student and school reports are distinct this last assumption seems reasonable.

Equations (4)–(8) yield

\[
P(U = u, Z = z|x, \text{HPMU}) = \frac{(1 - u)e^{\gamma}z(1 - \epsilon_2)^{u}\epsilon_1^{(1-u)}(1 - \epsilon_1)\epsilon_2^{(1-z)}(1 - \epsilon_2)^{z}}{1 + e^{\beta x + \gamma \text{HPMU}}} \quad (9)
\]

From Equation (9), we derived a pseudo log-likelihood function for the observed pairs of \((U, Z)\), weighted by the propensity score weights, to obtain estimates of \((\beta, \epsilon_1, \text{and } \epsilon_2)\). We estimated standard errors for the parameter estimates using a cluster-adjusted sandwich estimator (Liang and Zeger, 1986) based on the weighted pseudo log-likelihood function to account for possible correlation among responses from students attending the same school. To account for the imputation of predictor variables, we repeated the estimation of parameters and standard errors with each of the five imputation completed datasets and combined the resulting estimates using standard methods (Schafer, 1997).\(^{13}\)

\(^{12}\)The Equations (5)–(8) yield that \(\Pr\{U = 1\} = (1 - \epsilon_1)p_u\) and \(\Pr\{Z = 1\} = (1 - \epsilon_2)p_z + \epsilon_2(1 - p_z)\) which can be solved by averaging over \(p_u\) to identify the error rates, \(\epsilon_1\) and \(\epsilon_2\).

\(^{13}\)We tested model specification by allowing the probability of errors in student self-reported data to depend on student variables and using alternative probit link functions. The results were qualitatively invariant to the model; consequently, we report the results from the parsimonious model of Equation (9) rather than alternatives.
5. RESULTS

Many of the students who were not HPMU differed from the HPMU students and received little weight in the analysis. The average weight was about 0.13 with 1% greater than 1 and 4% greater than 0.5. The effective sample size of the weighted comparison sample is 615. Table I presents the balance in selected variables before and after weighting; Figure 1 demonstrates the balance between variable distributions for the HPMU and other students in terms of the absolute standardized bias for all pre-existing variables controlled in our analysis. For each variable, the absolute standardized bias equals the absolute value of the difference in the mean for the marijuana users and the (weighted) mean for other students divided by the standard deviation for the marijuana users. If the groups are comparable these values should be close to zero. Values of greater than 0.25 are often considered problematic (Ho et al., 2007).

As shown in Figure 1, the groups differed substantially on many variables before weighting for baseline differences in observable characteristics, with the absolute standardized bias being greater than 0.2 for the majority of variables and over 0.5 for 12% of the variables. After weighting, the largest absolute standardized bias is just under 0.2 and only six differences are significant. We also explored alternative specifications with additional pre-existing variables included in the logistic regression model for dropout and our results were qualitatively invariant to these changes.

Table III presents results from our baseline models that evaluate the impact of persistent marijuana use during Grades 9 and 10 on high school dropout status. In Model 1, which accounts only for attrition (using nonresponse weights), the odds of high school dropout are nearly six times higher for persistent marijuana users than nonusers or casual users (10 versus 38% or 28 percentage point difference), and the finding is statistically significant. However, Model 2 shows that the effect size of marijuana use on
The dropout status is cut in half when we also use propensity score weights to account for differences in baseline characteristics between persistent marijuana users and nonusers. The result remains statistically significant, but marijuana use is now associated with just over a 2.4-fold increase in the odds of dropout.

Table III. Results from logistic regression models examining the effects of persistent Marijuana use on high school dropout status

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>High school dropout</td>
<td>Odds ratio</td>
<td>Odds ratio</td>
<td>Odds ratio</td>
<td>Odds ratio</td>
<td>Odds ratio</td>
<td>Odds ratio</td>
</tr>
<tr>
<td>Persistent marijuana use (Gr 9 and 10)</td>
<td>5.595***</td>
<td>2.406***</td>
<td>2.797***</td>
<td>1.273</td>
<td>1.883***</td>
<td>1.014</td>
</tr>
<tr>
<td>Age</td>
<td>1.112</td>
<td>0.557</td>
<td>1.088</td>
<td>0.640</td>
<td>1.086</td>
<td>0.677</td>
</tr>
<tr>
<td>Female</td>
<td>1.201</td>
<td>0.390</td>
<td>1.156</td>
<td>0.527</td>
<td>1.011</td>
<td>0.963</td>
</tr>
<tr>
<td>White</td>
<td>0.957</td>
<td>0.924</td>
<td>1.009</td>
<td>0.983</td>
<td>0.837</td>
<td>0.737</td>
</tr>
<tr>
<td>Native American</td>
<td>2.299</td>
<td>0.124</td>
<td>2.351</td>
<td>0.112</td>
<td>2.529</td>
<td>0.140</td>
</tr>
<tr>
<td>Father’s education</td>
<td>1.364**</td>
<td>0.014</td>
<td>1.379**</td>
<td>0.016</td>
<td>1.349**</td>
<td>0.022</td>
</tr>
<tr>
<td>Mother’s education</td>
<td>1.462***</td>
<td>0.008</td>
<td>1.495***</td>
<td>0.008</td>
<td>1.394**</td>
<td>0.026</td>
</tr>
<tr>
<td>Nuclear family</td>
<td>0.625***</td>
<td>0.007</td>
<td>0.628**</td>
<td>0.013</td>
<td>0.677**</td>
<td>0.043</td>
</tr>
<tr>
<td>Experimental condition: ALERT only</td>
<td>0.761</td>
<td>0.181</td>
<td>0.760</td>
<td>0.177</td>
<td>0.657</td>
<td>0.237</td>
</tr>
<tr>
<td>Experimental condition: control</td>
<td>0.936</td>
<td>0.749</td>
<td>0.936</td>
<td>0.748</td>
<td>0.770</td>
<td>0.204</td>
</tr>
<tr>
<td>Days alone after school, Gr 7</td>
<td>1.015</td>
<td>0.824</td>
<td>1.018</td>
<td>0.804</td>
<td>0.989</td>
<td>0.871</td>
</tr>
<tr>
<td>Hours alone after school, Gr 7</td>
<td>1.036</td>
<td>0.461</td>
<td>1.040</td>
<td>0.414</td>
<td>1.039</td>
<td>0.509</td>
</tr>
<tr>
<td>Used alcohol 0 day in past month, Gr 8</td>
<td>1.042</td>
<td>0.925</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 1 day in past month, Gr 8</td>
<td>1.016</td>
<td>0.973</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 2–4 days in past month, Gr 8</td>
<td>1.339</td>
<td>0.559</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 5–8 days in past month, Gr 8</td>
<td>1.243</td>
<td>0.713</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 0 days in past month, Gr 9</td>
<td>1.897</td>
<td>0.304</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 1 day in past month, Gr 9</td>
<td>1.083</td>
<td>0.877</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 2–4 days in past month, Gr 9</td>
<td>1.615</td>
<td>0.428</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 5–8 days in past month, Gr 9</td>
<td>1.178</td>
<td>0.720</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 0 days in past month, Gr10</td>
<td>1.185</td>
<td>0.821</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 1 day in past month, Gr10</td>
<td>0.896</td>
<td>0.877</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 2–4 days in past month, Gr10</td>
<td>1.245</td>
<td>0.733</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used alcohol 5–8 days in past month, Gr10</td>
<td>0.953</td>
<td>0.937</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gr 8: freq. of cig. use</td>
<td>1.168**</td>
<td>0.014</td>
<td>1.150*</td>
<td>0.088</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gr 9: freq. of cig. use</td>
<td>1.096</td>
<td>0.229</td>
<td>1.052</td>
<td>0.491</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gr10: freq. of cig. use</td>
<td>1.190**</td>
<td>0.016</td>
<td>1.161**</td>
<td>0.019</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grades in Gr 8</td>
<td>1.686***</td>
<td>0.005</td>
<td>1.547**</td>
<td>0.032</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grades in Gr 9</td>
<td>1.545***</td>
<td>0.004</td>
<td>1.553**</td>
<td>0.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grades in Gr10</td>
<td>1.653***</td>
<td>0.000</td>
<td>1.663***</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Odds ratio is significant at the p = 0.05 level; **it is significant at the p = 0.05 level; ***it is significant at the p = 0.001 level.
'aOther race is the reference group for ethnicity.
'bALERT Plus is the reference group for the Treatment condition.
'cUsed Alcohol more than 8 days in the last month the group for alcohol use.
(15 percentage point difference). If we can assume strong ignorability, then we can conclude that heavy and persistent marijuana use increases the risk of high school dropout.

To test the strong ignorability assumption, we explore the effect of adding contemporaneous measures of substance use that might share common unobservables with marijuana use (Models 3 and 4). Because students who use marijuana are more likely to drink alcohol (Gfroerer et al., 2002) and drinking can cause cognitive impairments and affect high school graduation (Cook and Moore, 1993), we first consider alcohol. Including days of alcohol use during Grades 8–10 does not change the marijuana results qualitatively. In fact, the odds ratio on persistent marijuana use actually increases.

Next, we consider cigarettes (Model 4). Unlike alcohol, there is no physiological reason why cigarette smoking would affect school performance or dropout status, as smoking is not known to impair cognitive functioning nor is it known to offset the deleterious effects on cognitive functioning associated with marijuana use. However, numerous studies have shown that smoking is a strong predictor of marijuana use (Gfroerer et al., 2002; Ellickson et al., 1998; Sommer, 1985). Model 4 shows that including cigarette smoking in Grades 8–10 causes a substantial reduction in the magnitude of our marijuana use measure (30% increase in the odds or 4 percentage point increase in dropout rate), which is no longer a statistically significant predictor of high school dropout status.

If heavy and persistent marijuana use was only associated with high school dropout because of its impact on cognitive functioning, then including cigarette use in our regression model should have no impact on the coefficient (or odds ratio) on marijuana use. The fact that it does suggests that the association is largely generated by an omitted variable bias. Recall that the propensity score weights are constructed using variables representing a wide range of constructs previously reviewed, but the constructs are all measured at baseline (Grade 7 or 8). If the influence of particular constructs changes over time, then baseline corrections will be insufficient to represent them.

Models 5 and 6 evaluate whether the omitted variable bias is caused by lack of controls for school performance. Economic theory suggests that poor performance will increase the likelihood that someone decides to leave school and hence represents an important factor when examining the decision to drop out of school. However, as described in the previous section, the mechanism through which marijuana might lead to the decision to dropout is by diminishing academic performance. Hence, including a measure of academic performance directly into the regression should significantly reduce if not eliminate the direct effect of marijuana on dropping out of school if this is the primary mechanism through which marijuana influences the decision to drop out. What we see in Model 5 is that including grades in the 8th, 9th and 10th grade has only a very small impact on the estimated effect of marijuana use on dropping out when compared with Model 2. Furthermore, marijuana use remains statistically significant in Model 5, suggesting that a reduction in student achievement at school is not the primary mechanism through which marijuana influences the decision to drop out of school. Interestingly, when we re-introduce cigarette smoking (Model 6), the odds ratio for marijuana use again drops substantially and is no longer significant. The use of cigarettes, therefore, appears to be significantly correlated with some personal characteristics that are the primary driver of the observed association between marijuana use and drop out status. The question remains, what is that personal characteristic?

Table IV provides the results of sensitivity analyses that explore the impact of probable sources of the relationship between marijuana use and dropout being picked up by measures of cigarette use. In the first row, we include three separate indices of deviance in Grades 8, 9 and 10, finding that the odds ratio for marijuana use is reduced but remains statistically significant unless cigarette use is also included (row 2). Indices of the student’s bonds to social institutions (religious and school) in Grades 8, 9 and 10 also do not account for the relationship between marijuana use and high school dropout. The odds ratio in this specification (Row 3) remains greater than 2 and statistically significant, unless cigarette use is also added (Row 4). We get the exact same findings when we add rates of time preference (Rows 5 and 6), emotional distress (Rows 7 and 8) and family stress (Rows 9 and 10). Including attitudes toward drugs yields a somewhat larger drop in the odds ratio for marijuana use (Row 11), although the odds
ratio is statistically significant at the 6% level and only becomes completely insignificant when measures of cigarette use are included (Row 12). In Rows 13 and 15, we finally identify two factors that explain the relationship between marijuana use and dropout: family influence and peer effects in Grades 8, 9 or 10. When these indices are included (without cigarette use), marijuana use has a much smaller odds ratio and is no longer a significant predictor of high school dropout status. Cigarette use is significant when it is also included (Rows 14 & 16).

### 6. DISCUSSION AND CONCLUSIONS

Several important conclusions can be drawn from these results. First, the results of Tables I and III indicate that important differences in baseline characteristics exist between individuals who choose to use marijuana and those who do not, even before most of these individuals ever initiate marijuana. Ignoring the selection bias indicated by these differences can lead to a significant over-estimation of the association between marijuana use and schooling, and is consistent with results presented by Chatterji (2006). Once we accounted for these baseline differences using propensity score weights, the odds ratio on marijuana use was cut in half, although it was still quite large and statistically significant.

Second, Models 2, 5 and 6 of Table III indicate that the primary mechanism through which marijuana might influence the decision to drop out is probably not a reduction in educational achievement. Indeed, including grades in school for 8th, 9th, and 10th grade led to only a 22% reduction in the estimated odds ratio of marijuana use on the decision to drop out. The association remained statistically significant and marijuana users were still more than twice as likely to drop out of school even after including measures of school achievement in the model.

Surprisingly, it is the inclusion of indicators of cigarette smoking during 8th, 9th and 10th grade that leads to a reduction in the association between marijuana use and schooling in Table III. There are at least four potential interpretations of this result. First, marijuana use causes cigarette smoking and controlling for smoking in the model is inducing a negative bias on the coefficient for marijuana use. This interpretation, however, is not supported by scientific evidence. We are not aware of any scientific evidence showing that cigarette use has an independent and direct negative effect on cognition; moreover, controlling for grades has almost no effect on the odds ratio for marijuana use. The second
possible interpretation of the cigarette result is that there is common unexplained heterogeneity among students who smoke marijuana and cigarettes and including cigarette use in the model results in negative endogeneity bias in the odds ratio for marijuana use. A negative endogeneity bias requires that, conditional on these unobserved factors for smoking, students with greater unobserved risks for marijuana use have smaller risks for dropout. This seems unlikely. In all observed data from our study and many other studies, youth who use marijuana have greater risk factors for negative behaviors and outcomes including negative peer associations, weak social bonds, low aspirations, and increased deviant behaviors. While we cannot rule out the possibility that unobserved heterogeneity creates a situation where conditioning on smoking reverses the strong relationship between marijuana use and negative risk factors, this sort of endogeneity bias seems much less likely than omitted-variable bias between marijuana use and dropout.

However, there is some evidence for two other explanations of the results: (1) marijuana influences an unobserved set of behaviors that is highly associated with both smoking and dropout and (2) omitted variable bias. In the former case, one might expect marijuana use to lead students to associate with more deviant peers or to develop opposition to traditional values and institutions which devalues schooling and leads to dropout. Students with such associations and attitudes are also at high risk for smoking (Ellickson et al. 2008). We test for many of these alternative pathways, finding that peer associations might explain our results.

Omitted variable bias, which arises from a failure to fully account for pre-existing differences between students who use marijuana in Grades 9 and 10 and those who do not, is also a defensible explanation. Earlier behavioral problems and risk factors not captured by our measures but known to be associated with marijuana and other problem behaviors in adolescents are one possible source of omitted variable bias. Cigarette smoking is known to be correlated with multiple demographic and psychosocial risk factors for negative outcomes (Collins and Ellickson, 2004; Tucker et al., 2006). In this study, both peer associations and family influences also accounted for the relationship between marijuana use and dropout. Although peer associations could be endogenous and causally influenced by marijuana use, they could also be correlated with omitted variables that better explain baseline differences. Family influences are less likely to be endogenous, which supports the conclusion that the relationships between marijuana use during Grades 9 and 10 and dropout is the spurious result of omitted variables. However, it is possible that parental attitudes towards children’s substance use (a component of our family influences) could change in response to use or that children’s perception of their parents’ attitudes may change following use. Hence our data do not allow us to provide a definitive conclusion about whether the effects of marijuana use on dropout reflect the influence of marijuana use on other behaviors such as peer associations or omitted variable bias. We can conclude, however, that the data do not support a causal model in which marijuana results in dropout through cognitive impairment.

One other key finding of this study is that both time-varying and time persistent factors influence the observed relationship between marijuana use and dropping out. Our attempt to control for a very rich set of variables at Grade 7 was insufficient for explaining the correlation between marijuana use and dropout status. Instead, variation in many of these constructs over time (in 8th, 9th and 10th grade) had additional influence on the relationship between marijuana use and high school success, suggesting that individual fixed-effects techniques would be insufficient for eliminating the bias caused by unobserved heterogeneity.

When interpreting the above results, two study limitations should be kept in mind. First, we examine student behaviors in only one state, South Dakota. Because South Dakota is very rural, with only two major cities, this sample may not accurately reflect the experience of all U.S. students. In particular, self-reported rates of marijuana use in South Dakota from the Youth Risk Behavioral Surveillance System were about 6 (lifetime) or 4 (current) percentage points lower than the national average of 43 (lifetime) and 24% (current) for 1999–2003, the years during which our study cohort was in high school. Smoking
and alcohol use rates were, in contrast, generally a little higher in South Dakota than across the nation (Centers for Disease Control and Prevention, 2000, 2002, 2004). In addition, recent estimates for the period between 2000 and 2003 found higher graduation rates (by about nine percentage points) in South Dakota than nationally (Education Week, 2009). Thus, marijuana use and dropout might be somewhat more deviant in South Dakota than in the rest of the nation and this could alter the relationship between deviant behaviors and dropout.

Second, inherent measurement error or possible limitations in our measurement of specific baseline constructs could partially explain the insufficiency of baseline measures to remove differences between marijuana users and other students that contribute to differences in dropout rates. In other words, there may still be unobservable factors biasing our results. Finally, the estimate of the effect of heavy and persistent marijuana use during Grades 9 and 10 accounts only for the effects of use during this period. Effects from earlier use are not included and may represent one of those unobserved factors still biasing results.

In addition to providing new interpretations of the observational relationship between marijuana use and high school dropout, this study also provides insights regarding appropriate instruments when trying to identify causal associations using instrumental variables techniques. Our results show that measures of cigarette use, peer substance use and parental substance use, which have been used in previous analyses, would be poor instruments as they are heavily correlated with high school completion as well as marijuana use.

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