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What I think I will do versus what I say I do: Mispredicting marijuana use among teenage drug users

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ABSTRACT

Past research examines factors that impact marijuana use. However, there is limited empirical evidence regarding the combined role of previous experience, attitudes and the situation in determining present and future marijuana use. We fill this gap by studying factors that affect misprediction of marijuana use among teenagers. Specifically, we study (1) whether individuals are able to correctly predict their future marijuana use, (2) the direction of misprediction (over versus under prediction) and (3) the factors that affect errors in prediction.

We use data from a federally sponsored survey about teenagers' marijuana consumption in the United States. We find that, teenagers under predict future marijuana use and that this inaccuracy is moderated by the extent of use. We also find that misprediction is affected by both attitudes and the situation through main and interaction effects. We outline some policy implications of our findings.

1. Introduction

We often engage in behavior contrary to our best predictions and intentions. We expect to eat less and exercise more than we really do. For example, the average gym member in the United States pays $55 per month (inside of a $30 billion industry) but only goes to the gym at most twice a week, and a full two-thirds of those purchasing a gym membership never use it at all. Exercise and diet companies routinely focus on sales around January 1 of each year in an attempt to cash in on our mispredictions.

One important reason for this misprediction is that one anticipates future decisions to occur under a "hot" state while presently being in a "cold" state (Loewenstein, 1996). That is, individuals often predict what they will do in the face of some powerful visceral influence on their behavior (i.e., a "hot state, e.g., hunger) while not currently experiencing that same state (i.e., being in a cold state, e.g., being full after a meal). Anecdotal evidence, however, may lead one to simplistically—and incorrectly—conclude that, like the perpetual dieter, individuals are always overly optimistic about their future behavior. In the present work, we use data on reported marijuana use by teenagers to explore the possibility that misprediction is neither random nor unidirectional and it depends on several predictable factors. Past research has provided valuable insights on what psychological factors affect consumption of addictive substances such as alcohol and cigarettes (Davis & Grier, 2015; Hwang & Yun, 2015). Yet what remains unknown is how a teenager's attitude *and* situation combine to affect her propensity to use marijuana in the future.

Marijuana is *the* most widely used drug today. According to the latest report from the National Institute on Drug Abuse (NIDA) in 2013, 19.8 million people had used marijuana in the past month, up from 14.5 million in 2007 (NIDA Report on Nationwide Trends, 2014). Forty percent of *all* teenagers had tried marijuana in 2012, up from 32% in 2008. This increase comes at a time when use of other drugs has remained the same or declined over the past decade. Further, using marijuana has become "normalized" behavior. What we will refer to as "perceived severity" (i.e., perceptions that using marijuana is serious) of marijuana use is low: 71% of teens said they have a close friend who uses marijuana regularly. However, Meier et al. (2012) show that a teenager who starts smoking marijuana loses much more of her brain power (measured as IQ) than does an adult who smokes just as much. This shows that marijuana use is not just harmful; it is particularly harmful to the developing mind. Therefore, studying marijuana use among teens is an important issue from multiple perspectives. Our interest is in answering these questions:

1. How do teenagers' predictions of future use compare with actual marijuana use?
2. Are these mispredictions systematic?

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3. What factors (external and internal) cause the mispredictions?
4. What are the public policy implications?

2. Theory development

We use several distinct, yet interrelated, research streams to develop our hypotheses. First, we incorporate prior research addressing behavior prediction accuracy. Second, we use research on expertise and prior use to examine how prior experience affects individuals' prediction accuracy. Third, we use research examining situational and attitudinal influences on behavior prediction. We proceed by examining each, developing hypotheses that build on each other.

2.1. Prediction accuracy

Prior evidence shows that, for a variety of reasons, people inaccurately predict their own future preferences (e.g., Loewenstein & Schkade, 1999). The most relevant framework for our paper comes from work on visceral factors and the *hot-cold empathy gap* (Loewenstein, 1996). According to this research, when individuals are in a "cold" state (i.e., not hungry, or, in our case, not craving a drug), they are unable to accurately predict how they will behave when they are aroused, generally tending to underestimate the likelihood that they will engage in the relevant behavior. Building on this research stream, we hypothesize that teens, on average, will underpredict their level of future drug consumption:

H1. Individuals will, on average, underpredict their level of future drug consumption.

2.2. Misprediction of future behavior and past experience

One important consideration when examining misprediction is the role of prior experience, that is, whether the teenager has used drugs in the past. The "traditional" learning perspective has been that forecasting improves with experience and feedback (Alba & Hutchinson, 1987; Cambridge Handbook, 2006), presumably due to improved memory and elaboration on similar past consumption occasions. On the other hand, other research (Kahneman & Klein, 2009) suggests subjective experience is often not a reliable indicator of judgment accuracy; that is, *expertise can sometimes be a liability rather than an asset with respect to accurate forecasting.* With respect to marijuana use, we hypothesize that more regular drug users may become overconfident about their ability to limit their drug use and underestimate future usage as a result, consistent with experience as a liability. This finding would suggest that higher levels of previous use (experience) lead to a greater level of underprediction:

H2a. The extent of prior use affects prediction accuracy. Specifically, underprediction of future use will increase with level of past use.

2.3. The role of attitudes and the situation

To understand the behavioral factors that could lead users to underpredict future use, we examine the possible effect of attitudes and situation on these users. Early attitude research assumed attitudes were the key to decoding human behavior (Watson, 1925). However, later research showed the relationship between attitudes and behavior is not as strong, or direct, as once assumed and that it plays a more central role in driving behavior (Mischel & Philip, 1982). In this paper, we examine the role of an external factor (situation) versus an internal factor (attitudes) on misprediction, and therefore examine each in turn.

2.3.1. Situation

We consider the situation to include both environmental and social elements. We explore whether users with more peers who use marijuana and those who have more access to it (i.e., our situational variables) will overpredict future marijuana use. In many circumstances in which the situational variables are not naturally salient at the time of prediction compared to usage, these conditions could lead to underprediction of use (e.g., Loewenstein, 1996). In our specific context, having greater access and more peers who use more often are likely to be relatively salient features at the time of prediction, and possibly more salient when predicting than at the time of usage. Thus, this would be associated with a greater over-prediction. We test this theory via the following hypothesis:

H2b. Greater presence of situational variables (having more peers and greater access) present at the time of prediction will lead to greater overprediction of future marijuana use.

2.3.2. Attitude

We explore whether users with more negative attitudes will underpredict their future use to greater extent. They may do so because their current negative attitude toward drugs will cause their expectation of future use to be low. However, at the time of actual use, they will be more influenced by the situation around them and the "hot state" they face at time of choice. Therefore, consistent with recent research using laboratory studies (Pronin, Olivola, & Kennedy, 2008), we hypothesize that having negative attitudes at the time of prediction will lead to a lower level of predicted use, thereby exacerbating the underprediction error:

H2c. More extreme negative attitudes toward drug use at the time of prediction will lead to greater underprediction of future marijuana use.

3. Empirical application: the data set and methodology

We develop an exploratory econometric model of drug use, tying the constructs above to individual choice behavior. The basis for the framework is a well-established economic model of individual behavior (Hanemann, 1984) and has been used previously in the context of drug-choice behavior (Block, Morwitz, Putsis Jr, & Sen, 2002). However, we make some important modifications to accommodate for the non-panel nature of our data set. Therefore, before attempting to understand the modeling approach, we turn to a discussion of the data set.

3.1. The data

The Partnership for Drug Free Kids (PDFK), formerly The Partnership for a Drug-Free America, is a nonprofit organization founded in 1985 to help curb increasing teenage drug use. To assess changing national attitudes toward illegal drug use and changes in drug consumption, the PDFK has established an annual research program. The first such research program, the Partnership Attitude Tracking Survey (PATS), began in 1987. Every year (from 1987 through 1996) the survey collected data in waves through multiple-site central-location sampling. The PATS data we use in our analysis are from 1995 and 1996 (we will refer to these as "Wave 1" and "Wave 2" throughout the paper). In the first stage, we selected a sample of counties to include in the study; we selected sampling sites to match the population of the contiguous United States. In the second stage, we drew schools from among all those in each selected county. In the third stage, we drew a sample of classes from grades 9 through 12, from each school, followed by a systematic random sample of these classes, drawn separately for each school. All students in these selected classes constituted the selected sample of students for the study. On the scheduled interviewing day, an interviewer visited each class in turn to administer the questionnaires. All interviewing was conducted with the teacher present in the room. Once the interviewer had introduced the study and explained the procedures, the students completed the questionnaires at their own pace.

Responses were confidential—students did not put their names on the questionnaires. Research suggests this mode of interview should result in increased willingness to reveal illicit or undesirable behaviors, especially among minorities and those who are more distrustful of others (Aquilino, 1994). The external validity and realism achieved by employing a large federally sponsored, nationally representative sample of teenagers make this data set particularly unique for addressing the research questions at hand.

3.2. Setting up the dependent and independent variables

The PATS surveys (Waves 1 and 2) have rich responses to the dependent variable measures: respondents indicated *how many times* in the past 12 months they had used marijuana, as well as *how many times* in the next 12 months they expected to use the drug. They provided their answers by checking off one of the following seven response alternatives for volume as follows: 1 = none, 2 = once, 3 = 2–3, 4 = 4–9, 5 = 10–19, 6 = 20–39, and 7 = 40+. As noted above, volume = 1 indicates no past use. The rest of the values (2–7) indicate at least *some* marijuana use. Thus, for the dependent variables, the data contain seven logically ordered categories.[1]

The independent variables peer influence (PEERINFL), access to drugs (ACCESS), and negative attitude toward drugs (NEGATIVEATT) are factor loadings from a detailed factor analysis of raw data scores; this factor analysis and a more detailed description of the independent variables used and the underlying theoretical support are discussed in Table 1. Peer influence and access to drugs load onto the factor "Situation," whereas the negative attitudes load onto the "Attitude" factor.

To demonstrate the consistent underprediction of future consumption in the context of marijuana use, the first step clearly has to be estimating a model of actual marijuana use and comparing it with predicted marijuana use. To provide this comparison, we need the actual and predicted (future) marijuana consumptions from our sample of teenagers. Therefore, we first use the data set to estimate misprediction, as discussed below.

3.3. Using data from Waves 1 & 2

We estimate two separate equations: one equation for those who *have* used marijuana in the past year (defined as those with values greater than or equal to 2) and one for those who *have not* (defined as those with the value 1). We use this approach because we recognize that prior users are likely to differ in numerous ways from those who have not previously tried marijuana. From these separate estimations, we are able to assess the level of misprediction differently as a function of prior use. In our data set, we have information from two waves of data; however, the respondents who took the two surveys were not the same. That is, we do not have panel data. Consequently, we develop a methodology used to construct the prediction variable.

3.4. A methodology to capture predicted responses with non-panel data

Recall that our objective is to examine differences between what respondents *think they will do* in the future and *what they report doing*. Were we to have a panel of individuals over time, we could examine differences between what an individual said they would do in the upcoming period versus what they reported doing during the same period. With our data, each wave represents a different set of respondents. Thus, we develop a detailed econometric methodology that enables us to systematically compare predicted future and reported actual drug use over the same time period. Specifically, the point of comparison we

Table 1
Defining dependent and independent variables.

Dependent variables:

POTYEAR: respondents indicated how many times in the past 12 months they had used marijuana.

POTNEXTYEAR: respondents indicated how many times in the next 12 months they expect to use marijuana.

Theoretical support: available evidence indicates that self-reported drug use behaviors have a high degree of reliability and validity (see Sickles & Taubman, 1991 for a detailed discussion of self-reported drug data accuracy). Additionally, there is precedent for using self-reported survey data of this type. For example, Evans and Farrelly (1998) use self-reported data to examine the role of taxes on cigarette consumption. We split the data into two depending on whether or not marijuana was used in the past (volume = 1 (indicating no prior use) was one group; all the others were in the second group). We performed our analyses on the two groups separately since we believed that, fundamentally, prior drug users differ substantively from those who had not used drugs in the past.

Independent variables:

PEERINFL: respondents indicate how many of their close friends use marijuana occasionally such as at parties or social events, and how many of their close friends get "stoned" or "high" on marijuana once a week or more.

Theoretical support: consistent with the desire to "fit in," the health belief literature suggests that beliefs regarding compliance are strongly influenced by social norms and peer pressure (Case & Katz, 1991). This is particularly true of adolescents and drug use behaviors. Rose, Bearden, and Teel (1992) report that teen drug users tend to have friends who are drug users, and these friendships have a strong causal influence on drug abuse. Thus, having friends who use drugs propagates drug use. Similarly, friends who do not use drugs also exert peer pressure, which functions as a cost to drug consumption. Thus, this measure in our empirical analysis reflects peer pressure by querying respondents on the number of their friends who use marijuana occasionally such as at parties or social events, and how many of their close friends get "stoned" or "high" on marijuana once a week or more. Each item was rated on a five-point scale where a *low score* corresponds to no close friends, and a *high score* correspond to all close friends. The average score served as the peer pressure index.

ACCESS: indicates the availability of drugs in a teen's immediate neighborhood, defined as areas near their school and their home.

Theoretical support: the supply or availability of drugs is a significant factor in drug use. Two of General Barry McCaffrey's original five objectives as head of the Office of National Drug Control Policy (ONDCP) were to limit drug accessibility in the U.S. by interdicting drugs entering the U.S. and to lower world-wide drug supply by eradicating drugs and drug cartels in their source countries (McCaffrey, 1997). Implicit is the idea that limited availability of drugs will lead to reduced drug consumption. This suggests that lower (greater) drug availability will be associated with increased disutility (utility) of using drugs. Respondents rated the difficulty they would have in obtaining the drug on a five-point scale (where low scores correspond to very difficult and high scores correspond to very easy). Note that higher numbers on this measure indicate drugs are easily available.

NEGATIVEATT: measures a teenager's negative attitudes toward drug use.

Theoretical support: general attitudes toward drugs serve as either perceived benefits or costs to drug use, thus providing utility or disutility to drug use depending on the valence of the attitude. For teenagers, a negative attitude toward drugs might include the belief that drugs can make a person engage in dangerous behavior. On the other hand, positive beliefs toward drugs include the perception that drugs make you relax, make you feel good, help you get away from your problems, give you more energy, provide insight and understanding, and help with anger or frustration (Johnston & O'Malley, 1986). Thus, the more favorable teens' attitudes toward drugs, the higher their utility to use drugs; the more unfavorable teens' attitudes toward drugs, the higher their disutility to use drugs. Here, attitude toward drugs was measured by asking respondents to indicate their level of agreement (5 point scale where 1 = strongly agree and 5 = strongly disagree) with eleven items describing statements relating to drug use. The average of the scores for each respondent provides an index of attitude toward drug use and drug users. Note that a high score indicates an *unfavorable attitude toward drug use and drug users*.

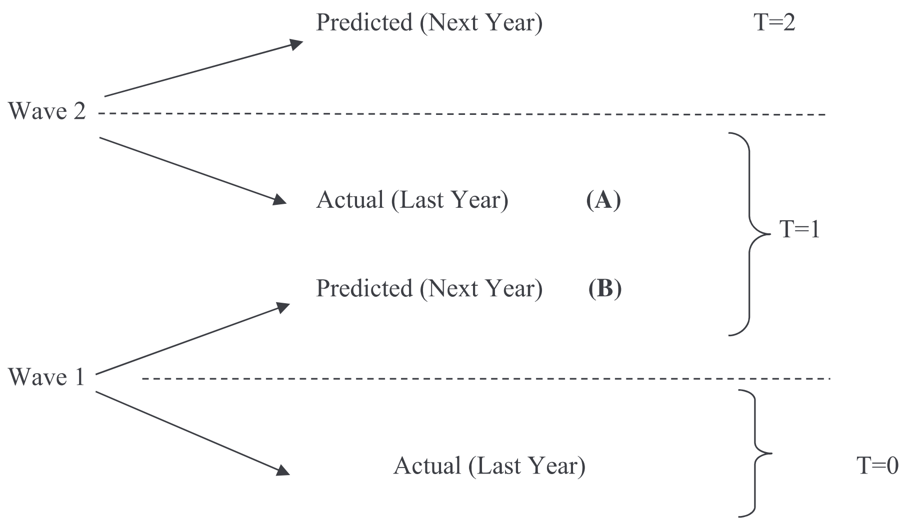
Sex: control indicator variable with 1 = male and 2 = female.

Race: indicator variable that captured if teen was White, Black, Asian, Hispanic or other.

Area: indicates whether teen lived in an urban, suburban or rural area.

[1] One concern with using reported-use data is that respondents may under-report actual usage. Under-reporting of actual use would lead us to conclude respondents overpredict rather than underpredict actual use (thereby strengthening our results).

are interested in are points (A) and (B) in the diagram below, namely, predicted versus actual in period T = 1.



As noted above, the problem is that the respondents in (A) and (B) are not the same; that is, this is not a panel data set. So what do we do? We predict what Wave 2 respondents would have predicted they would have done were we to have sampled them a year earlier and compare this prediction to their reported actual use over that year (which we have). We refer to *what individuals in Wave 2 would have predicted* as "predicted hat."

Methodologically, to create an appropriate and consistent "predicted hat" equation, a key assumption we will make is that the functional form of the "prediction" equation does not change from (**A**) to (**B**) (in the time between Waves 1 and 2). Note this does NOT imply assuming the characteristics of the sample (e.g., different demographic make-up, different attitudes, etc.) or that the magnitude and direction of the influence of any factor does not change over time, only that the functional form is consistent from one wave to the next. Because this is a crucial piece of our modeling, we tested the assumption that the underlying functional form of the choice decision does not change within one year. A formal statistical test of functional-form change across the two waves revealed that (at $p < .01$) both the functional form and magnitude of the coefficients estimated do not change.

Therefore, we proceed with our estimation of the predicted hat variable, as outlined in the steps below:

Step 1: We begin by estimating ordered probits using Wave 1 data for both previous users and non-users. Future prediction (POTNEXTYEAR) serves as the dependent variable ((**B**) in the figure above), whereas the attitudinal, situational, and demographic variables are the independent variables. We then use the functional form from this estimation and data from Wave 2 to create a fitted value (we label this value "predicted hat") that predicts what individuals in Wave 2 *would have predicted had we observed them a year earlier*.
Step 2: Next, we create the difference between actual use of marijuana by respondents in Wave 2 ((**A**) in the figure above) and the predicted hat variable created in *Step 1*. Mathematically, the difference variable (DIFF) equals "predicted hat" minus actual use for each individual across both sets of teenagers—those with and without past drug use. Note that if DIFF < 0 (> 0), the implication is that teens under- (over-) predict future marijuana use.
Step 3: We model the difference between the predicted hat and actual-use variable as a function of attitudinal, situational, and demographic variables.

The descriptive statistics for Waves 1 and 2 are presented in Table 2A and B.

The estimation results from the ordered probits (in Step 1) are presented in detail in the Appendix A (we refer to these results as the "Baseline" Models). We discuss the results from the estimation first and then turn to a validation of the hypotheses.

4. Empirical results

The first model (Appendix Table A1) studies the effect of attitudinal, situational, and demographic variables on predicted marijuana consumption (POTNEXTYEAR), *only for past users* of marijuana. The greater the influence of peers, the more likely a teen is to predict a higher level of marijuana use in the next year. Similarly, greater access to drugs increases a teen's prediction of future drug use. These results reaffirm the important role situational variables play in a teenager's drug-related choices. With regards to attitudes, the more an individual perceives drug use and drug users to be "uncool," the less likely the respondent is to predict future marijuana use. In terms of demographic variables, note that race is non-significant for past users, and males living in urban areas predict higher future use. These results are consistent with the behavioral research noted earlier and with our theoretical framework.

In the Appendix Table A2, we estimate predicted marijuana use as a function of the same independent variables (attitudes, the situation, and demographic variables), but for those who have *not* consumed drugs in the past. Much like for those *with* past marijuana use, peer influence

Table 2
A. Summary statistics for Wave 1 data. B. Summary statistics for Wave 2 data.

Variable	Mean	Standard deviations	Min	Max
A				
Actual use	4.787	2.262	2	10
PEERINFL	.7366	.9376	−1.506	3.308
ACCESS	.5423	1.106	−1.687	4.987
NEGATIVEATT	−.8831	.9675	−2.681	1.257
B				
Actual use	4.692	1.897	2	7
PEERINFL	.8188	.9711	−1.446	3.308
ACCESS	.5904	1.191	−1.687	4.668
NEGATIVEATT	−.9805	.9314	−2.681	1.257

Table 3
Predicted versus actual use of marijuana for those with past use.
(1 = no future use, 2 = once, 3 = 2–3 times, 4 = 4–9 times, 5 = 10–19 times, 6 = 20–39 times, and 7 = 40 + times).

Predict higher than actual by 1	75 (11.2%)	Predict lower than actual by 1	156 (23.3%)
Predict higher than actual by 2	43 (6.4%)	Predict lower than actual by 2	123 (18.4%)
Predict higher than actual by 3	13 (1.9%)	Predict lower than actual by 3	61 (9.1%)
Predict higher than actual by 4	9 (1.3%)	Predict lower than actual by 4	37 (5.5%)
Predict higher than actual by 5	1 (0.1%)	Predict lower than actual by 5	6 (0.8%)
Predict higher than actual by 6	0	Predict lower than actual by 6	9 (1.3%)
Total % overpredicting	21.2%	Total % underpredicting	58.6%

positively affects predictions of future use, and having a negative attitude toward drugs negatively affects these predictions. However, those with no past marijuana use think that access to drugs is an insignificant factor in predicting future consumption. This finding is interesting because those *with past use* strongly believe access to drugs plays a positive role in predicting future use. Therefore, this result suggests that those who have not consumed marijuana in the past *undervalue the role of the situation* (i.e., access to drugs) in their predictions of future use. Further, the race variable is now significant. Whereas blacks who are non-users think they are more likely to use marijuana in the future, blacks who have used in the past do not (the race variable is non-significant in the prediction of future use for past users).

Next, we use the functional form of the above estimations and data from Wave 2 to create the "predicted hat" variable; we use this variable in the discussion of hypotheses below.

4.1. *Underprediction of future use (H1)*

The sample contains a total of 668 individuals with past marijuana use. Predicted use is exactly equal to reported use for 135 (20.2%) of these individuals (i.e., the respondent predicted correctly, or, DIFF = 0). Among the remaining 533 individuals who predicted incorrectly, approximately 59% underpredicted future use (i.e., those with DIFF ≤ 1 to DIFF ≤ 6) and 21% overpredicted future use (i.e., those with DIFF ≥ 1 to DIFF ≥ 6). Further, of those who underpredicted future use, more teens were off by greater than three categories (about 13%) than those who overpredicted (6%). Table 3 denotes the number of observations (percent of overall sample in Wave 2) for each category of those who mispredicted future use.

To summarize the results of Table 3, among those who had *used marijuana in the past*, the vast majority predicted they would use *less* than they actually did (i.e., they underpredicted). By contrast, of the 2325 teenagers in our sample who had *not used marijuana in the past*, 99.6% correctly predicted no future drug use (i.e., DIFF = 0).

Therefore, unlike past drug users, an overwhelming majority of teen non-users accurately predict no future use. We note that past non-users correctly predicting future non-use speaks to the validity of our empirical approach. In other words, the fact that past non-users do not predict future use gives us confidence in our estimation methodology, because we expect that those who have not used in the past will, typically, state they will not use in the future.

Table 4
Means of DIFF variable as a function of actual marijuana use.
(2 = once, 3 = 2–3 times, 4 = 4–9 times, 5 = 10–19 times, 6 = 20–39 times, and 7 = 40 + times).

Actual use	"Diff"
2	0.39
3	−0.14
4	−0.67
5	−1.50
6	−1.72
7	−2.07

Table 5
Ordered probit results for DIFF variable.

Variable	Coefficient	Standard error	z = b/s.e.
1. Main effects only model			
Actual use	−1.743***	.077	−22.42
PEERINFL	.6538***	.063	10.23
ACCESS	.3008***	.049	6.05
NEGATIVEATT	−1.813***	.096	−18.85
Sex	−.679***	.108	−6.26
Race	−.139**	.073	−1.97
Age	.349***	.056	6.21
Area	.089*	.040	2.23
Pseudo $R^2 = 0.51$	Log likelihood = −493.68		
2. Main and interaction effects model			
Actual use	−1.558***	.083	−18.70
PEERINFL	1.628***	.176	9.24
ACCESS	0.663***	.141	4.69
NEGATIVEATT	−3.96***	.257	−15.39
PEER * ACT	−.171***	.032	−5.24
ACCESS * ACT	−.055**	.026	−2.07
NEGATIVEATT * ACT	.391***	.041	9.33
Sex	−.797***	.114	−6.94
Race	−.194**	.073	−2.65
Age	.106***	.042	2.53
Area	.370***	.059	6.20
Pseudo $R^2 = 0.58$	Log likelihood = −422.53		

N = 519.
*** $p < .001$.
** $p < .05$.
* $p < .1$.

The results from past users and non-users partially support H1. Whereas H1 states that *all* individuals underpredict their level of future consumption, we find that for teenage marijuana use, the result holds only for *past users* of marijuana.

To understand how prior use affects misprediction of future use, we examine the role of extent of use.

4.2. *The role of extent of use (H2a)*

We have demonstrated that teenagers who have used drugs in the past are (relatively) bad at predicting their own future usage of marijuana. This finding brings up the question of whether *the amount of drug consumption in the past* plays a role in the extent of misprediction (H2a). To examine this possibility, we look at the means of the misprediction variable (DIFF) for each level of actual use. Recall that if DIFF < 0, this result implies underprediction (Table 4).

Those teens that have a higher level of actual marijuana use display an increased underprediction of future use. The pattern is clear and strong.[2] We confirmed the significant and negative relationship between the variables by conducting a linear regression with "DIFF" as the dependent variable and actual use as the independent variable.[3] Thus, H2 is supported.

[2] Given that a systematic bias in the prediction equation might also produce a similar result, we plotted residuals for the predicted equation for both Waves 1 and 2 and checked for heteroskedastic errors. Residuals revealed neither heteroskedastic errors nor visual patterns to the errors.

[3] The slope coefficient was negative (−0.987) and significant at $p < .01$.

4.3. The main effect of situation on misprediction (H2b)

To understand the impact of situational variables (access and peer influence) on underprediction, we estimate a model with all the independent variables, and examine the main effects of the situation variable as shown by the variables PEERINFL and ACCESS in Table 5.[4]

Looking at the main effects of peer influence (PEERINFL) and access (ACCESS) variables, we see that at $p < .05$, the more access to drugs and the more close friends who do drugs, the greater the overprediction of future consumption. Thus, H2b is supported.

4.4. The main effect of attitudes on misprediction (H2c)

From looking at the main effects of the attitude variable (NEGATIVEATT) in Table 5, we see that at $p < .05$, the more negative the attitudes about marijuana use, the greater the underprediction of future consumption.

4.5. Exploring the interaction effect of attitudes and past use and of situation and past use on misprediction

Now that we have tested for the individual main effects of past use (H2a), of the situation (H2b), and of attitudes (H2c) on prediction accuracy, we next assess the interaction effect of situation and of attitudes as the level of past use changes. We perform this analysis because we believe the interaction effects of the attitude and situation variables with past use may not be the same as the main effects. However, because we are unaware of any prior work that has investigated the interaction of our focal effects with the extent of prior use, we present tentative ideas based on prior work that we then test empirically.

4.5.1. Situation and past use

In a consumer choice domain, Zauberman (2003) found that consumers mispredict their own future purchase intensity because they do not take into account the future switching costs they will subsequently face. This effect is consistent with the systematic inability to correctly incorporate the effect of situation into predictions of future behavior. In our setting, teens may underestimate the impact of peer pressure or the ease of access to drugs (the situational variables in this study). To the extent that those with higher marijuana use have a higher switching cost (i.e., switching to lower levels of use is harder for frequent users than for recreational users), we would expect higher users to incorrectly assess the impact of situation when predicting future use. In other words, based on this conjecture, we expect a change in coefficient sign of the interaction term compared to the main effect. That is, for those with lower past use, a greater presence of situational variables (i.e., more access to drugs, more peers who use it) at the time of prediction will lead to overprediction of future use. By contrast, for those with higher past use, a greater presence of situational variables will lead to an underprediction.

To verify this conjecture, we divide users into high and low based on their past use of marijuana. Specifically, those who have used marijuana less than three times in the past year are classified as low users (L), and those who had used marijuana 4 to 40+ times are classified as high users (H).[5]

[4] We also used a 30-day (monthly) recall, and multiplied it by 12 to obtain yearly recall instead of directly using the 12-month recall, in order to identify any issues related to people incorrectly calculating how many times they used marijuana in the past based on different timeframes. We redid the estimation in Table 5. All of the significant variables and the directions of the significance remained the same. We thank an anonymous reviewer for this suggestion.

[5] We tried other cutoffs for L and H users, and doing so did not result in any substantive differences.

4.5.2. Attitude and past use

Research on attitude formation suggests attitudes correlate with future behavior more strongly when those attitudes are more accessible (Glasman & Albarracin, 2006). Thus, the more accessible the attitude, the more it predicts future use. If, in the current context, higher levels of past drug use lead to more readily accessible attitudes toward use, these top-of-mind accessible attitudes would lead high users to overpredict future use compared to low users. That is, one would expect the extent of past use to moderate the impact of attitudinal variables on future use. Specifically, for those with lower past use, higher levels of attitudinal variables (i.e., having more negative attitudes toward drug use) will lead to an underprediction of future use. By contrast, for those with higher past use, higher levels of negative attitudes will lead to an overprediction of future use.

These tentative predictions offer a more nuanced view of how attitudes and situation affect misprediction for teens who have used marijuana in the past. To test these interactions, we create three interaction terms: peer influence ∗ actual use (PEER ∗ ACT); access ∗ actual use (ACCESS ∗ ACT); negative attitude ∗ actual use (NEGATIVEATT ∗ ACT).

Looking at the interaction-effects model (Table 5, Model 2), we examine the interaction effects for the situation variables (PEER ∗ ACT, ACCESS ∗ ACT). We find the interaction terms between actual use and the situational variables (PEER ∗ ACT, ACCESS ∗ ACT) are negative and significant, as conjectured. The interaction between actual use and attitude toward drugs (NEGATIVEATT*ACT) is positive and significant, again as conjectured.

5. General discussion

Our paper presents several key results that suggest a complex picture of choice decision and prediction with respect to teenage drug use. We demonstrate that teenagers mispredict future marijuana use, and that the misprediction is not uniform. On average, teenagers with past marijuana use underpredict future consumption, and negative attitudes toward drug use appear to be associated with greater underprediction (H2c). In our context, experience is in fact a liability in terms of predictive accuracy (H2a). Because the power of the situation plays a dominant role during the time of prediction, situational variables such as peer influence and access increase the level of overprediction (H2b). Finally, misprediction of future use appears to depend on the interaction of attitude and situational factors on past use; the signs flip with an interaction term, suggesting that looking merely at the main effects of attitudinal and situational variables could be misleading.

5.1. Policy implications

Our results have interesting policy implications. First, differential dollars must be allocated to campaigns targeting non-users and users, and indeed between low and high users of marijuana. Past research shows that marketing campaigns can prevent addiction (Martin et al., 2013). The Department of Health and Human Services issues a "Marijuana Use Map" that shows the concentration of marijuana users in the contiguous United States. We suggest using this map to focus different advertising campaigns depending on various levels of past marijuana use. This is particularly important and timely as marijuana legalization initiatives have hit full throttle throughout the United States and increasing calls are being made for national legalization (Hudak, 2015).

Because peer influence and access to drugs play a role in underestimation of predicted use, advertising campaigns may want to highlight these issues for high-volume users. We find high users are more prone to underestimating the effect of the situation. Therefore, high users need targeted messages that show the link between these external influences and their future use. Specifically, the effect of "seemingly harmless" things, such as having close friends who get stoned on marijuana regularly or having increased access to drugs around the home, on increased drug use needs to be clarified.

For low-volume users, a different set of messages with an internal focus need to be created. Low users have less negative attitudes about marijuana use, which is one of the factors that causes them to use more drugs than they predict they will (i.e., leads to underprediction). Therefore, we suggest a two-pronged approach. The first is to instill negative attitudes among low users through effective fear-appeal campaigns. Recent research suggests such campaigns have high efficacy in reducing tobacco use among people who have recently started smoking (Akyuz, 2015), which is something that could work for low users. These threat-oriented messages have been shown to increase users' motivation to quit (Wong & Cappella, 2009). Second, a clear message of how simply having negative attitudes toward drug use and users can impact future prediction and lower actual use needs to be crafted. Done effectively, these two campaigns together could move low users to non-users.

The Federal Office of National Drug Control Policy has committed over $10 billion to drug-prevention programs and campaigns. Several more privately (NotMyKid.org) and publicly funded organizations (Drug Free Amssa Foundation, D.A.R.E.) spend millions of dollars on several campaigns each year. Our results suggest ways to better spend those dollars toward more effective measures in slowing marijuana use across teenagers.

Further, we speculate these results would extend to any situation involving a “desired” versus “not desired” behavior: consumption ranging from cigarettes to high-calorie foods to the current opioid crises that has gripped the United States. Our research suggests that patients prescribed these addictive painkillers will underestimate its effect. Policy (and business) practices that will allow us to mediate the drug's impact would include limits on prescription duration and volume. This can be voluntary through industry agreement (the negative publicity has had a huge negative impact on ethical drug manufacturers) or public policy. Clearly, our research suggests voluntary and/or patient-induced solutions will be ineffective.

The business of such vices is under-researched, the implications are enormous, and this research effort is, hopefully, a first step toward understanding how the consumption of such “vices” is in some fundamental ways different from “traditional” goods. Considerably more research is needed, however, before we can definitively extend our results to each of these areas.

5.2. Limitations and suggestions for future research

Consistent with our theoretical framework, we find predictable systematic differences between what teenagers say they will do and what they actually do. We study the systematic factors that affect this misprediction, by addressing the relative roles of attitudes, the situation, and level of past use. We believe we are the first to study, in such a detailed manner, the factors that affect misprediction of future drug use with survey data and not experimental methods. We also create an estimation approach that can be generalized to another setting where a researcher lacks panel data but would like to compare current with future behavior.

Nonetheless, our paper has its limitations, some of which can be addressed in future research. First, we do not consider the “interconnectedness of vices” that typically exists in teenagers. In other words, does being an alcohol addict have an effect on marijuana consumption? Second, researchers could formally expand on our understanding of the role of past use on future prediction in a panel-data setting. We hope future work will build on this research idea to curb our ever-growing drug-addiction problem.

Appendix A. Baseline models

We begin by presenting the results from the baseline ordered probits for those with past experience of marijuana and then for those who have not used in the past. Table A1 presents the results for the marijuana-prediction equation for past marijuana users who say they will use marijuana in the future, using Wave 1 data. The dependent variable here is Wave 1 respondents' prediction of future marijuana use.

Table A1
Ordered probit results for predicted marijuana use among past users.
Dependent variable: POTNEXTYEAR with PASTYEAR = 1.

Variable	Coefficient	Standard error	z = b/s.e.
PEERINFL	.3607097***	.0756068	4.77
ACCESS	.1681827**	.0604903	2.78
NEGATIVEATT	−.7843948***	.078633	−9.98
Sex	−.2309073*	.1247294	−1.85
Race	−.0429893	.0843127	−0.51
Area	.1515057**	.0675882	2.24
/CUT1	.0374314	.2732428	
/CUT2	.2973168	.2741234	
/CUT3	.8590603	.2779385	
/CUT4	1.346389	.2812217	
/CUT5	1.865526	.2860736	
/CUT6	2.315591	.2917671	
Pseudo R^2 = 0.17	Log likelihood = −492.11		

N = 319.
*** $p < .001$.
** $p < .05$
* $p < .1$.

Next we present the estimation of predicted marijuana consumption for those who have not used drugs in the past.

Table A2
Ordered probit results for predicted marijuana use among non-past users.
Dependent variable: POTNEXTYEAR with PASTYEAR = 0.

Variable	Coefficient	Standard error	z = b/s.e.
PEERINFL	.2063506*	.1066739	1.93
ACCESS	−.0690426	.1026491	−0.67
NEGATIVEATT	−.696512***	.1239167	−5.62
Sex	.5648469**	.206901	2.73
Race	−.7802387**	.2888763	−2.70
Area	−.0739449	.0928994	−0.80
/CUT1	1.739229	.5427581	
/CUT2	2.60554	.5658683	
/CUT3	3.226735	.6340716	
Pseudo $R^2 = 0.20$	Log likelihood = −123.65		

N = 1123.
*** $p < .001$.
** $p < .05$.
* $p < .1$

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