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Working Paper No. 2011-7

September, 2011

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Alcohol use and pregnancies among youth:
Evidence from a semi-parametric approach[*]

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Abstract
Despite a well-established correlation between alcohol intake and various risk-taking sexual behaviors, the causality remains unknown. I model the effect of alcohol use on the likelihood of pregnancy among youth using a variety of estimation techniques. The preference is given to the semi-parametric model where the cumulative distribution of heterogeneity is approximated by a 4-point discrete distribution. Using data on 17-28 year-old women from the National Longitudinal Survey of Youth, I find that alcohol consumption increases the likelihood of pregnancy by 4.7 percentage points. Quantitatively similar but statistically weaker effects were found in the fully parametric models such as the two-stage least squares model and the bivariate probit model. Finally, the fully parametric models that ignore the effect of unobserved heterogeneity failed to establish this relationship.

Keywords: Alcohol use, Youth pregnancy rate, Bivariate probit, Discrete factor approximation estimator, Endogeneity
JEL classification: J13; C14; C30

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[*] I thank Thomas Mroz for advice and helpful comments.
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Introduction

For the past several decades, the United States has had the highest teenage pregnancy and birth rates among developed countries (UNICEF, 2001). According to the Youth Risk Behavior Surveillance Surveys conducted for the past two decades, about a quarter of sexually active high school students nationwide report alcohol consumption or drug use before their last sexual intercourse.[1] Given these facts, the public policy question is whether substance use among young adults leads to more pregnancies. I attempt to establish a causal effect of alcohol use on the likelihood of pregnancy among youth using fully parametric and semi-parametric estimation strategies.

Numerous studies cite a positive association between alcohol consumption and various risky sexual behaviors, but fail to provide convincing evidence of causality.[2] The observed association can be easily attributed to the influence of underlying unobserved individual characteristics rather than the influence of alcohol use. In recent years some researchers attempted to address the endogeneity issue by estimating both outcomes simultaneously using a bivariate probit model.[3] However, the bivariate probit model is an appropriate econometric technique only if the heterogeneity term follows a normal distribution (in this case the distribution of error terms will reduce to a joint normal). Otherwise, the procedure will produce inconsistent estimates. A fully parametric distributional assumption, such as normal, can be easily avoided by approximating the cumulative distribution of the heterogeneity using a discrete distribution with *k* points of support. I consider 2, 3, and 4-support point models with the

[1] Between 1991 and 2009 slightly more than one third of high school students were sexually active.
[2] For a discussion and excellent review of the literature see Leigh and Stall (1993) and Donovan and McEwan (1995). For a list of more recent studies see Rashad and Kaestner (2004).
[3] For example see Grossman et al. (2004). Literature review is provided in the next section.

preference given to the latter model based on the upward-testing approach.[4] This semi-parametric discrete factor approximation method has not yet been used as an identification strategy for the relationship between alcohol use and risky sexual behavior and, therefore, this paper improves the existing literature on this topic.

For the empirical analysis, I use data on young women from the National Longitudinal Survey of Youth 1979 cohort. Due to survey limitations, described later in the text, I am able to use only four years of data for the period 1982-1985. Preliminary analysis of the raw data showed that pregnancy rates among women who reported alcohol consumption are *lower* than rates for women who reported *no* alcohol consumption. When distribution of heterogeneity is approximated by a 4-point discrete distribution, I find that alcohol consumption increases the likelihood of pregnancy by 4.7 percentage points. A positive but slightly smaller effect is found in a model with 3-point discrete distribution.

Results from the single-equation probit model indicate that alcohol consumption has a negative effect on probability of pregnancy though the effect is close to zero. The effect predicted by the bivariate probit model is positive and numerically similar to the 4-point discrete model, yet it is fairly imprecise compared to the 4-points model. However, these results might be driven by model misspecification as both these models are rejected in favor of the less restrictive discrete factor models. The discrete factor models indicate that there is unobserved heterogeneity ignored by the single-equation model and the normality assumption embodied in the bivariate probit model does not hold.

Researchers seem to agree that when attempting to establish the effect of alcohol consumption on risky behaviors one should account for the effects of unobserved characteristics.

[4] The general description of the semi-parametric method is provided later in the text. For the detailed description consult Mroz (1999).

The findings from this paper suggest that one should not only question results drawn from the naïve models that ignore the effects of unobservables but also should be suspicious about the results drawn from models that embody restrictive assumptions regarding the distribution of unobserved heterogeneity (such as a bivariate probit model). In the presence of unobserved heterogeneity, the use of more flexible econometric techniques, such as the discrete factor approximation method, might be desirable and beneficial in expanding our understanding of the true nature of the relationship between alcohol consumption and risky (sexual) behaviors.

Literature review

It is widely believed that alcohol use provokes risk-taking behaviors including risky sexual behaviors such as non-use of contraception during intercourse and sex with multiple or unfamiliar partners. If this is the case, then the hypothesized association between alcohol use and unintended pregnancy seems straightforward. If substance use impairs one's judgment and triggers unsafe sexual behaviors, including non-use of contraception, then the likelihood of pregnancies should be positively affected by alcohol use, after controlling for effects of other observable characteristics.[5]

Despite the undeniable well-established positive correlation between alcohol use and risk-taking sexual activity the causality mechanism nevertheless remains unknown (Leigh and Stall, 1993). The unobserved heterogeneity, such as individual attitudes toward risk and the future, thrill and sensation seeking personality, or simply individual preferences, can influence all kinds of risk taking. Furthermore, these unobserved factors can either motivate a person to

[5] However, the reported effect of alcohol on contraception use varies across studies, ranging from a negative association to no association with some studies reporting mixed results. Cooper (2002) examines a number of recent studies. For a list of earlier studies see National Center on Addiction and Substance Abuse (1999) and Leigh and Stall (1993).

engage in all kinds of risk-taking behaviors or to engage only in some risk-taking activities while maintaining a strong intolerance regarding other risky activities. Thus, someone with a thrill seeking personality may have a higher propensity to consume alcohol, smoke, and engage in risky sex. However, it is possible that someone who realizes the harmful consequences of risk-taking behaviors still engages in one risky behavior due to personal preferences, beliefs or sexual desires. For example, a person who despises smoking might enjoy alcohol consumption, or someone who seeks thrilling sexual experiences might have a strong opinion against alcohol intake. In either case, the endogeneity problem created by the unobserved heterogeneity poses a difficulty for establishing the causal nature of the relationship empirically.

Several econometric techniques that are intensively used in the literature to identify the causal relationship between alcohol use and risk-taking sexual activity include linear probability, univariate probit, and reduced form models; two-stage least squares (e.g., Kaestner and Joyce, 2001; Grossman and Markowitz, 2005; Gil-Lacruz *et al*., 2009); and bivariate probit models (e.g., Rees *et al*., 2001; Sen, 2002 and Grossman *et al*., 2004).[6] Researchers acknowledge that these procedures can be flawed when the underlying assumptions are not met. For instance, the linear probability and single-equation probit models produce biased estimates in the presence of unaccounted endogeneity. The two-stage least squares estimates often suffer from the problems associated with weak instruments.[7] Finally, although the bivariate probit model addresses the endogeneity problem by estimating both outcomes simultaneously, the consistency of estimates heavily relies on the assumptions regarding the distribution of unobserved heterogeneity and the joint distribution of error terms. Mroz (1999) shows that, in limited dependent variable models where an outcome depends on an endogenous dummy variable, the misspecification of the joint

[6] The notable exceptions are studies by Acworth et al. (2007) who use the Difference-in-Difference Propensity Score Matching estimator and Grossman et al. (2004) who use the individual, fixed-effects regression model.
[7] French and Popovici (2009) provide a literature review and discuss limitations of this approach.

distribution of error terms leads to inconsistent estimates. Additionally, the efficacy of the bivariate probit model requires the presence of valid exclusion restrictions – variables that determine alcohol use but not sexual behavior. Mroz's (1999) study shows that this problem is suppressed in the semi-parametric model where identification could be achieved through the functional form and distributional assumptions.

Further, a few studies that attempted to establish the causal effect of alcohol on risky sex using a bivariate probit model report contradicting results. For instance, Rees *et al*. (2001), using a nationally representative sample of teens ages 11-18 in 1995, find a weak positive correlation between substance use and the probability of being sexual active or having sex without contraception. They also assert that this association is often attributed to the influence of unobservable factors. A similar conclusion is reached in Grossman *et al*. (2004), who use a nationally representative sample of teens ages 15-17 in 1997. It is suggested that the lower bound of the alcohol use effect on risky sexual behavior should be zero. However, their estimates, from constrained bivaraite probit models and a model suggested in Altonji *et al*. (2005), indicate that alcohol use significantly reduces the probability of sexual intercourse and risky sex for female respondents. On the other hand, Sen (2002), using a similar sample of teens ages 14-16 in 1997, reports that drinking significantly positively affects the likelihood of sexual intercourse and non-contracepted intercourse. The contradiction is astounding given the similarity of methods and data employed in above mentioned studies. One should be cautious with these results as they are likely to be corrupted by model misspecification as all studies failed to question the validity of underlying assumptions of bivariate probit model.[8] As a result, these

[8] Rashad and Kaestner (2004) provide a detailed inspection of identification strategies and results of Rees et al. (2001) and Sen (2002).

studies might not advance our understanding regarding the causal relationship between alcohol consumption and risky sexual behavior and the topic requires further inquiries.

Challenging findings, as well as assessing precision of estimated effects, reported in Rees *et al*. (2001), Sen (2002), and Grossman *et al*. (2004) are beyond the scope of this study.[9] The goal is rather to evaluate performance of a variety of econometric techniques, widely used in the literature and ranging from fully parametric to semi-parametric, while studying the effect of alcohol use on the probability of pregnancy among youth (where pregnancy is considered an indicator of risky sexual behavior). Although the binary choice models are not generally estimated using least squares, I start my analysis with estimation of linear probability (LPM) and two-stage least squares (2SLS) models.[10] Then I proceed with a univariate probit model (Probit) and a standard recursive bivariate probit model (Biprobit). Finally, the validity of the bivariate probit model is tested by implementing a less restrictive semi-parametric discrete factor method. The latter approach has evident advantages as it relaxes the assumption of joint normality: instead, the cumulative distribution of heterogeneity is approximated by a step function. Since the application of this method to the question at hand is new to the literature, specific attention is devoted to the comparison of the bivariate probit model and the model obtained with the help of the discrete factor method. Furthermore, for each model, I calculate a change in the predicted probability of pregnancy associated with the change in consumption of alcohol.

[9] I acknowledge that it would be useful to test the robustness of the results reported in all above mentioned studies by applying a semi-parametric estimation technique. However, this is not done in this paper for two reasons. First, I use data from 1979 cohort of the National Longitudinal Survey of Youth. This survey covers a different time period and, due to some survey's shortcoming discussed later in the paper, my data sample will include older respondents (17-28 years old). Second, the data available do not permit identifying the events studied in Rees et al. (2001), Sen (2002), and Grossman et al. (2004).
[10] Greene (1998).

Methods

A model, where two outcomes (i.e., drinking and pregnancy) for a randomly selected individual i are modeled simultaneously, is summarized below:

$$D_{irt}^{*} = \beta'_1 X_{1irt} + \gamma' X_{2irt} + \delta_{1r} + \tau_{1t} + \varepsilon_{1irt}\,, \qquad \begin{matrix} D_{irt} = 1 \text{ if } D_{irt}^{*} > 0 \text{ and} \\ D_{irt} = 0 \text{ if } D_{irt}^{*} \leq 0 \end{matrix} \tag{1a}$$

$$P_{irt}^{*} = \alpha D_{irt} + \beta'_2 X_{1irt} + \delta_{2r} + \tau_{2t} + \varepsilon_{2irt}\,, \qquad \begin{matrix} P_{irt} = 1 \text{ if } P_{irt}^{*} > 0 \text{ and} \\ P_{irt} = 0 \text{ if } P_{irt}^{*} \leq 0 \end{matrix} \tag{1b}$$

where i indexes individuals, r indexes region of residence, t indexes calendar year.[11] D_{irt}^{*} and P_{irt}^{*} are latent variables that represent the propensity to consume alcohol and the propensity to become pregnant, respectively. The pregnancy status (P_{irt}) depends on alcohol use (D_{irt}) and a set of personal and household characteristics (X_1). The personal characteristics considered are race, age, Armed Forces Qualifications Test (AFQT) score, marriage status at $t-1$, and an indicator of whether an individual attends college. Household characteristics include religion in which the individual was raised, whether it was a two-parent household, mother's and father's education, and poverty status at $t-1$. I use lagged values of marital status and poverty status as current statuses might be endogenous to both current fertility and alcohol consumption decisions. For example, pregnancy might facilitate marriage and vice versa. The use of lagged values provides some remedy for this issue. However, the use of lagged values makes it harder to interpret the effect on both dependent variables. Yet, a simple omission of the above mentioned variables from the model might introduce omitted variable bias as for all models these variables are individually and jointly significant.

[11] Ideally, both equations would rather include a full set of state fixed effects. However, due to data limitations discussed in the next section as well as data requirements for the discrete-factor approximation model, this is not feasible here.

The individual alcohol consumption (D_{irt}) is determined by a set of personal and household characteristics, same as specified above, and an additional indicator of whether an individual can legally consume alcohol in her state of residence as well as vector of policy variables (X_2) that do not have a direct effect on P_{irt}^*. A vector (X_2) contains the following policy variables: state per gallon beer tax, cigarette tax rate, per capita police expenditure, per capita consumption of distilled spirits, and whether the minimum legal drinking age in a state is set to 21.[12] Chosen exclusion restrictions are in fact statistically significant determinants of alcohol use but not pregnancy status.[13] To capture the effect of time invariant and location invariant factors, I include a set of year fixed effects (τ) and region fixed effects (δ) in equations (1a) and (1b).

The key parameter of interest α captures the causal effect of alcohol consumption on pregnancy status, after controlling for the effects of other observable factors. However, depending on the estimation procedure, the sign and especially magnitude of α might not provide meaningful information regarding the estimated effect (Greene, 1998). In the binary choice models, the absolute scale of the estimated coefficients provides a misleading picture. Therefore, rather than concentrate on interpretation of estimates, I will focus on interpretation of discrete changes in the probability of pregnancy due to changes in the explanatory variables.

If the zero-mean error terms in (1a) and (1b) are uncorrelated one can estimate both equations using two independent probability models (one for each outcome). However, if unobserved factors influence alcohol consumption and pregnancy status through risky sexual behavior, then the univarite probit procedure will produce a biased estimate of parameter α. For the same reason, estimates from the linear probability model will be biased as well. To illustrate

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[12] Other policy variables considered and rejected as valid instruments are indicator for the presence of alcoholics in the family, minimum legal drinking age is 20 or 21, per capita consumption of malt beverages, per capita alcohol consumption, average cigarette price, total arrests in a state for DUI and juvenile arrests for DUI, number of arrests per crime and per violent crime.

[13] Results are reported in Appendix B.

the effect of unobserved heterogeneity, let decompose the error terms in (1a) and (1b) further into correlated and uncorrelated components:

$$\varepsilon_{1ist} = \rho_1\theta + \upsilon_{1ist} \, , \tag{2a}$$

$$\varepsilon_{2ist} = \rho_2\theta + \upsilon_{2ist} \, , \tag{2b}$$

where terms θ, υ_{1i}, and υ_{2i} are assumed to have a zero mean and to be mutually independent as well as independent of the exogenous variables in the model. The parameter θ reflects a common factor of unobserved selection such as a thrill-seeking personality and personal preferences that can affect both drinking and sexual behaviors in such a way that the latter leads to pregnancy. Terms υ_{1i} and υ_{2i} represent uncorrelated components of unobserved selection that are unique for a given outcome.

The identification difficulty stems from the fact that the distribution of the heterogeneity term θ is not known a priory. If θ follows a normal distribution then the model described in equations (1a)-(2b) becomes a standard recursive bivariate probit model where error terms ε_{1i} and ε_{2i} follow a joint normal distribution with a correlation term ρ (Greene, 2008b). A positive ρ indicates that unobserved factors increase both the probability of alcohol consumption and the probability of becoming pregnant. On the contrary, a negative ρ is likely to imply that unobserved personal preferences increase the probability of one outcome and decrease the probability of the other outcome. As mentioned earlier, the invalid distributional assumption can lead to a model misspecification resulting in implausible estimates. One way to impose the minimum restrictions and avoid the a priory parametric specification of distribution of θ is to approximate the cumulative distribution of θ by a step function with k points of support (η_k) each of which has a probability π_k:

$$\text{Prob}(\theta = \eta_k) = \pi_k \, , \; k = 1, \ldots K, \tag{3}$$

where $\pi_k>0$ and $\sum_{k=1}^{K}\pi_k = 1$. After some trivial normalizations, the model parameters α, β_1', β_2', γ', ρ_1, ρ_2, $\{\eta_k\}$, and $\{\pi_k\}$ can be jointly estimated using the maximum likelihood technique.[14] The likelihood function used in estimation of the discrete factor model is reported in the Appendix A.

The Monte Carlo simulations reported in Mroz (1999) reveal that the semi-parametric discrete factor approximation estimator compares favorably to the normal maximum likelihood estimator in terms of precision and bias when the true distribution of the error terms is indeed joint normal. When the true distribution of the error terms is not normal, the semi-parametric discrete factor approximation estimator outperforms the maximum likelihood estimator that relies on incorrect assumption of normality.

Little guidance is provided in the literature on how to choose the number of support points. Mroz (1999) suggests a step-by-step estimation procedure with an upward-testing approach that is adopted in this paper. First, I estimate a model with 1-support point which corresponds to two independent probit models. Its coefficient estimates are used as the initial value in a 2-support point model. Then a likelihood ratio "Chi-square" test is performed to assess a change (increase) in the quasi-likelihood function value. If the one-support point model is rejected in favor of a 2-support point model then I proceed with a 3-support point model using estimated coefficient from the 2-support point model as initial values, and so on. With a relatively small sample size and a relatively large number of right-hand side variables estimation is time consuming; often resulting in numerical difficulties (encountered with a 4-point and higher models). This study stops at the 4-support point discrete distribution. The simulation

[14] The mean of θ is set to zero, but the scale of θ is not restricted. Also following Mroz (1999) suggestion, one of the factor loadings (ρ_1) is set to 1.

results in Mroz (1999) indicate that the 4-support point model behaves well in terms of consistency as well as accuracy.

Data

This paper studies the relationship between alcohol use and youth pregnancy using the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). The NLSY79 contains data on a nationally representative random sample (national sample) of young men and women ages 14-22 in 1979 and supplemental oversamples of young blacks, Hispanics, poor whites, and members of the military. However, the black, Hispanic, and disadvantaged white oversamples, members of the military, and men sample are excluded from the analysis.

Despite the vast amount of personal data, including fertility history and data on geographic location collected annually, the series of questions about alcohol consumption were asked only during the 1982-85, 1988-89, 1992, 1994, and 2002 surveys. The discontinuity of surveys introduces some limitations on the data that I can use in empirical analysis. Overall, after taking into account aging of the cohorts, I decided to use only data from the 1982-85 surveys. This implies that my panel is limited to four years of data and includes women whose ages range from 17 to 28 years.

As outlined in the equations (1a) and (1b), two outcomes of interest are pregnancy status and alcohol use status in a given year. The NLSY79 provides detailed fertility histories that enable one to identify whether a woman was pregnant or not in a given year. The information about alcohol consumption is somewhat limited. For example, respondents were asked if they had any alcoholic beverages in the past month. Such formulation of the question does not allow one to precisely identify alcohol consumption behavior during a given year. Following the literature, I assume that alcohol use in the preceding month is a reasonable indicator of alcohol use throughout the entire year (Sen, 2002 and Acworth *et al*., 2007). Among other shortcomings, this generalization creates a problem especially in situations when a pregnant woman was surveyed. Knowing the negative impact of alcohol on the fetus, pregnant women are less likely to consume alcohol. Thus, if a pregnant woman reports no consumption of alcohol in the previous month, there is no way to distinguish whether this is her "typical" behavior or behavior induced by pregnancy. To address this issue I analyzed the sequence of the following dates: month when pregnancy began, month of the interview, and month for which alcohol consumption question was answered. Based on the sequence of events, I identified and eliminated from the dataset 97 person-year observations. These observations represent women who became pregnant at least two months before the interview date and hence were answering alcohol consumption questions while being pregnant. Further, analysis indicates that the majority (57 observations) of these women reported that they did not consume alcohol. After additional exclusion of all missing values, the final sample includes 9,152 person-year observations on 2,492 women.

Table 1 shows summary statistics for variables included in the analysis. Composition wise the majority of women in my dataset are white (84%), 10% are black, and the rest are Hispanic. Across four years of data, on average about 12% of women in the sample became pregnant in a given year. Among all women on average 66% reported alcohol consumption. Comparison of pregnancy rates by status of alcohol consumption, which is reported in Table 2, reveals that on average non-drinkers tend to have higher pregnancy rates than women who reported alcohol consumption. Overall these differences are statistically significant.

Fertility decisions might differ across age cohorts. An ideal extension of this paper would include a sensitivity test which involves estimation using different sub-samples of the data. For example, a restricted sample comprised of women from the youngest five cohorts of the NLSY79 could be used instead of the initial sample. However, given the relatively small size of the initial sample, further decreases in the number of observations generate additional computational difficulties and, therefore, are not considered.

The NLSY79 data identifies state of residence that allows one to control for time invariant, state level unobservable factors. However, the inclusion of state fixed effects creates several complications. First, such action might affect the precision of policy estimates that are included in equation (1a). Recall, I assume that youth alcohol consumption in a given state-year is partially determined by policies that regulate alcohol consumption such as the minimum legal drinking age, per gallon beer tax, etc. In the presence of state fixed effects, the accurate estimation of the effects of state policy variables requires a substantive within-state variation in these policy variables. For example, during the four-year period only 13 states changed per gallon beer tax and 12 states changed minimum drinking age. A relatively small sample size combined with a modest within-state policy variation will cause the effects of policy variables to be mostly absorbed by the state fixed effects. Second, the inclusion of a large number of right-hand side variables not only slows down estimation but also creates numeric problems for maximum likelihood estimation. I address both issues by using four sub-region dummies rather than state dummies. If states within a sub-region share similar cultural values and attitudes then the sub-region fixed effects will be good substitutes for the state fixed effects.[15] To validate this assumption, I estimate LPM, 2SLS, Probit, and Bibropit models with state fixed effects. The

[15] Although both Rees et al. (2001) and Sen (2002) used nationally representative samples, it appears that neither one included location fixed effects in the model.

specification affects the magnitude of the estimates but not quality. For example, the estimate for drinking dummy in pregnancy equation maintains the sign in all models.[16]

Results

As mentioned earlier, estimated coefficients in the binary models estimated with the maximum likelihood method are not particularly informative. Therefore, the general discussion of these results is omitted (estimates of all parameters for each model are reported in Appendix D). To test the validity of exclusion restrictions included in equation (1a), I performed a series of tests of joint significance of corresponding estimates; in all cases the null hypothesis was rejected confirming the validity of the instruments.[17]

The key question is whether alcohol use affects the likelihood of pregnancy among youth. I assess the magnitude of the effect by computing a (discrete) change in the predicted probability of pregnancy associated with a change in alcohol consumption variable (where the latter is exogenously assigned value 1 for all observations and then 0).[18] The change in the predicted probability is computed for each person-year observation and then averaged across observations.

$$\text{Average Effect} = \frac{1}{N}\sum_{i=1}^{N}\left[\Phi\left(\alpha + \beta_2' X_{1irt} + \delta_{2r} + \tau_{2t}\right) - \Phi\left(\beta_2' X_{1irt} + \delta_{2r} + \tau_{2t}\right)\right] \qquad (4)$$

where Φ is the standard normal distribution function, N is a number of person-year observations.

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[16] I also test validity of exclusion restrictions included in equation (1a) and conclude that, once the state fixed effects are used, only two variables (drinking age set to 21 and beer tax) predict drinking behavior and other policy variables are not individually or jointly significant. Furthermore, only drinking age set to 21 is a valid exclusion restriction as the beer tax is a statistically significant predictor in the pregnancy equation. I re-estimate LPM, 2SLS, Probit, Bibropit, and 2-point models with state fixed effects and a reduced set of instruments included in drinking equation (1a) and an additional variable (beer tax) in pregnancy equation (1b). The estimates, reported in Appendix C, are quite robust in terms of the sign.

[17] The F-test for 2SLS model; the Wald test for Probit model; the Wald test and the likelihood ratio test for Biprobit model; the Wald test for the discrete factor models.

[18] Discrete changes are discussed in Long (1997). Additionally, I do not constraint the values of explanatory variables included in X_1 to their means. Instead, I use X_{1irt} thus calculating the effect of alcohol for each person-year observation given the specific characteristics of that person in a given year.

Table 3 summarizes the average effect of alcohol use on the predicted probability of pregnancy among youth from all estimation techniques considered. Standard errors are obtained using a parametric bootstrap method with 1,000 repetitions; the corresponding 95% confidence interval was calculated using a bootstrap percentile method (Efron and Tibshirani, 1993).

A considerable variation exists across models. For example, the linear probability model, which ignores the potential effect of endogeneity, predicts that alcohol consumption decreases the probability of pregnancy by 0.7 percentage points. This is an opposite effect of the expected relationship between alcohol consumption and pregnancy. The picture changes dramatically once the model is corrected for endogeneity (2SLS): the estimated effect becomes much larger and the sign flips, indicating that alcohol consumption increases the probability of pregnancy by 5.2 percentage points. However, the estimate lacks statistical significance.

The average effect from the single-equation probit model is almost identical to the one from the linear probability model (the corresponding estimate is -0.6 percentage points). After the model is corrected for endogeneity (i.e., the bivariate probit model), the effect increases significantly and becomes positive (an increase of 5.1 percentage points). Interestingly that quantitatively and qualitatively estimates from the two-stage least squares model and the bivariate probit model are almost identical. However, both are very imprecise. The results from the bivariate model also indicate a negative correlation between the errors in equations (1a) and (1b). Given a fairly large standard error, I fail to reject the null hypothesis that this estimate is statistically different from zero. Despite a quite modest and imprecise correlation estimate, one should not quickly dismiss the bivariate probit model. The value -0.1878 measures the correlation between the outcomes after the influence of other factors included in the model (which *includes* the effect of alcohol consumption) is accounted for (Greene, 2008a). A formal likelihood ratio test (LR) indicates that one would not reject the simple single-equation probit model in favor of the bivariate probit model (LR test statistics equals 1.13 and the 5% critical value with one degree of freedom is 3.84). The bivariate probit model is also rejected when compared to the discrete factor models (2-points and higher).[19] This likely indicates that the normality assumption embodied in the bivariate model does not hold.

However, the single-equation probit model that corresponds to a 1-point support model is rejected in favor of the 2-points and higher discrete factor models. An introduction of the 2-point discrete distribution yields a qualitatively similar effect: the effect of alcohol is negative. Models that involve a better approximation of the cumulative distribution of heterogeneity (3-points and 4-points models) indicate that alcohol consumption has a positive effect on the probability of pregnancy. After controlling for unobserved heterogeneity, the corresponding average "alcohol" effects are an increase of 2.5 percentage points in the probability of pregnancy (3-points model) and an increase of 4.7 percentage points (4-points model). The results of the upward-testing criterion suggest that one should use the model with 4 points of support.[20] Taking into account that the preference is given to the 4-points model, the precision of the estimate should be addressed. The lower bound of the 95% confidence interval is -0.0027. However, 97% of all repetitions produced a positive effect (972 replications out of 1,000).

Interestingly, the magnitude of the "alcohol" effect on the probability of pregnancy from the 4-points model is numerically close to the estimates from the 2SLS and Biprobit models. However, the discrete factor model produces more precise estimate: the standard error is smaller and the 95% confidence interval is narrower.

[19] The null hypothesis: a restricted model is a true model. The test results are available on request.
[20] The null hypothesis: a model with the smaller number of points of support is a true model. The test results are available on request.

The effects of other covariates included in X_1 and X_2 obtained from the 4-points model are of secondary interest (reported in Table 4). All effects are calculated as discrete changes in the predicted probability of the corresponding outcome due to a change in the explanatory variable. In the drinking equation, the numerically strongest effect is associated with the cigarette tax. The average effect of a unit change in the tax rate is +0.1649. This variable, however, is measured in cents with an average of $0.27. Therefore, it might be more informative to look at a 10 cents change rather than a dollar change. An increase in the tax rate by 10 cents raises the probability of drinking by only 1.6 percentage points. This suggests that smoking and drinking are substitutes. Not surprisingly, an increase in the beer tax per gallon decreases the probability of drinking (a 10 cents increase reduces the probability by 2.1 percentage points). Among other variables, the relatively large effects are observed for race indicators, religion in which a woman was raised, and South. All these variables lead to an increase in the probability of drinking, holding all other factors fixed. In the pregnancy equation, the strongest effects appear to be exerted by the lagged values of marital status and poverty status of women; the corresponding values are -0.1127 and -0.045. However, the interpretation of both might not be informative.

Conclusion

When studying effects of alcohol consumption on risky behaviors, researchers acknowledge that observed positive association could be due to confounding influence of unobserved characteristics (and, therefore, omitted from the model) such as a thrill-seeking personality. Commonly, the attempts to correct for these effects involve estimation of both outcomes (risky sexual behavior and alcohol consumption) simultaneously while allowing for correlation between the error terms (e.g., bivariate probit model). The identification in such model relies on validity of exclusion restrictions. Consistency of estimates in models with limited dependent variables depends on the validity of the underlying assumption about the distribution of the unobserved heterogeneity (in case of the bivariate probit model it is normality). One can easily avoid such strict distributional assumptions by approximating the cumulative distribution of heterogeneity with a step function. One would expect the discrete factor estimator to perform better than the maximum likelihood estimator based on an incorrect specification of joint normality.

I study the effect of alcohol consumption on the probability of pregnancy among 17-28 year-old women using fully parametric techniques popular in the literature and a semi-parametric discrete factor approximation method that has not previously been used in this application. I find that, after approximating the distribution of unobserved heterogeneity with a 4-point discrete distribution, alcohol consumption increases the likelihood of pregnancy by 4.7 percentage points. The two-stage least squares model and the bivariate probit model yield numerically similar effect, but both are quite imprecise comparing to the discrete factor model. The single-equation probit fails to establish a positive relationship between alcohol consumption and pregnancy. Furthermore, both the single-equation probit and the bivariate probit models are firmly rejected in favor of the discrete factor models. The rejection of the bivariate probit model indicates that the normality assumption embodied in the bivariate probit model does not hold.

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Table 1: Summary statistics, 1982 – 1985

	Mean	Std. Dev.
DEPENDENT VARIABLES		
Had pregnancy in a given year	0.124	0.330
Consumed alcohol in a given year	0.658	0.474
INSTRUMENTS [a]		
Legal drinking age is 21	0.406	0.491
Cigarette tax per pack, in 2000 $	0.272	0.102
Police expenditure per capita, in 2000 $	22.555	21.736
Per capita distilled spirit consumption, gallons	1.794	0.480
Legally eligible to drink	0.903	0.297
Per gallon beer tax, in $2000	0.283	0.282
TIME VARIANT VARIABLES		
In poverty last year	0.159	0.365
Woman was married last year	0.332	0.471
In college	0.208	0.406
Northeast	0.185	0.388
North Central	0.301	0.459
South	0.351	0.477
West	0.164	0.370
TIME INVARIANT VARIABLES		
Black	0.103	0.304
White	0.836	0.371
Hispanic	0.061	0.240
Raised as Atheist	0.038	0.191
Raised in a Baptist family	0.230	0.421
Raised in other religion	0.395	0.489
Raised in a Catholic family	0.337	0.473
AFQT score/ 10 000	5.192	2.777
Mother's education	11.609	2.714
Father's education	11.801	3.525
Two-parent household at age 14	0.799	0.401
Number of observations = 9,152 on 2,492 women.		

Note. – Data sources: beer tax – Brewers Almanac (1996) and Hedlund *et al*. (2001); cigarette tax – Annual Report on Tobacco Statistics, 1982-1985; police expenditure – Expenditure and Employment Data for the Criminal Justice System, various years; consumption of malt beverages, distilled spirit – Brewers Almanac (1996); legal drinking age - O'Malley and Wagenaar (1990).

[a] If policy change was during the course of the year then corresponding policy variable reflects situation that prevailed for the most part of the year.

Table 2: Differences in pregnancy rates among drinkers and non-drinkers

		Overall	By year			
			1982	1983	1984	1985
Pregnancy rate among drinkers	Mean	0.114	0.117	0.106	0.112	0.118
	(Std. error)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Pregnancy rate among non-drinkers	Mean	0.145	0.124	0.142	0.183	0.130
	(Std. error)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Difference	**Mean**	**0.031****	**0.007**	**0.035***	**0.071****	**0.012**
	(Std. error)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Number of total person-year observations		9152	2290	2275	2312	2275

** significant at 1%; * significant at 5%; $^{+}$ significant at 10%

Table 3: The average effect of alcohol consumption on the predicted probability of pregnancy among youth

Model	Effect	Parametric Bootstrap Std. error	95% confidence interval		Log-Likelihood value
LPM	-0.0070	0.0032	-0.0134	-0.0007	-
2SLS	0.0515	0.1081	-0.1541	0.2665	-
Probit	-0.0064	0.0032	-0.0129	-0.0001	-8456.702
Biprobit	0.0514	0.0750	-0.1023	0.1915	-8456.049
2-points	-0.0302	0.0277	-0.0859	0.0229	-8447.827
3-points	0.0253	0.0121	0.0031	0.0516	-8434.936
4-points	0.0473	0.0354	-0.0027	0.1560	-8425.053

Note. – The reported effect is an average across 9152 observations. The effect for each observation is calculated as a difference between two predicted probabilities:
Prob.[P_{irt}=1|D_{irt}=1, $X_{1irt,}$ region, year] – Prob.[P_{irt}=1|D_{irt}=0, X_{1irt}, region, year]
Parametric bootstrap estimates of standard errors are obtained using 1,000 bootstrap repetitions; confidence interval is obtained using the bootstrap percentile method.

Table 4: Discrete changes in the probability of outcome, 4-point discrete factor model

	Average Effect	Std. Dev.	Min	Max	Type of variable, mean	
Pregnancy equation						
Alcohol consumption	0.0473	0.0296	0.0059	0.2918	Endogenous	0.658
Black	-0.0310	0.0207	-0.1747	-0.0022	Binary	0.103
Hispanic	-0.0094	0.0064	-0.0574	-0.0002	Binary	0.061
Raised as Atheist	0.0125	0.0081	0.0003	0.0791	Binary	0.038
Raised in a Baptist family	-0.0037	0.0025	-0.0228	-0.0001	Binary	0.230
Raised in other religion	-0.0151	0.0101	-0.0924	-0.0007	Binary	0.395
Mother's education	0.0016	0.0011	0.0001	0.0092	Binary	11.609
Father's education	0.0012	0.0008	0.0001	0.0071	Binary	11.801
Two-parent household at age 14	0.0217	0.0140	0.0012	0.1287	Binary	0.799
Poverty status last year	-0.0451	0.0262	-0.2440	-0.0041	Binary	0.159
Woman was married	-0.1127	0.0394	-0.4790	-0.0624	Binary	0.332
In college	0.0327	0.0192	0.0012	0.2017	Binary	0.208
Year 1983	0.0023	0.0015	0.0001	0.0143	Binary	0.249
Year 1984	-0.0003	0.0002	-0.0019	0.0000	Binary	0.253
Year 1985	0.0164	0.0107	0.0003	0.1032	Binary	0.249
North Central	-0.0236	0.0160	-0.1409	-0.0010	Binary	0.301
South	-0.0142	0.0095	-0.0865	-0.0003	Binary	0.351
West	-0.0312	0.0214	-0.1795	-0.0008	Binary	0.164
Drinking equation						
Black	0.1220	0.0253	0.0093	0.1459	Binary	0.103
Hispanic	0.1249	0.0273	0.0099	0.1511	Binary	0.061
Raised as Atheist	0.1225	0.0279	0.0097	0.1495	Binary	0.038
Raised in a Baptist family	0.0901	0.0184	0.0057	0.1076	Binary	0.230
Raised in other religion	0.0786	0.0185	0.0050	0.0977	Binary	0.395
Mother's education	-0.0095	0.0023	-0.0116	-0.0013	Binary	11.609
Father's education	-0.0064	0.0014	-0.0077	-0.0007	Binary	11.801
Two-parent household at age 14	-0.0037	0.0008	-0.0045	-0.0002	Binary	0.799
Poverty status last year	0.0063	0.0015	0.0003	0.0078	Binary	0.159
Woman was married	0.1483	0.0286	0.0128	0.1751	Binary	0.332
In college	-0.0058	0.0013	-0.0071	-0.0002	Binary	0.208
Year 1983	0.0273	0.0063	0.0013	0.0337	Binary	0.249
Year 1984	0.0030	0.0007	0.0001	0.0037	Binary	0.253

Table 4 (Continued)

	Average Effect	Std. Dev.	Min	Max	Type of variable, mean	
Year 1985	0.0158	0.0037	0.0007	0.0196	Binary	0.249
North Central	-0.0197	0.0046	-0.0244	-0.0007	Binary	0.301
South	0.0823	0.0160	0.0021	0.0979	Binary	0.351
West	0.0151	0.0035	0.0007	0.0187	Binary	0.164
Legal drinking age is 21	0.0176	0.0041	0.0008	0.0218	Binary	0.406
Legally eligible to drink	-0.0281	0.0064	-0.0346	-0.0013	Binary	0.903
Beer tax	-0.0594	0.0138	-0.0736	-0.0024	Continuous	0.283
Cigarette tax	0.1649	0.0383	0.0067	0.2042	Continuous	0.272
Per capita police expenditure	0.0004	0.0001	0.0000	0.0005	Continuous	22.555
Per capita distilled spirit consumption	0.0742	0.0172	0.0030	0.0919	Continuous	1.794

Note. – The reported effect is an average across 9152 observations. The effect for each observation is calculated as a difference between two predicted probabilities. For a binary variable Z in the drinking equation, the discrete change in the probability = Prob.[D=1|Z=1,X_1,X_2] – Prob.[D=1|Z=0,X_1,X_2]. For a continuous variable Z, the discrete change in the probability = {(Prob.[Drink=1|Z=(z+0.5*s_z), X_1,X_2] – Prob. [Drink=1|Z=(z - 0.5*s_z), X_1,X_2])/s_z} where z is a value of variable Z for a person *i* and s_z is standard deviation of Z. For simplicity of notation individual, location, and time subscripts as well as location and time fixed effects are omitted.

Appendix A: Likelihood function

The discrete factor, quasi-likelihood function for the model is:

$$\prod_{i=1}^{N}\sum_{k=1}^{K}\pi_k\left\{\left[\int_{-\beta_1' X_1-\gamma X_2-\rho_1\eta_k}^{\infty}\phi(u)du\right]^D\left[1-\left(\int_{-\beta_1' X_1-\gamma X_2-\rho_1\eta_k}^{\infty}\phi(u)du\right)\right]^{1-D}\right.$$

$$\left.\left[\int_{-\beta_2' X_1-\alpha D-\rho_2\eta_k}^{\infty}\phi(u)du\right]^P\left[1-\left(\int_{-\beta_2' X_1-\alpha D-\rho_2\eta_k}^{\infty}\phi(u)du\right)\right]^{1-P}\right\}$$

where N is a sample size, K represents a number of the support points $\{\eta_k\}$ chosen from the discrete factor distribution, each of which has a probability $\{\pi_k\}$; $\phi(\cdot)$ is the standard normal density function. The model parameters α, β_1', β_2', γ', ρ_1, ρ_2, $\{\eta_k\}$, and $\{\pi_k\}$ are jointly estimated subject to trivial normalizations discussed in the text. For simplicity of notation individual, location, and time subscripts as well as location and time fixed effects are omitted.

Appendix B: Test of validity of instruments in pregnancy equation

Dependent variable: Pregnancy status equals 1 if pregnant, 0 otherwise

	Linear probability model	**Two-Stage Least Squares**	**Univariate Probit**	**Bivariate probit**
Consumed alcohol in a given year	-0.008*	dropped	-0.036**	0.278
	(0.00)		(0.01)	(0.30)
Legal drinking age is 21	-0.005	-0.005	-0.027	-0.019
	(0.01)	(0.01)	(0.05)	(0.05)
Cigarette tax per pack	0.021	0.019	0.105	0.05
	(0.03)	(0.03)	(0.15)	(0.14)
Per capita police Expenditures	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Per capita consumption of distilled spirits	0.008	0.007	0.042	0.015
	(0.01)	(0.01)	(0.07)	(0.06)
Legally eligible to drink	-0.018	-0.018	-0.111	-0.122
	(0.02)	(0.02)	(0.09)	(0.10)
Beer tax per gallon	0.003	0.004	0.008	0.024
	(0.01)	(0.01)	(0.06)	(0.06)
Black	0.041*	0.042*	0.217**	0.249**
	(0.01)	(0.01)	(0.05)	(0.06)
Hispanic	0.016	0.017	0.085	0.125
	(0.02)	(0.02)	(0.11)	(0.14)
Raised as Atheist	-0.033^{+}	-0.032^{+}	-0.174*	-0.128*
	(0.01)	(0.01)	(0.08)	(0.06)
Raised in a Baptist Family	-0.007	-0.006	-0.021	0.011
	(0.01)	(0.01)	(0.04)	(0.06)
Raised in other religion	0.008	0.009	0.046	0.074
	(0.01)	(0.01)	(0.06)	(0.08)
AFQT score/10,000	0.002	0.002	0.018	0.006
	(0.00)	(0.00)	(0.02)	(0.02)
AFQT score square	0.000	0.000	-0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Age (in years)	0.005	0.004	0.016	-0.044
	(0.04)	(0.04)	(0.19)	(0.14)
Age square	0.000	0.000	0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)

Appendix B (Continued)

	Linear probability model	Two-Stage Least Squares	Univariate Probit	Bivariate probit
Mother's education	0.001	0.001	0.003	0.000
	(0.00)	(0.00)	(0.00)	(0.01)
Father's education	-0.001	-0.001	-0.004	-0.006
	(0.00)	(0.00)	(0.00)	(0.01)
Two-parent household	-0.028*	-0.028*	-0.136**	-0.136**
at age 14	(0.01)	(0.01)	(0.04)	(0.04)
Poverty status last year	0.057*	0.057*	0.272**	0.271**
	(0.01)	(0.01)	(0.05)	(0.04)
Woman was married last	0.105**	0.106**	0.492**	0.536**
Year	(0.01)	(0.01)	(0.05)	(0.06)
In college	-0.057*	-0.057*	-0.382**	-0.380**
	(0.01)	(0.01)	(0.05)	(0.05)
Year 1983	-0.002	-0.001	-0.011	-0.003
	(0.02)	(0.01)	(0.08)	(0.08)
Year 1984	0.010	0.010	0.045	0.046
	(0.02)	(0.02)	(0.10)	(0.10)
Year 1985	-0.008	-0.008	-0.045	-0.039
	(0.02)	(0.02)	(0.09)	(0.09)
North Central	0.026**	0.026**	0.149**	0.138**
	(0.00)	(0.00)	(0.02)	(0.01)
South	-0.004	-0.004	-0.005	0.024
	(0.00)	(0.00)	(0.02)	(0.04)
West	0.028**	0.027**	0.160**	0.160**
	(0.00)	(0.00)	(0.01)	(0.02)
Constant	0.054	0.065	-1.479	-0.848
	(0.41)	(0.42)	(2.20)	(1.63)
Observations	9152	9152	9152	9152
F-test for joint significance of instruments	Fail to reject Ho	Fail to reject Ho	-	-
Wald test for joint significance of instruments	-	-	Fail to reject Ho	Fail to reject Ho
Likelihood ratio test for instruments	-	-	Fail to reject Ho	Fail to reject Ho

** significant at 1%; * significant at 5%; + significant at 10%. Standard errors are clustered by region. Excluded categories are White, raised in Catholic families, 1982, and Northeast region.

Appendix C: Comparison of estimates for alcohol consumption variable in pregnancy equation (Equation 1b) across specifications

Model	Estimated coefficient	Specification with region fixed effects†	Specification with state fixed effects‡
LPM	Consumed alcohol in a given year	-0.01 (0.00)	-0.01 (0.01)
Probit	Consumed alcohol in a given year	-0.03* (0.02)	-0.04 (0.03)
2SLS	Predicted drinking	0.05 (0.11)	0.28 (0.38)
Biprobit	Consumed alcohol in a given year	0.27 (0.39)	0.23 (0.24)
2-point	Consumed alcohol in a given year	-0.15 (0.14)	-0.23 (0.15)

Note. – Region fixed effect model and state fixed effect model are not directly comparable due to differences in specifications described in the text. Standard errors reported in parenthesis are clustered by region in specification with region fixed effects and by state in specification with state fixed effects. Estimates are not reported for 3-point and 4-point models due to difficulties associated with the estimation of state fixed effects specification. With a relatively small sample size and a large number of right-hand side variables estimation is time consuming and often results in numerical difficulties.
† Includes a full set of policy variables in drinking equation (legal drinking age is 21; cigarette tax per pack; per capita police expenditure; per capita distilled spirit consumption; legally eligible to consume alcohol; beer tax). No policy variables are included in pregnancy equation.
‡ Includes a reduced set of policy variables in drinking equation (legal drinking age is 21 and beer tax). Beer tax is not a valid exclusion restriction and is also included in pregnancy equation.

Appendix D: Coefficient estimates from linear probability (LMP), two-stage least squares (2SLS), univariate probit (Probit), bivariate probit (Biprobit), 2-support point, 3-support point, and 4-support point models

	LPM	**1SLS**	**2SLS**	**Probit**		**Biprobit**		**2-points**		**3-points**		**4-points**	
Dep. Variable:	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant
Consumed alcohol in a given year	**-0.01** (0.00)				**-0.03*** (0.02)		**0.27** (0.39)		**-0.15** (0.14)		**0.61*** (0.28)		**1.28**$^{+}$ (0.69)
Predicted drinking			**0.05** (0.11)										
Legal drinking age is 21		-0.02^{+} (0.01)		-0.08** (0.02)		-0.08** (0.02)		-0.08^{+} (0.04)		-0.08* (0.04)		-0.08^{+} (0.05)	
Cigarette tax per pack		0.17^{+} (0.06)		0.47** (0.18)		0.47** (0.18)		0.66** (0.25)		0.50* (0.20)		0.72** (0.27)	
Per capita police expenditure		0.00 (0.00)		0.00 (0.00)		0.00 (0.00)		0.00 (0.00)		0.00 (0.00)		0.00 (0.00)	
Per capita distilled spirit consumption		0.08* (0.02)		0.25** (0.06)		0.25** (0.06)		0.30** (0.05)		0.26** (0.04)		0.33** (0.06)	
Legally eligible to consume alcohol		0.04 (0.02)		0.11^{+} (0.06)		0.10 (0.06)		0.14^{+} (0.08)		0.11 (0.07)		0.12 (0.09)	
Beer tax		-0.05* (0.01)		-0.16** (0.04)		-0.16** (0.03)		-0.23* (0.10)		-0.19* (0.08)		-0.26* (0.11)	
Black	0.04* (0.01)	- 0.11** (0.01)	0.05^{+} (0.02)	-0.31** (0.04)	0.22** (0.06)	-0.31** (0.04)	0.25** (0.08)	-0.48** (0.09)	0.21** (0.06)	-0.33** (0.06)	0.62** (0.21)	-0.52** (0.10)	0.73** (0.27)
Hispanic	0.02 (0.02)	-0.12* (0.03)	0.02 (0.03)	-0.37** (0.10)	0.09 (0.10)	-0.37** (0.10)	0.13 (0.15)	-0.51** (0.10)	0.07 (0.08)	-0.39** (0.07)	0.18 (0.26)	-0.54** (0.11)	0.24 (0.32)
Raised as Atheist	-0.03* (0.01)	-0.13^{+} (0.04)	-0.03 (0.02)	-0.41** (0.12)	-0.18** (0.07)	-0.41** (0.12)	-0.13 (0.09)	-0.51** (0.10)	-0.20^{+} (0.10)	-0.44** (0.08)	-0.36 (0.29)	-0.53** (0.11)	-0.33 (0.34)

Appendix D (Continued)

	LPM	1SLS	2SLS	Probit		Biprobit		2-points		3-points		4-points	
Depend. Variable:	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant
Raised in a Baptist family	-0.01	-0.10*	-0.00	-0.29**	-0.03	-0.30**	0.01	-0.36**	-0.04	-0.31**	0.05	-0.38**	0.09
	(0.01)	(0.02)	(0.02)	(0.06)	(0.04)	(0.06)	(0.08)	(0.06)	(0.06)	(0.05)	(0.18)	(0.07)	(0.21)
Raised in other religion	0.01	-0.08**	0.01	-0.27**	0.04	-0.27**	0.07	-0.33**	0.03	-0.28**	0.31*	-0.35**	0.38
	(0.01)	(0.01)	(0.02)	(0.02)	(0.05)	(0.02)	(0.08)	(0.05)	(0.05)	(0.04)	(0.14)	(0.05)	(0.20)
AFQT score	0.00	0.04^{+}	0.00	0.11*	0.02	0.11*	0.01	0.17**	0.02	0.11**	-0.01	0.19**	-0.03
	(0.00)	(0.02)	(0.00)	(0.05)	(0.02)	(0.05)	(0.01)	(0.03)	(0.03)	(0.02)	(0.09)	(0.04)	(0.10)
AFQT score square	0.00	-0.00	0.00	-0.01	-0.00	-0.01	-0.00	-0.01**	-0.00	-0.01**	-0.01	-0.01**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Age in years	-0.01	0.18**	-0.02	0.56**	-0.08	0.57**	-0.15^{+}	0.68**	-0.06	0.60**	-0.03	0.77**	-0.12
	(0.02)	(0.01)	(0.02)	(0.04)	(0.13)	(0.04)	(0.08)	(0.14)	(0.12)	(0.12)	(0.35)	(0.12)	(0.58)
Age square	0.00	-0.00**	0.00	-0.01**	0.00	-0.01**	0.00^{+}	-0.01**	0.00	-0.01**	0.00	-0.02**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Mother's education	0.00	0.01**	0.00	0.03**	0.00	0.03**	0.00	0.04**	0.00	0.03**	-0.04	0.04**	-0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.04)
Father's education	-0.00	0.01*	-0.00	0.02**	-0.00	0.02**	-0.01	0.03**	-0.00	0.02**	-0.02	0.03**	-0.03
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
At age 14 two-parent household	-0.03*	0.01	-0.03*	0.02	-0.14**	0.02	-0.14**	0.02	-0.14**	0.01	-0.50*	0.02	-0.54**
	(0.01)	(0.02)	(0.01)	(0.06)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)	(0.16)	(0.05)	(0.19)
Poverty status last year	0.06*	-0.01	0.06*	-0.01	0.27**	-0.01	0.27**	-0.02**	0.27**	-0.02	0.91**	-0.03	1.05**
	(0.01)	(0.02)	(0.01)	(0.06)	(0.05)	(0.06)	(0.04)	(0.06)	(0.05)	(0.04)	(0.20)	(0.06)	(0.38)
Woman was married last year	0.10**	-0.15**	0.11*	-0.45**	0.49**	-0.45**	0.53**	-0.59**	0.48**	-0.48**	3.17^{+}	-0.63**	3.49
	(0.01)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)	(0.08)	(0.05)	(0.04)	(0.04)	(1.82)	(0.06)	(6.74)
In college	-0.06**	0.01	-0.06**	0.02	-0.39**	0.02	-0.38**	0.03	-0.39**	0.02	-0.76**	0.03	-0.85**
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)	(0.14)	(0.05)	(0.21)
Year 1983	-0.00	-0.03**	-0.00	-0.08**	-0.02	-0.08**	-0.01	-0.10^{+}	-0.02	-0.08^{+}	-0.09	-0.12*	-0.06
	(0.02)	(0.00)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)	(0.05)	(0.05)	(0.04)	(0.15)	(0.06)	(0.17)
Year 1984	0.01	-0.01	0.01	-0.01	0.04	-0.01	0.04	-0.01	0.04	-0.01	-0.00	-0.01	0.01
	(0.02)	(0.01)	(0.02)	(0.02)	(0.10)	(0.02)	(0.10)	(0.06)	(0.05)	(0.05)	(0.16)	(0.06)	(0.19)

Appendix D (Continued)

	LPM	1SLS	2SLS	Probit		Biprobit		2-points		3-points		4-points	
Depend. Variable:	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant	drink	pregnant
Year 1985	-0.01 (0.02)	-0.02^{+} (0.01)	-0.01 (0.02)	-0.05** (0.01)	-0.06 (0.10)	-0.05** (0.02)	-0.05 (0.10)	-0.06 (0.06)	-0.07 (0.06)	-0.05 (0.05)	-0.41* (0.17)	-0.07 (0.06)	-0.43* (0.21)
North Central	0.0** (0.00)	0.03^{+} (0.01)	0.02** (0.00)	0.07* (0.03)	0.14** (0.00)	0.07* (0.03)	0.14** (0.01)	0.08 (0.06)	0.13* (0.05)	0.07 (0.05)	0.49* (0.16)	0.09 (0.06)	0.59* (0.30)
South	-0.01 (0.00)	-0.09* (0.02)	0.00 (0.01)	-0.26** (0.05)	-0.02 (0.02)	-0.26** (0.05)	0.02 (0.05)	-0.34** (0.07)	-0.04 (0.06)	-0.27** (0.06)	0.19 (0.18)	-0.35** (0.08)	0.36** (0.34)
West	0.03** (0.00)	0.00 (0.01)	0.03** (0.00)	-0.04 (0.03)	0.15** (0.01)	-0.04 (0.03)	0.16** (0.00)	-0.06** (0.07)	0.15* (0.06)	-0.04 (0.06)	0.62** (0.19)	-0.07 (0.08)	0.75^{+} (0.39)
Constant	0.23 (0.28)	-1.86** (0.20)	0.36 (0.21)	-7.20** (0.48)	-0.35 (1.48)	-7.29** (0.44)	0.29 (0.97)						
Rho				0.0000 (0.00)		-0.1878 (0.24)							
π_1								0.7605		0.8040		0.6112	
π_2								0.2395		0.1508		0.1134	
π_3										0.0452		0.1945	
π_4												0.0809	
R square	0.04	0.14	0.04										
Log Likelihood				-5212.2	-3244.5	-8456.1		-8447.8		-8434.9		-8425.1	
F-test for instruments		Ho rejected											
Wald test for instruments				Ho rejected		Ho rejected		Ho rejected		Ho rejected		Ho rejected	
Validity of exclusion restrictions		Valid		Valid		Valid		Valid		Valid		Valid	

** significant at 1%; * significant at 5%; + significant at 10%. Standard errors are clustered by region. Excluded categories are White, raised in Catholic families, 1982, and Northeast region. Both the F-test and the Wald tests of joint significance of instruments were performed only for drink equation. π_k is the 'probability' that the unobserved factor takes on the 'value' η_k.
Number of observations in all models is 9152.