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Economic Analyses of Multiple Addictions for Men and Women

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Abstract

Background: This study seeks to address analytical issues regarding the joint usage of alcohol, tobacco, and drugs, focusing on incomes, taxes, and gender-related differences.
Aims of the Study: Many studies analyze a single addictive substance, with the maintained assumption (often due to data inadequacies) that the use of other addictive substances does not matter. Using a database that is uniquely suited to the task, this study examines economic determinants of addiction probabilities and decomposes the differences between men and women into risk factors and probabilities.
Methods: The study uses the 2001-2002 National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) database. The NESARC, representing the entire non-institutionalized U.S. population age 18 and over, is the primary source for information and data on: (i) alcohol and drug use; (ii) alcohol and drug abuse and dependence; and (iii) associated psychiatric and other medical comorbidities. The study then proposes a multinomial logit modeling strategy that addresses endogeneity of smoking, drinking, and drug use. Parameter estimates then predict absolute and marginal probabilities and look at gender and age related differences. The study also develops and demonstrates a new decomposition for analyzing the differences between men's and women's uses of addictive substances.
Results: Women, Blacks, and Hispanics are less likely to engage in addictive behaviors. Increased cigarette and beer taxes negatively affect probabilities of smoking and drinking. Increasing both cigarette and beer taxes is related both to more abstinence (none of the three types of substances), and to more use of drugs (which are untaxed).
Discussion: The measured impacts of current income and current taxes on addictive goods are strong even though addictive decisions are almost certainly longer term decisions, reflecting both current and past prices. However, the impacts of current incomes and taxes in the multinomial logit formulations are highly significant and the results are plausible.
Implications for Health Care Provision and Use: To the extent that taxes can reduce harmful addictive behaviors, the utilization and cost of health care attributable to addiction may be reduced.
Implications for Health Policy: Higher taxes have strong potential negative impacts on addictive behaviors. The effects differ, however, by gender, race, and age, and ethnicity.
Implications for Further Research: The analysis could be extended to two part models, in which quantities and/or expenditures on alcohol, tobacco, or drugs may be examined, conditional on the individuals' specific categories of addictive substance used. With panel data, decisions on starting and/or stopping drinking, smoking, or ingesting drugs may also be considered.

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Introduction

Researchers have long sought to characterize and identify statistical risk factors for the use of single or multiple addictive substances. Many databases and analyses have concentrated on single addictions such as smoking, alcohol, or drugs, and analysts have implicitly assumed that contemporaneous addictions are unrelated to each other. This assumption is almost certainly incorrect. It is necessary to examine co-occurring addictions on the assumption that they may reflect some underlying psychological or physical factors, with methods that recognize that none of the addictions necessarily cause the others.

In a full econometric treatment of addictive substances, one might model the ingestion of alcohol, cigarettes, and/or drugs as at least a two part model, in which the quantities ingested, total expenditures on individual commodities, or all of them together, constitute a second stage, conditional on the decision to drink, smoke, or take drugs. The potentially joint nature of these addictions makes the first modeling stage an important study in itself. How much people drink, smoke, or use drugs, depends on whether they use substances or not, and in what combinations.

This article starts with a brief literature discussion, followed by a description of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) database, designed and conducted as the primary source for information and data on the U.S. population for: (i) alcohol and drug use; (ii) alcohol and drug abuse and dependence; and (iii) associated psychiatric and other medical comorbidities. It then proposes a multinomial logit modeling strategy that addresses the joint determination of smoking,

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drinking, and drug use. This model then predicts absolute and marginal probabilities, and looks at gender and age related differences. The article also develops and demonstrates a new decomposition for analyzing the differences between men's and women's uses of addictive substances.

Literature Review

Analysts have recognized issues of co-occurring conditions in terms of episode length, treatment modality, and treatment costs for some time. However, health services databases, which typically begin and end at arbitrary dates, often force researchers to assume that one condition seen ''came first'', and that other conditions were either caused by the first condition, or are not causally related (that is, exogenous) to the first.

Goodman *et al.* look at the impacts of comorbidities on drug abuse treatment and cost.[1,2] Goodman *et al.*[1] examine drug abuse treatment location (inpatient v. outpatient) and find that additional drug, alcohol, or smoking comorbidities led to inpatient treatment location.[1] Goodman *et al.*[2] find that more comorbidities and increased severity of conditions related to increased treatment costs. Because the analyses use insurance claims data over a three-year period, from persons with at least one drug abuse treatment during that three-year period, they implicitly view the drug abuse treatment as the initial diagnosis, accompanied by the other comorbidities.

Dee examines ''cross-effects'' between smoking and drinking in an econometric study, to determine whether drinking and smoking are substitutes (one activity performed rather than the other) or complements (both substances used, possibly together).[3] He finds that teen drinking roughly doubles the mean probability of smoking participation. Similarly, higher cigarette taxes and reductions in teen smoking are related to a lower prevalence of teen drinking.

Falck *et al.* show the importance of comorbidities by assessing the lifetime prevalence of psychiatric disorder among 313 not-in-treatment crack cocaine users.[4] The most common dependencies involve cocaine (59.7%), alcohol (37.7%), and cannabis (12.1%). The most common nondependency disorders are antisocial personality disorder (ASPD; 24%), depression (17.8%), and posttraumatic stress disorder (PTSD; 11.8%).

Helstrom *et al.* examine substance use among two cohorts of adolescents in a 2 year period (cohort 1 = 245, cohort 2 = 299) in which participants report frequency of cigarette, alcohol, marijuana, and other substance use.[5] Employing path analysis, the investigators suggest that smoking and alcohol act as mediators between externalizing problems and marijuana and other drug use. They also report some mean differences by gender, but that the pattern of relationships among variables did not differ by gender.

Grant and colleagues have conducted a number of analyses using the NESARC.[6,7] Their largely descriptive work focuses on disorder, with a 7.35% prevalence of alcohol use disorder only, a 0.90% prevalence of drug use disorder, and comorbid alcohol and drug use disorder of 1.10%. Their studies are generally epidemiological in method, and do not attempt to look at economic determinants of behavior.

Database

The NESARC database used in this analysis is a representative sample of the U.S. population, with 43,093 participating in the first wave between August 2001 and April 2002. It targets the non-institutionalized household population 18 years and older and it provides estimates for the nation as a whole on alcohol and drug use, abuse and dependence and their associated disabilities.

The NESARC over-sampled young adults (18 through 24), non-Hispanic Blacks, and Hispanics, with weights provided for adjustment. Survey weights reflected the oversampling, and all estimates and variances were weighted. Grant *et al.*[6] provide further information on the database. All analyses presented in this article use SAS Version 9.1.

This database provides a population-based sample with adequate sample sizes to address both single and multiple addictions. This article will use multinomial logit analysis to look at both the unconditional and the conditional probabilities of smoking, drinking, and the use of addictive or illicit drugs. There are substantial gender differences in both base rate usage and in the parameters of the varying probabilities. Even controlling for age, family circumstance, education, and wealth, men and women act differently in terms of substance use.

Table 1 (a) examines smoking, drinking and drug use for sample men and women who reported positive personal (as opposed to household or family) incomes from working and/ or from non-labor forms of income, excluding subjects that report zero incomes (2,462 subjects), as well as small numbers with missing or inconsistent data (293 subjects). Personal income is used because the study is looking at addiction at the individual level. The 17,979 men in the sample represent approximately 96.5 million in the overall population. The substance use measures come from self-reports on drinking, smoking, or drug use within the previous 12 months. The three largest categories are *none* (no smoking, drinking, or drugs in the previous 12 months) with 22.4% (representing a population-weighted 20.8% of all males), *drinking only* (42.7%, representing 42.5% of all males), and *smoking/drinking* (21.9%, representing 23.0% of all males). The categories *drugs only* (no smoking or drinking) and *smoke/drugs* (no drinking) had 68 and 48 observations respectively (of the 17,979), suggesting potential instability in subsequent parameter estimates due to low statistical degrees of freedom.

The 22,359 women in the sample represent approximately 96.7 million women in the overall population. As with the men, the three largest categories for women are *none* with 36.2% (representing 33.1% of the female population), *drinking only* (40.4%, representing 42.5% of all females), and *smoking/drinking* (13.2%, representing 14.2% of all females). As with men, categories *drugs only* and *smoke/ drugs (no drinking)* were small cells, with 76 and 51 observations respectively. These are slightly larger cells than the men, but they again suggest potential parameter instability.

Table 1 (b) provides weighted estimates of the populations for both men and women. It is apparent that total abstainers

Table 1: Potentially Addictive Behaviors for Subjects with Positive Personal Income

	Figure 1	Men		Women	
	Category	Number	Pct.	Number	Pct.
a. Count					
None		4,019	22.4	8,087	36.2
Smoke Only	A	1,030	5.7	1,270	5.7
Drink Only	B	7,676	42.7	9,024	40.4
Drugs Only	C	68	0.4	76	0.3
Smoke/Drink	AB	3,936	21.9	2,959	13.2
Smoke/Drugs	AC	48	0.3	51	0.2
Drink/Drugs	BC	441	2.5	349	1.6
All 3	ABC	761	4.2	543	2.4
Total		17,979	100.0	22,359	100.0
b. Weighted Totals					
None		20,079,307	20.8	31,973,895	33.1
Smoke Only	A	5,766,528	6.0	5,246,125	5.4
Drink Only	B	40,991,270	42.5	41,070,552	42.5
Drugs Only	C	351,763	0.4	297,197	0.3
Smoke/Drink	AB	22,174,535	23.0	13,737,826	14.2
Smoke/Drugs	AC	234,890	0.2	196,503	0.2
Drink/Drugs	BC	2,313,402	2.4	1,603,820	1.7
All 3	ABC	4,577,991	4.7	2,603,989	2.7
Total		96,489,686	100.0	96,729,907	100.0

have slightly smaller weights than those who use tobacco, alcohol or drugs. **Figure 1** provides a graphical analysis with Venn diagram percentages drawn to scale. The two major differences are in total abstention (33.1 percent of women v. 20.8 percent of men) and in the smoke/drink category (23.0 percent of all men v. 14.2 percent of all women). In all subsequent analyses, weighted estimates will be used with the weights normalized to unity.

Modeling the Joint Probabilities

Describing multiple addictions produces problems of causality when the jointly determined variables (i.e. the addictions), as noted by Maddala and Lee,[8] are ''completely interrelated; for instance, if there are three variables y_1, y_2, and y_3 then y_1 influences y_2 and y_3, y_2 influences y_3 and y_1, and y_3 influences y_1 and y_2.'' These relationships can be estimated properly by multinomial logit methods (MNL) as follows.

Begin with a model in which vector $\mathbf{x}$ refers to demand determinants of alcohol, cigarette, or drug use. Letting y_1 refer to smoking, y_2 to drinking, and y_3 to drug use, write:

$$P_{ijk} = \Pr(y_1 = i, y_2 = j, y_3 = k) \quad i, j, k = 0 \text{ or } 1$$

Then, if $D = 1 + \sum_{i=1}^{7} e^{\mathbf{x}\beta_i}$,

$$P_{000} = 1/D \quad \text{(1a)}; \qquad P_{110} = e^{x\beta 4}/D \quad \text{(1e)}$$

$$P_{100} = e^{x\beta 1}/D \quad \text{(1b)}; \qquad P_{101} = e^{x\beta 5}/D \quad \text{(1f)}$$

$$P_{010} = e^{x\beta 2}/D \quad \text{(1c)}; \qquad P_{011} = e^{x\beta 6}/D \quad \text{(1g)}$$

$$P_{001} = e^{x\beta 3}/D \quad \text{(1d)}; \qquad P_{111} = e^{x\beta 7}/D \quad \text{(1h)}$$

where $\beta_m (m = 1,7)$ refer to separate vectors of simultaneously estimated coefficients.

The multinomial logit equation provides the well defined conditional distributions:

$$Log \frac{P(y_1 = 1|y_2, y_3)}{P(y_1 = 0|y_2, y_3)} = \beta_1 x + (\beta_4 - \beta_2 - \beta_1)xy_2 + (\beta_5 - \beta_3 - \beta_1)xy_3 + (\beta_7 - \beta_6 - \beta_5 - \beta_4 + \beta_3 + \beta_2 + \beta_1)xy_2y_3 \quad \text{(2a)}$$

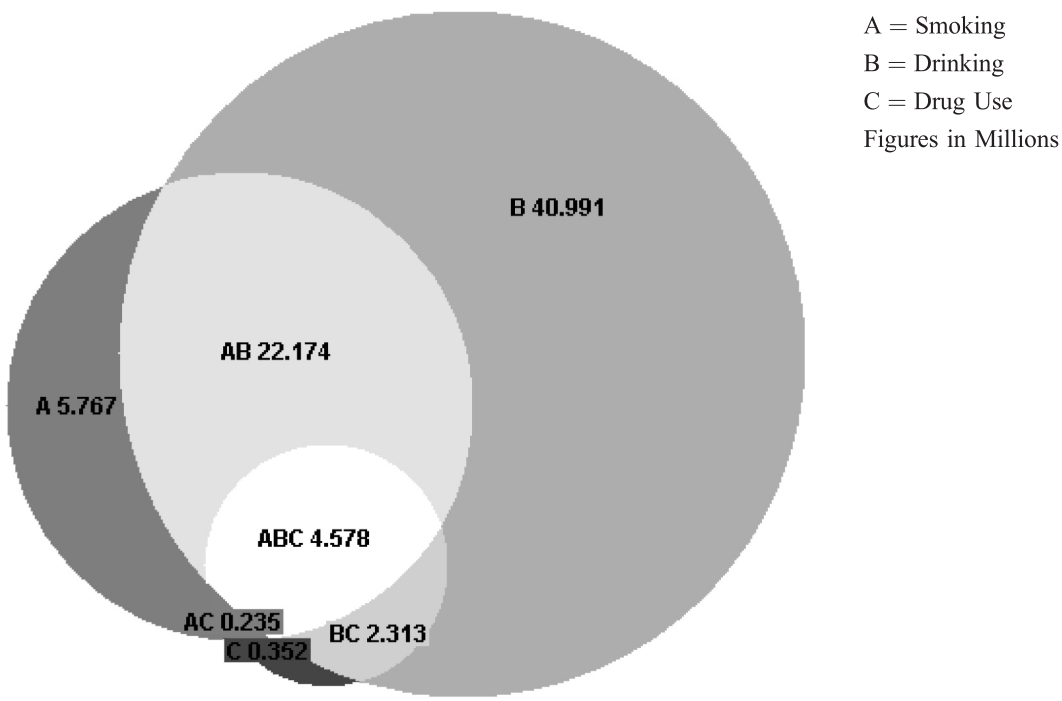
$$Log \frac{P(y_2 = 1|y_1, y_3)}{P(y_2 = 0|y_1, y_3)} = \beta_2 x + (\beta_4 - \beta_2 - \beta_1)xy_1 + (\beta_6 - \beta_3 - \beta_2)xy_3 + (\beta_7 - \beta_6 - \beta_5 - \beta_4 + \beta_3 + \beta_2 + \beta_1)xy_1y_3 \quad \text{(2b)}$$

$$Log \frac{P(y_3 = 1|y_1, y_2)}{P(y_3 = 0|y_1, y_2)} = \beta_3 x + (\beta_5 - \beta_3 - \beta_1)xy_1 + (\beta_6 - \beta_3 - \beta_2)xy_2 + (\beta_7 - \beta_6 - \beta_5 - \beta_4 + \beta_3 + \beta_2 + \beta_1)xy_1y_2 \quad \text{(2c)}$$

As a result, this formulation estimates the absolute probabilities of being in one of eight mutually exclusive data cells, impacts of changes in explanatory variables x_m, and conditional probability of drinking, smoking, or drug use, given the use (or non-use) of one or both of the others.

The MNL model provides relative ease in estimation and interpretation, but it does impose some assumptions. If the utility of each choice depends on both individual-specific

Men’s Population (Total = 96,489,686)



Women’s Population (Total = 96,729,907)

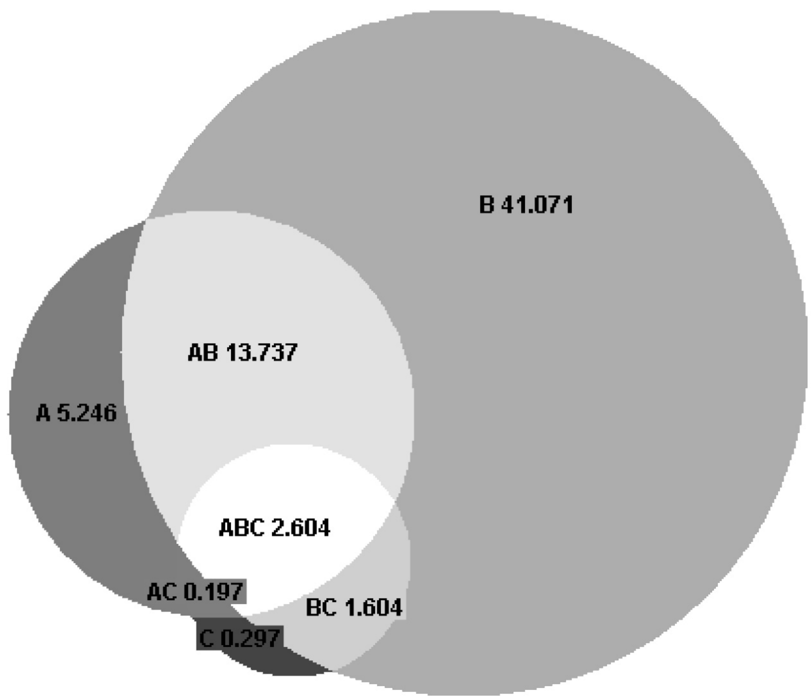


Figure 1 - Men’s and Women’s Totals and Percentages for Smoking, Drinking, and Drug Use - Venn diagram areas are proportional to percentages.

Note: Graphs from http://theory.cs.uvic.ca/venn/EulerianCircles/, last accessed April 4, 2008.

and attribute-specific (the prices of the factors) variables, a mixed logit model would result. Furthermore, the MNL implicitly assumes that the errors are uncorrelated across alternative choices (zero covariances in the cross-diagonal). This may lead to the potentially unrealistic assumption of independence-of-irrelevant-alternatives (IIA) with the relative probability of choosing between two existing alternatives unaffected by the presence of additional alternatives. The initial MNL analyses in the following section will address this concern.

Table 2: Mean Bundles by Gender

	Men (N = 17,979)		Women (N = 22,359)		
	(a) Mean	(b) St. Dev.	(c) Mean	(d) St. Dev.	**(e) Mean**
AGE - Age in years	44.5513	17.0379	46.8045	18.4371	**45.6779**
BLACK - 1 if Black, 0 otherwise	0.1040	0.3053	0.1312	0.3376	**0.1176**
HISP - 1 if Hispanic, 0 otherwise	0.1221	0.3274	0.1006	0.3009	**0.1114**
EDUCATION					
Elementary - Omitted Category	0.0627	0.2425	0.0565	0.2309	**0.0596**
Some High School (SOMEHS)	0.0935	0.2911	0.0918	0.2888	**0.0927**
High School (HIGHSCH)	0.2885	0.4531	0.2983	0.4575	**0.2934**
Some College (SOMECOLL)	0.2885	0.4531	0.3168	0.4652	**0.3026**
BA Degree (BACH)	0.1409	0.3479	0.1232	0.3287	**0.1321**
Past BA (GRAD)	0.1259	0.3317	0.1133	0.3170	**0.1196**
SPOUSE – 1 if in spousal relationship, 0 otherwise	0.6062	0.4886	0.5213	0.4996	**0.5637**
HEALTH					
Excellent - Omitted Category	0.3155	0.4647	0.2894	0.4535	**0.3025**
Very good (H_VG)	0.3154	0.4647	0.2963	0.4566	**0.3058**
Good (H_GOOD)	0.2336	0.4231	0.2480	0.4319	**0.2408**
Fair (H_FAIR)	0.0962	0.2948	0.1169	0.3213	**0.1065**
Poor (H_POOR)	0.0393	0.1944	0.0494	0.2168	**0.0444**
LOGY - natural log of income	10.1595	1.0204	9.5830	1.0877	**9.8712**
FULLPT - 1 if working full or part time, 0 otherwise	0.8265	0.3787	0.7304	0.4438	**0.7784**
CIGARETTE TAX in $ per pack	0.5008	0.3202	0.5013	0.3195	**0.5011**
BEER TAX cents per (12 ounce) drink	2.3457	1.6804	2.3768	1.7143	**2.3613**

Demand theory suggests that vector **x** would include income and price terms. Personal income is used from the NESARC, and state level cigarette and beer taxes have been appended to the model from other sources.* The cigarette taxes are for 2001, and they vary from $0.025 per pack in Virginia to $1.11 per pack in New York. The beer taxes (for 2000) vary from $0.0018 per drink in Wyoming to $0.098 per drink in Alabama.† No state-by-state data are readily available on prices (or taxes) for addictive drugs.*

Alcohol, tobacco, and drugs are economic ''goods'' subject to negative price and positive income effects, but health demand (from Grossman's model) is also a normal good.[12] To the extent, then, that smoking and drug use are negative inputs into health, the income effect is ambiguously signed. Higher beer or cigarette taxes are expected to reduce individual substance probabilities, although joint impacts depend on substitutions (goods used instead of each other) or complementarities (goods used with each other) and must be determined empirically.

Other explanatory variables, as noted in **Table 2**, include age (both linear and squared), self-identified African American (Black) race and Hispanic heritage, education (six categories), self-reported health status (five categories), logarithm of income, and whether the subject worked full or part-time. Sample men were younger than women (44.6 v. 46.8), and slightly more educated (higher percentages of men with BA degrees and higher). Men were more likely to be married, and to have higher incomes, and they were more likely to work either full or part-time.

Women were more likely Black (0.1312 v. 0.1040) and less likely Hispanic (0.1006 v. 0.1221). Women reported higher levels of fair or poor health than men, although contemporaneous clinical health evaluations generally view women to be in slightly better health. These findings of self-related health are consistent with 2002 data reported by the National Center for Health Statistics where 8.9% of men report fair or poor health, compared to 9.6% of women, even though the age-adjusted mortality rate for men is 53.5 per 100,000 population v. 37.4 per 100,000 population for women.[12]

* Cigarette taxes are from the Tax Policy Center documents for 2001.[9,10] Since the tobacco question used from the NESARC refers to the previous 12 months, the use of 2001 taxes seems appropriate. The alcohol question also refers to the previous 12 months. Each state regulates alcohol differently, and it is difficult to find comprehensive sources across all states. State level beer taxes refer to 2000.[11] Similar sources for 2001 or 2002 were not available.

† Taxes are also available for wine and spirits.[11] Including more than one alcohol tax leads to multicollinearity problems in estimation, without substantive differences in results, so the beer tax is used in preference to the others.

* DEA's System to Retrieve Information on Drug Evidence (STRIDE) data are potentially useful, but collected for specific cities as opposed to states. Moreover, in email communication Dr. Rosalie Pacula reports that aggregation to the state level is difficult and arbitrary. Also, no data series are publicly available (due to confidentiality, Dr. Pacula could not provide the series that she has created) unless calculated by the researcher. This task is well outside the scope of the project, and it is unclear that the resulting price series would improve the analyses.

Table 3: Chi-Squared IIA tests

		(a)		(b)		(c)	
		Add Drugs		Add Drink		Add Smoke	
		Smoke/Drink Add Drugs	Accept/ Reject IIA	Smoke/Drugs Add Drink	Accept/ Reject IIA	Drink/Drugs Add Smoke	Accept/ Reject IIA
Men	χ^2 (3)	0.9441	Accept	24.8254	Reject	4.3212	Accept
	Signif. level.	0.8148		0.0000		0.2288	
Women	χ^2 (3)	7.1004	Accept	7.6209	Accept	2.4906	Accept
	Signif. level.	0.0688		0.0545		0.4770	

Determinants of Estimated Probabilities

This section presents the MNL estimates that underlie the major analyses. As noted earlier, it is first necessary to address the IIA assumption – that is, the relative probability of choosing between two existing alternatives being unaffected by the presence of additional alternatives. Looking at smoking and drinking alone, for example, generates 4 cells (none, smoking, drinking, smoking/ drinking). Adding drugs generates 4 additional cells (drugs, smoking/drugs, drinking/drugs, smoking/drinking/ drugs). The MNL analysis generates predicted numbers of observations in each cell, as well as relative probabilities. IIA assumes that the relative probabilities of the initial cells do not change with the introduction of a new choice. The resulting differences in the relative probabilities generate different predicted numbers of observations in the cells, and by implication different probabilities. Because there are four additional categories, the changed cell predictions are distributed χ^2, with 3 degrees of freedom.

Table 3 presents three sets of IIA tests for the MNL regressions. In test (a), the drug category is added to those who smoke/drink/neither. In both cases IIA is not rejected (i.e. accepted) at the 5% level. For test (b), adding drinking, IIA is rejected for men, but not for women. For test (c), adding smoking, IIA is accepted for both men and women. Therefore, in two of the three tests for men, and in all three tests for women, IIA is supported, suggesting that subsequent analyses using MNL are generally appropriate.

Table 4 examines the estimated probabilities for men and women from equations 2a – 2c and compares the socioeconomic variable impacts between women and men. The supporting multinomial logit equations are included as **Appendix, Table A1** (Men, m) and **Appendix, Table A2** (Women, w). The calculated probabilities are calculated with the mean vectors of gender-specific characteristics (x_m and x_w) constant (columns a and c in **Table 2**). Reflecting the underlying cell sizes, the three most prevalent cell predictions for men are *none* (19.1%), *drinking only* (41.0%) and *smoking/drinking* (28.0%). For women, there is a considerably larger category of *none* (31.1%); *drinking only* is slightly larger than men (42.2%) and *smoking/drinking* is smaller (17.8%).

With more than one choice, marginal impacts depend on magnitudes as well as signs of the various coefficients. With seven vectors of coefficients, an intuitive comparison of continuous variables examines variations around the gender means and calculates percentage probability responses to one percent changes in explanatory variables, or *elasticities*. For example, a 1% increase in men's ages increases the probability of *none* (no smoking, drinking, or drugs) by 0.69% (from 0.1906 to 0.1919) and decreases the probability of *all three* (smoking, drinking, and drugs) by 3.36% (from 0.0323 to 0.0312). For women the impact of age on the *none* category is +0.72% (about the same as men), and –3.67% (slightly larger) for *all three*.* These are similar age patterns for men and women, with decreasing use as age increases.

For the discrete individual descriptors, percentage differences relate to a change from 0 to 1, holding all other variables constant. For example, Black men are 48.2% more likely than are non-black men to engage in none of the three addictive activities (column a), and 34.4% less likely to engage in all three addictive activities (column h). In comparison, Black women are 63.8% more likely (than non-Black women) to engage in none of the three addictive activities and 51.6% less likely (than non-Black women) to engage in all of them.

The health and education variables compare the discrete categories. For example, men in very good health are 26.5% more likely to smoke/drink than those in excellent health; those in poor health are 27.1% more likely to smoke/drink than those in excellent health. For women, the percentages are 29.0% and 53.5% respectively. Regarding education, men with bachelors degrees (–26.6%) or graduate work (–39.0%) are less likely to smoke/drink than those with less than a high school diploma. Women with bachelors degrees or graduate work (a single category) are 35.1% less likely to smoke and drink than those with less than a high school diploma.

* While the probabilities must sum to one, there are no such restrictions on the elasticities. In particular, small changes in small probabilities may lead to fairly large elasticities.

Table 4: Marginal Percent Impacts of Explanatory Variables on Cell Probabilities

	None	Smoke Only	Drink Only	Drugs Only	Smoke/Drink	Smoke/Drugs	Drink/Drugs	All 3
Men								
Base Probability	0.1906	0.0657	0.4101	0.0027	0.2797	0.0022	0.0168	0.0323
Elasticities[a]								
Age	0.6911	0.6163	0.1844	–0.3920	–0.3995	–0.9903	–1.4541	–3.3629
Income	–0.1532	–0.1685	0.1055	–0.2258	0.0305	–0.2547	–0.1805	–0.2271
Cig. Tax	0.0001	–0.3446	0.1230	0.5567	–0.1295	0.0734	0.2800	0.0622
Beer Tax	0.1629	0.1828	–0.0685	0.2555	–0.0320	0.1375	–0.1615	–0.1332
Marginal Effects[b]								
Black	48.2124	–30.7692	2.5496	23.9708	–24.5367	–49.0142	31.3869	–34.3560
Hispanic	23.3045	–47.1395	33.1341	98.2952	–39.0010	–68.6800	–20.5080	–61.6997
Spouse	0.4423	–13.6781	13.6568	–3.9966	–5.8976	–44.4500	–38.2445	–36.7318
Work	–3.5350	–32.9740	–5.0567	–37.4179	20.6845	101.7804	51.9239	11.2834
Heath Very Good: Health Excellent	–10.1128	–10.2466	–10.4645	128.7559	26.4764	–11.0606	20.1037	58.7381
Health Poor: Health Excellent	13.1582	101.2578	–54.9764	529.7901	27.1143	1246.6653	69.8111	451.4696
HS: Less than HS	–11.2208	–38.5175	10.8028	30.6801	4.6428	330.0718	216.4775	197.0357
Bach: Less than HS	–18.1536	–80.5986	67.3427	–38.8308	–26.5839	47.1782	477.6938	82.2253
Grad: Less than HS	–7.5675	–83.7128	70.6609	–11.6701	–39.0241	150.1544	630.6820	87.4249
Women								
Base Probability	0.3107	0.0629	0.4220	0.0022	0.1775	0.0012	0.0103	0.0133
Elasticities								
Age	0.7167	0.3002	0.1234	0.0896	–1.2752	–0.6138	–1.7453	–3.6738
Income	–0.1018	–0.1659	0.0703	–0.0687	0.0650	–0.3135	–0.0078	0.1084
Cig. Tax	–0.0509	–0.2544	0.0943	0.0470	–0.0763	0.0495	0.2502	0.2130
Beer Tax	0.1728	0.1761	–0.1255	0.2424	–0.0702	–0.0645	–0.0177	0.0289
Marginal Effects								
Black	63.7639	–5.5448	–18.2206	5.0279	–49.1629	13.9461	–31.4389	–51.6278
Hispanic	46.1501	–57.1959	–0.0136	145.6811	–48.0836	–70.3923	–27.3877	–62.3801
Spouse	2.3720	–22.3033	15.7361	17.1099	–22.7603	–20.0091	–19.2779	–32.8175
Work	–17.0088	–13.6305	8.7699	–16.5118	16.7850	19.8612	98.7872	35.2378
Heath Very Good Health Excellent	–4.3408	27.6755	–9.3422	43.5082	28.9587	5.9526	32.0779	83.4224
Health Poor: Health Excellent	21.8789	271.1579	–57.8840	360.1846	53.5042	333.9493	3.3817	413.8995
HS: Less than HS	–34.8802	–31.3838	56.8560	103.1467	36.8285	–56.4623	267.5753	204.6392
BA-Grad: Less than HS	–38.2013	–77.7491	138.9568	110.6468	–35.0523	–96.0335	528.1524	44.5149

[a] Impact of 1% change in explanatory variable.
[b] Impact of change in explanatory variable from 0 to 1.

Table 5: Marginal Percent Impacts of Explanatory Variables on Individual Activities

	Men				Women			
	(a) None	(b) Smoke	(c) Drink	(d) Drugs	(e) None	(f) Smoke	(g) Drink	(h) Drugs
Base Probability	0.1906	0.3798	0.7388	0.0540	0.3107	0.2548	0.6230	0.0269
Continuous								
Age	0.6911	–0.4788	–0.2287	–2.5228	0.7167	–1.0086	–0.3869	–2.4981
Income	**–0.1532**	**–0.0274**	**0.0561**	**–0.2137**	**–0.1018**	**0.0086**	**0.0683**	**0.0313**
Cigarette Tax	0.0001	**–0.1493**	0.0283	0.1556	–0.0509	**–0.1046**	0.0508	0.2066
Beer Tax	0.1629	–0.0024	**–0.0596**	–0.1114	0.1728	–0.0043	**–0.1047**	0.0244
Discrete								
Black	48.1935	–26.6203	–8.9418	–12.6471	64.1367	–38.7572	–28.2263	–36.9784
Hispanic	23.3045	–42.6272	–1.4165	–42.9548	46.4684	–51.1295	–16.0434	–35.0163
Spouse	0.4423	–10.7812	1.4251	–36.2492	2.4708	–23.1237	1.3326	–23.9719
Work	–3.5350	6.6170	5.2730	19.7572	–17.0767	8.6522	12.3729	47.3807
Some College: (less than high school)	–18.4178	–41.0705	25.7208	151.2429	–43.9993	–11.0301	66.4641	123.8470
Health Excellent: (health very good)	–10.1128	21.1965	3.2967	43.3618	–4.3408	30.5712	0.1320	51.3301

Usages of Individual Substances

Combining the cell-specific probabilities permits the calculation of overall elasticities for the usage of the individual substances. In **Table 5** smokers, for example, fall into four categories (smoke only, smoke/drink, smoke/drugs, all three), so the calculated percentage of men who smoke is 0.3798. Calculations for drinking and ingesting drugs are 0.7388 and 0.0540 respectively. Similar percentages are calculated for women.

Ta**ble 5** shows that women's and men's responses to increases in income (line 2) were qualitatively and quantitatively similar with respect to abstaining from all three substances (for men, column a, –0.1532; for women, column e, –0.1018) and drinking (+0.0561 for men, and +0.0683 for women). Increased income led to decreased probabilities of both smoking (–0.0274) and drugs (–0.2137) for men. In contrast, women's probabilities for smoking were essentially unchanged (+0.0086) and increased slightly (+0.0313) for drugs.

Price differences in U.S. cigarette and beer prices come largely from differential state level excise taxes. Many have investigated tax impacts on start-stop or quantity decisions, but probabilities have not been analyzed in the context of multiple substances. Holding other factors constant, a one percent increase in cigarette taxes (line 3) for men is related to a 0.1493 percent decline in probability of smoking. The impact for women is 0.1046 percent. Both suggest that doubling cigarette excise taxes might have substantive impacts on decisions to smoke.

Similar calculations for drinking indicate similar, although smaller, negative impacts. For men, holding everything else constant, a one percent increase in beer tax was associated with a 0.0596 percent decline in the probability of drinking (less than half of the impact on smoking). For women, the impact was larger, –0.1047 percent.

It is useful to relate these elasticities to those reported in the literature. Chaloupka, Tauras, and Grossman[14] report a prevalence elasticity for smoking with respect to price between –0.1 and 0.2, Harris[15] calculates –0.24, and Lewitt, Coate, and Grossman[16] calculate 0.26. For alcohol, Kenkel[17] reports participation elasticities of –0.74 for men and –0.81 for women (see also Badenes-Plá and Jones[18]). In the analysis presented here, assuming that increases in the beer and cigarette tax are fully passed onto consumers, the beer tax elasticity (for males) in **Table 5** translates into a price elasticity of about –0.66, and for females, a little higher at -1.15. The calculated cigarette tax elasticity implies a price elasticity of about –0.30 for males and –0.22 for females.* The findings here are roughly consistent with literature, recognizing that other studies use different methods and do not account for the joint usages of two or more substances.

Following up on Dee's examination of the ''cross-effects'' between smoking and drinking, here (unlike Dee's findings) higher cigarette taxes are correlated with slightly higher probabilities of drinking, suggesting a modest amount of substitution.[3] Cross-elasticities with respect to the beer tax are almost certainly insignificant (elasticities less than -

* Start with $E_T = \dfrac{\%\Delta Probability}{\%\Delta Tax}$, and price elasticity $E_P = E_T \dfrac{\%\Delta Tax}{\%\Delta Price}$. With cigarette taxes about one-half the cigarette price and beer taxes about one-eleventh the beer price, multiply E_T by 2 for cigarettes and by 11 for beer to get price elasticities.

Table 6: Impacts of Equal Percent Beer and Cigarette Tax Increases

Tax Increase (%)	(a) None	(b) Smoke	(c) Drink	(d) Drugs
Men				
0	0.1906	0.3798	0.7388	0.0540
10	0.1937	0.3741	0.7365	0.0542
20	0.1968	0.3683	0.7341	0.0545
30	0.2000	0.3626	0.7317	0.0547
40	0.2031	0.3570	0.7292	0.0550
50	0.2063	0.3513	0.7267	0.0553
60	0.2095	0.3457	0.7242	0.0557
70	0.2127	0.3402	0.7216	0.0560
80	0.2159	0.3346	0.7190	0.0564
90	0.2191	0.3291	0.7163	0.0568
100	0.2223	0.3236	0.7136	0.0573
Pct. change (0 → 100)	+16.7%	–14.8%	–3.4%	+6.1%
Women				
0	0.3107	0.2548	0.6230	0.0269
10	0.3145	0.2521	0.6197	0.0276
20	0.3183	0.2493	0.6163	0.0282
30	0.3222	0.2466	0.6129	0.0288
40	0.3260	0.2439	0.6095	0.0295
50	0.3298	0.2413	0.6061	0.0302
60	0.3337	0.2386	0.6027	0.0309
70	0.3375	0.2360	0.5993	0.0316
80	0.3414	0.2334	0.5959	0.0323
90	0.3453	0.2308	0.5925	0.0330
100	0.3491	0.2283	0.5890	0.0338
Pct. change (0 → 100)	+12.4%	–10.4%	–5.5%	+25.5%

0.0050). Cross-effects of cigarette taxes on drug use are positive for both men (0.1556) and women (0.2066), suggesting substitution of drugs for cigarettes. Cross-effects of beer taxes on drug use are negative for men (-0.1114), but positive, although small (0.0244), for women.

Increased cigarette taxes imply increased probability of illicit drugs for both men and women, implying that the cigarettes and drugs are substitutes. The impacts of increased beer taxes on drugs are mixed. For men, a 10% beer tax increase implies a *decrease* of 0.1114% in the probability of using illicit drugs; for women, a 10% beer tax increase implies a very small increase (elasticity of +0.0244) in the probability of using illicit drugs.*

Table 6 traces the impacts of increasing both beer and cigarette taxes together. For men, doubling both taxes (100% increase) increases the percentage abstaining from all substances from 0.1906 to 0.2223, or about 16.7%; the percentage smoking falls from 0.3798 to 0.3236, or by about 14.8%. The impacts on drinking are smaller (–3.4%), and the incidence of drug use increases very slightly (from 0.0540 to 0.0573, or about 6.1%).

For women, doubling of both taxes leads to a 12.4% increase in the probability of abstaining. Smoking probability falls from 0.2548 to 0.2283, smaller absolute and percentage decreases than for men. Tax increases are related to reductions in drinking, although in this case the absolute (from 0.6230 to 0.5890) and percentage changes (–5.5%) are larger than for men. Like men, the percentage ingesting drugs increases – in this case, by over 25%, although the absolute incidence of 0.0338 is still small, and about 60% of men (0.0573).

These measured impacts of current taxes on addictive goods are strong ones when it is realized that addictive decisions may be longer term decisions, reflecting both current and past prices. Yet their inclusions in the multinomial logit formulations are highly significant, and their results are plausible.* Increased cigarette and beer taxes

* Although the joint impact of the beer tax variable in the seven regressions is significant at the 1% level (see footnote 8), significance levels for calculated elasticities are not readily available. Irrespective of significance, the elasticity of +0.0244 is quantitatively very small.

* For women, joint impact of 7 cigarette tax coefficients was χ^2 (7) = 83.76; for beer tax, it was χ^2 (7) = 180.48. For men, respective tests were χ^2 (7) = 125.91, and χ^2 (7) = 102.50. All were significant beyond the 0.01 level.

Table 7: Conditional Probabilities (Drug Use | Drinking, Smoking)

Probabilities				Ratios			
	Men	Smoke			Men	Smoke	
		No	Yes			No	Yes
Drink	No	**0.0142**	0.0319	Drink	No	**1.000**	2.244
	Yes	0.0393	**0.1034**		Yes	2.770	**7.285**
	Women	Smoke			Women	Smoke	
		No	Yes			No	Yes
Drink	No	**0.0070**	0.0182	Drink	No	**1.000**	2.602
	Yes	0.0238	**0.0696**		Yes	3.398	**9.938**

have expected negative impacts on probabilities of smoking and drinking. Moreover, increasing both taxes is related to more abstinence (none of the three types of substances), and to more use of drugs (which are untaxed).

Conditional Probabilities

Equations (2a) – (2c) also permit calculation of conditional probabilities for the numerous combinations of drinking, smoking and drugs. An example is provided in **Table 7**. The probability of men's drug use, given that the man neither smokes nor drinks, is 0.0142. If he smokes, the probability of drug use is 0.0319 or slightly more than twice as high, and if he both drinks and smokes, the probability of drug use is 0.1034, or about 7.3 times as high.

The relative impacts for women are a little larger, although they start from lower base probabilities than the men. The probability of drug use, if a woman neither smokes nor drinks, is 0.0070. If she drinks, the probability of drug use rises to 0.0182, a factor of 2.6. If she both smokes and drinks, her conditional probability of drug use is 0.0696. The absolute increases are all smaller than for men, but given the small baseline value (less than 1%), the incremental relative increase is almost 10 times as large as the probability if she neither smoke nor drank.

Decomposing Gender Differences

Men and women show different probabilities of addictive behaviors and these probabilities relate to the different endowments of risk factors, $\mathbf{x}_m = (x_{1m}, \ldots, x_{7m})$ and $\mathbf{x}_w = (x_{1w}, \ldots, x_{7w})$, and to the different vectors of probabilities $\beta_m = (\beta_{1m}, \ldots, \beta_{7m})$ and $\beta_w = (\beta_{1w}, \ldots, \beta_{7w})$. The differences can be decomposed into three effects.

Consider the calculated ratio R at gender means $\mathbf{x}_m$ and $\mathbf{x}_w$:

$$R = \frac{p_m(\mathbf{x}_m)}{p_w(\mathbf{x}_w)} \tag{3}$$

Multiplying by $\left[\frac{p_m(\bar{\mathbf{x}})}{p_w(\bar{\mathbf{x}})}\right]\left[\frac{p_w(\bar{\mathbf{x}})}{p_m(\bar{\mathbf{x}})}\right] = 1$, and rearranging, yields:

$$R = \frac{p_m(\mathbf{x}_m)}{p_w(\mathbf{x}_w)} = \left\{ \underset{\textbf{[A]}}{\left[\frac{p_m(\mathbf{x}_m)}{p_m(\bar{\mathbf{x}})}\right]} \Big/ \underset{\textbf{[B]}}{\left[\frac{p_w(\mathbf{x}_w)}{p_w(\bar{\mathbf{x}})}\right]} \right\} \underset{\textbf{[C]}}{\left[\frac{p_m(\bar{\mathbf{x}})}{p_w(\bar{\mathbf{x}})}\right]} \tag{3'}$$

[A] = ratio of the men's behavioral parameters evaluated at the *men's* vector relative to men's parameters evaluated at the *mean* vector;

[B] = ratio of the women's behavioral parameters evaluated at the *women's* vector relative to women's parameters evaluated the *mean* vector;

[C] = ratio of the differences due to the gender specific probability estimates, holding the vector of explanatory variables constant.

From this decomposition, term **[C]** refers to *behavioral impacts*, with endowments controlled. Terms **[A]** and **[B]** together give the combined *gender endowment impacts*.

Implementing this decomposition requires deciding which variables to adjust. While technically part of the difference results from a difference in the endowment of all risk factors across genders, differences in the racial composition, marital status, cigarette/beer taxes may not represent meaningful distinctions. It is not useful to explain differences across genders by relying on differences in racial composition (presumably close to equal in the population) and differences in marital status (also close to equal) *within* gender. The same applies to differences in cigarette and beer taxes which essentially rely on the possibility that differing percentages of males or females may reside in higher tax states. Thus, the main differences in endowment related to the *economic choices* made by each gender comes from: (i) education, (ii) health status, (iii) income, and (iv) employment. The forthcoming analyses will control for these factors in vector $\bar{\mathbf{x}}$, letting gender-specific values from the sample remain.*

* The referee provided a useful discussion on this topic. Alternative decompositions, adjusting for *all* of the vector elements, have also been calculated. The results (available on request) differ slightly, but not substantively.

Table 8: Probability Decomposition by Gender

a. Calculated Probabilities - Gender Means

	Men	Women	Difference	$R = \frac{p_m(\mathbf{x}_m)}{p_w(\mathbf{x}_w)}$ Ratio (M/W)
None	0.1906	0.3107	–0.1202	**0.6133**
Smoke Only	0.0657	0.0629	0.0029	**1.0454**
Drink Only	0.4101	0.4220	–0.0119	**0.9719**
Drugs Only	0.0027	0.0022	0.0006	**1.2523**
Smoke/Drink	0.2797	0.1775	0.1021	**1.5754**
Smoke/Drugs	0.0022	0.0012	0.0010	**1.8529**
Drink/Drugs	0.0168	0.0103	0.0065	**1.6318**
All 3	0.0323	0.0133	0.0190	**2.4295**

b. Calculated Probabilities - Adjusted Endowment

	Men	Women	Difference	$\left[\frac{p_m(\bar{\mathbf{x}})}{p_w(\bar{\mathbf{x}})}\right]$ Adjusted Ratio (M/W)
None	0.1992	0.2990	–0.0998	**0.6663**
Smoke Only	0.0718	0.0578	0.0139	**1.2407**
Drink Only	0.3934	0.4371	–0.0437	**0.9001**
Drugs Only	0.0031	0.0021	0.0010	**1.4493**
Smoke/Drink	0.2773	0.1790	0.0983	**1.5493**
Smoke/Drugs	0.0024	0.0010	0.0013	**2.2915**
Drink/Drugs	0.0173	0.0105	0.0068	**1.6463**
All 3	0.0355	0.0134	0.0221	**2.6511**

c. Difference Decomposition

	$R =$ Unadjusted Ratio (M/W)	{[A] $\frac{p_m(x_m)}{p_m(\bar{x})}$	/ [B]}* $\frac{p_w(x_w)}{p_w(\bar{x})}$	[C] Adjusted Ratio (M/W)
None	**0.6133**	0.9565	1.0393	**0.6663**
Smoke Only	**1.0454**	0.9156	1.0867	**1.2407**
Drink Only	**0.9719**	1.0424	0.9654	**0.9001**
Drugs Only	**1.2523**	0.8893	1.0292	**1.4493**
Smoke/Drink	**1.5754**	1.0086	0.9919	**1.5493**
Smoke/Drugs	**1.8529**	0.9075	1.1223	**2.2915**
Drink/Drugs	**1.6318**	0.9677	0.9763	**1.6463**
All 3	**2.4295**	0.9092	0.9921	**2.6511**

Table 8 (a) calculates relative probabilities R at the gender means. For the category *none*, the men's percentage was about 61% as likely as women. For ''drink only'' the ratio was 97.2%. For *all three* it was approximately 2.43.

Table 8 (b), however, shows that with the adjusted endowments $\bar{\mathbf{x}}$, men were about two-thirds (ratio = 0.6663) as likely to ''none'', about 90 % (ratio = 0.9001) as likely to drink only, and 265% as likely to do all three as women. The largest absolute differences in probabilities are in the *none* category and in the smoke/drink category. The largest ratios involve smoking/drugs (2.2915) and *all three* (2.6511).

Table 8 (c) reconciles the two sets of estimates. To interpret Table 8.c, recall that $R = \{\mathbf{A}/\mathbf{B}\} *\mathbf{C}$. In 6 of the 8 categories the men's risk factors x_m tend to reduce participation in the category ($\mathbf{A} < 1$) relative to the predicted value at the mean vector $\bar{\mathbf{x}}$. In 4 of the 8 categories, the women's risk factors $\mathbf{x}_w$ do likewise ($\mathbf{B} > 1$). Because the total effect relates to the ratio of these two gender-specific impacts, the men's probabilities conditional on the vectors x_m rise relative to those at the mean in one of the eight categories (*drink only* rises from 0.9001 to 0.9719), stay almost identical in smoke/drink and drink/drugs, and fall in the other five.

Tables 9 (a-c) recalculates **Table 8** for no substances,

Table 9: Individual Activity Decomposition by Gender

a. Calculated Probabilities - Gender Means

	Men	Women	Difference	$R = \dfrac{p_m(\mathbf{x}_m)}{p_w(\mathbf{x}_w)}$ Ratio (M/W)
None	0.1906	0.3107	–0.1202	**0.6133**
Smoke	0.3798	0.2548	0.1250	**1.4904**
Drink	0.7388	0.6230	0.1158	**1.1858**
Drugs	0.0540	0.0269	0.0270	**2.0039**

b. Calculated Probabilities - Adjusted Endowment

	Men	Women	Difference	$\left[\dfrac{p_m(\bar{\mathbf{x}})}{p_w(\bar{\mathbf{x}})}\right]$ Adjusted Ratio (M/W)
None	0.1992	0.2990	–0.0998	**0.6663**
Smoke	0.3869	0.2513	0.1357	**1.5400**
Drink	0.7235	0.6400	0.0835	**1.1305**
Drugs	0.0583	0.0271	0.0312	**2.1520**

c. Difference Decomposition

	$R =$ Unadjusted Ratio (M/W)	{[A] $\dfrac{p_m(x_m)}{p_m(\bar{x})}$	/ [B]}* $\dfrac{p_w(x_w)}{p_w(\bar{x})}$	[C] Adjusted Ratio (M/W)
None	**0.6133**	0.9565	1.0393	**0.6663**
Smoke	**1.4904**	0.9816	1.0143	**1.5400**
Drink	**1.1858**	1.0211	0.9735	**1.1305**
Drugs	**2.0039**	0.9255	0.9939	**2.1520**

smoking, drinking, and drugs. **Table 9** (b) shows that for no substances and drinking, equalizing endowments moves men and women slightly closer together – for the others they move slightly further apart. Alternatively, in **Table 9** (c), divergences in men's vector $\mathbf{x}_m$ and women's vector $\mathbf{x}_w$ reduce the ratios for no substances, smoking, and drugs, but increase the ratios for drinking (from 1.1305 to 1.1858).

Differences by Age

With NESARC's oversampling of young adults, it is a natural extension to stratify the overall sample (pooling gender) across age categories. There may be strong differential effects of price/income and other economic measures for young adults versus older adults. Several studies (see tables in Badenes-Plá and Jones[18]) have found that younger adults (ages 18 to 30) and much older adults (45+) are more sensitive to substance costs relative to middle age groups.

Table 10 presents gender-pooled summary results for samples in age brackets 30 and under, 31-45, and 46+. Those in the youngest bracket are more likely to smoke and drink, and much more likely (probability of 0.1154) to take drugs than the other brackets (0.0526 for those ages 31-45, and 0.0139 for those ages 46+). Similar MNL analyses were run as before.

The results defy easy generalization. Those in the youngest bracket display smaller cigarette tax elasticities than the others. Their beer tax elasticities are similar to the other two groups. Their income elasticity regarding smoking is positive (the other age groups are negative), and their drinking income elasticity is also positive (although smaller than the others).

The responsiveness of *none* (not drinking, smoking, or ingesting drugs) to higher taxes or higher incomes is larger for the ''30 and under'' than for the other groups. For example, a one percent increase in the cigarette tax reduces the probability of smoking for this group by almost 0.1 percent, and increases the probability of *none* (neither smoking, drinking or drugs) by 0.04 percent. The other ''30 and under'' impacts for *none* are even larger. A one percent increase in the beer tax increases the probability of *none* by 0.266 percent, twice as high as for the other groups. An increase in income reduces the probability of *none* by –0.15 percent, again considerably higher than the other two groups.

In short, the young are more responsive to prices and

Table 10: Tax and Income Impacts by Age

Age Category	30 and under	31-45	46+
Sample Size	8,654	12,402	19,282
Probabilities	30 and under	31-45	46+
None	0.1658	0.2047	0.3357
Smoking	0.3492	0.3039	0.2260
Drinking	0.8085	0.7445	0.5929
Drugs	0.1154	0.0526	0.0139
Elasticities	30 and under	31-45	46+
Response to 1% increase in Cigarette Tax			
None	+0.0440	+0.0161	–0.0828
Smoking	–0.0995	–0.1567	–0.1646
Drinking	–0.0075	+0.0151	+0.0906
Drugs	+0.0819	+0.2501	+0.3049
Response to 1% increase in Beer Tax			
None	+0.2660	+0.1418	+0.1476
Smoking	–0.0222	+0.0425	–0.0318
Drinking	–0.0655	–0.0526	–0.0965
Drugs	–0.0248	–0.0659	+0.0270
Response to 1% increase in Income			
None	–0.1517	–0.1175	–0.0828
Smoking	+0.0487	–0.0381	–0.0864
Drinking	+0.0314	+0.0412	+0.0765
Drugs	–0.0663	–0.1552	–0.0645

incomes than the other two groups but in complex ways that suggest shifting among categories. In particular, their propensity to engage in none of the addictive behaviors seems to be much more responsive to prices and incomes than the other two age groups.

Conclusions

This article has sought to address several analytical and policy issues regarding the joint usage of alcohol, tobacco, and drugs. Many studies analyze one substance, with the maintained assumption (often due to database characteristics) that the use of other substances does not matter. The use of multinomial logit analysis allows the assumption that the three categories are interrelated. It permits a wide range of parametric inferences about conditional and unconditional probabilities, and responses to changes in incomes and taxes. It also supports decompositions of differences among groups that are categorically identified, including gender (elaborated here), but also race, national origin, or health status.

Using this framework, the measured impacts of current income and current taxes on addictive goods are strong even though addictive decisions are almost certainly longer term decisions, reflecting both current and past prices. However, the impacts of current incomes and taxes in the multinomial logit formulations are highly significant and the results are plausible.

With respect to health services and health policy, higher taxes reduce harmful addictive behaviors, and by implication, the utilization and cost of health care attributable to addiction. The effects differ, however, by gender, race, and age, and ethnicity. People ages 18 to 30 respond more to changed prices and incomes than the older groups, but in complex ways that suggest shifting among categories. In particular, their propensity to engage in *none* of the addictive behaviors seems much more responsive to prices and incomes than the other two age groups.

In further research, this discrete analysis could be extended to two part models, in which quantities and/or expenditures on alcohol, tobacco, or drugs can be examined, conditional on individuals' being in one of the specific categories. With panel data, decisions on starting, continuing, and/or stopping drinking, smoking, or drug use may also be considered. In all cases, a version of Mill's ratio (as noted in Heckman[19] and numerous variants) may be used to consider the selection biases into specific categories, although issues about identifying first (the selection) and second stage (quantity) impacts will require further study.

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Appendix

Table A1: Multinomial Logit Equations of Men's Probabilities (Omitted category is no smoking, drinking, or drug use)

	Coefficient	Std. Error	*t*-ratio
Smoke Only			
ONE	–2.5955	0.4415	5.88
AGE	0.1434	0.0130	11.03
AGE^2	–0.0016	0.0001	12.46
BLACK	–0.7612	0.1156	6.58
HISP	–0.8470	0.1300	6.52
SPOUSE	–0.1515	0.0763	1.99
SOMEHS	0.0874	0.1404	0.62
HIGHSCH	–0.3674	0.1265	2.90
SOMECOLL	–0.7467	0.1378	5.42
BACH	–1.4395	0.1928	7.47
GRAD	–1.7361	0.2100	8.27
H_VG	–0.0015	0.1058	0.01
H_GOOD	0.3398	0.1049	3.24
H_FAIR	0.4975	0.1265	3.93
H_POOR	0.5758	0.1556	3.70
LOGY	–0.0154	0.0416	0.37
FULLPT	–0.3641	0.1115	3.27
CIG TAX	–0.6895	0.1183	5.83
BEERTAX	0.0085	0.0192	0.44
Drink Only			
ONE	–1.8132	0.2559	7.09
AGE	0.0003	0.0070	0.05
AGE^2	–0.0001	0.0001	1.88
BLACK	–0.3683	0.0651	5.66
HISP	0.0767	0.0652	1.18
SPOUSE	0.1236	0.0455	2.72
SOMEHS	0.1370	0.1044	1.31
HIGHSCH	0.2216	0.0892	2.48
SOMECOLL	0.4382	0.0916	4.78
BACH	0.7152	0.1029	6.95
GRAD	0.6132	0.1039	5.90
H_VG	–0.0039	0.0530	0.07
H_GOOD	–0.1835	0.0588	3.12
H_FAIR	–0.3120	0.0800	3.90
H_POOR	–0.9216	0.1212	7.60
LOGY	0.2587	0.0255	10.15
FULLPT	–0.0159	0.0720	0.22
CIG TAX	0.2452	0.0657	3.73
BEERTAX	–0.0986	0.0120	8.22
Drugs Only			
ONE	–4.3452	1.3767	3.16
AGE	0.0044	0.0402	0.11
AGE^2	–0.0003	0.0004	0.78
BLACK	–0.1786	0.3705	0.48
HISP	0.4751	0.3224	1.47
SPOUSE	–0.0452	0.2739	0.17
SOMEHS	0.5236	0.5419	0.97
HIGHSCH	0.3866	0.4973	0.78
SOMECOLL	0.6854	0.5051	1.36

(segue)

	Coefficient	Std. Error	*t*-ratio
BACH	–0.2912	0.7424	0.39
GRAD	–0.0454	0.7150	0.06
H_VG	0.9341	0.3900	2.40
H_GOOD	0.8895	0.4174	2.13
H_FAIR	1.0523	0.5035	2.09
H_POOR	1.7166	0.5453	3.15
LOGY	–0.0728	0.1333	0.55
FULLPT	–0.4327	0.4024	1.08
CIG TAX	1.1081	0.3775	2.94
BEERTAX	0.0394	0.0580	0.68
Smoke/Drink			
ONE	–2.3873	0.2909	8.21
AGE	0.0660	0.0087	7.63
AGE^2	–0.0010	0.0001	11.10
BLACK	–0.6750	0.0752	8.98
HISP	–0.7038	0.0795	8.85
SPOUSE	–0.0652	0.0514	1.27
SOMEHS	0.3348	0.1196	2.80
HIGHSCH	0.1644	0.1062	1.55
SOMECOLL	0.1800	0.1090	1.65
BACH	–0.1087	0.1245	0.87
GRAD	–0.4160	0.1288	3.23
H_VG	0.3415	0.0610	5.60
H_GOOD	0.3891	0.0668	5.82
H_FAIR	0.3821	0.0906	4.22
H_POOR	0.1163	0.1349	0.86
LOGY	0.1838	0.0289	6.36
FULLPT	0.2240	0.0878	2.55
CIG TAX	–0.2591	0.0757	3.42
BEERTAX	–0.0830	0.0137	6.06
Smoke/Drugs			
ONE	–9.4880	2.2078	4.30
AGE	0.2201	0.0746	2.95
AGE^2	–0.0029	0.0009	3.31
BLACK	–1.0671	0.5219	2.04
HISP	–1.3704	0.6707	2.04
SPOUSE	–0.5923	0.3236	1.83
SOMEHS	2.2384	1.2576	1.78
HIGHSCH	1.5778	1.2492	1.26
SOMECOLL	1.3693	1.2665	1.08
BACH	0.5868	1.4382	0.41
GRAD	0.9956	1.3982	0.71
H_VG	–0.0106	0.6256	0.02
H_GOOD	1.6265	0.5051	3.22
H_FAIR	1.9843	0.5724	3.47
H_POOR	2.4766	0.7007	3.53
LOGY	–0.1017	0.1568	0.65
FULLPT	0.7380	0.5658	1.30
CIG TAX	0.1463	0.4790	0.31
BEERTAX	–0.0108	0.0807	0.13
Drink/Drugs			
ONE	–1.9231	0.6923	2.78
AGE	–0.0358	0.0213	1.68
AGE^2	–0.0001	0.0002	0.58

(segue)

	Coefficient	Std. Error	*t*-ratio
BLACK	–0.1205	0.1522	0.79
HISP	–0.4390	0.1711	2.57
SPOUSE	–0.4864	0.1176	4.14
SOMEHS	1.1337	0.4827	2.35
HIGHSCH	1.2711	0.4589	2.77
SOMECOLL	1.6977	0.4577	3.71
BACH	1.9542	0.4712	4.15
GRAD	2.0675	0.4744	4.36
H_VG	0.2898	0.1236	2.34
H_GOOD	0.1995	0.1502	1.33
H_FAIR	0.2424	0.2375	1.02
H_POOR	0.4059	0.3683	1.10
LOGY	–0.0274	0.0551	0.50
FULLPT	0.4542	0.2420	1.88
CIG TAX	0.5579	0.1638	3.41
BEERTAX	–0.1383	0.0345	4.01
All 3			
ONE	–1.8262	0.5225	3.50
AGE	0.0779	0.0206	3.78
AGE^{2}	–0.0019	0.0003	7.14
BLACK	–0.8144	0.1280	6.36
HISP	–1.1692	0.1424	8.21
SPOUSE	–0.4622	0.0903	5.12
SOMEHS	1.7832	0.3104	5.74
HIGHSCH	1.2077	0.3046	3.96
SOMECOLL	1.3634	0.3059	4.46
BACH	0.8004	0.3326	2.41
GRAD	0.7069	0.3468	2.04
H_VG	0.5687	0.1080	5.27
H_GOOD	1.0587	0.1127	9.39
H_FAIR	1.3298	0.1527	8.71
H_POOR	1.5838	0.2312	6.85
LOGY	–0.0741	0.0422	1.76
FULLPT	0.1429	0.1675	0.85
CIG TAX	0.1239	0.1274	0.97
BEERTAX	–0.1262	0.0250	5.05

Table A2: Multinomial Logit Equations of Women's Probabilities (Omitted category is no smoking, drinking, or drug use)

	Coefficient	Std. Error	*t*-ratio
Smoke Only			
ONE	–3.4153	0.3728	9.16
AGE	0.1285	0.0112	11.49
AGE^2	–0.0015	0.0001	13.27
BLACK	–0.5503	0.0887	6.21
HISP	–1.2280	0.1373	8.94
SPOUSE	–0.2758	0.0669	4.12
SOMEHS	0.4966	0.1304	3.81
HIGHSCH	0.0523	0.1223	0.43
SOMECOLL	–0.2466	0.1315	1.87
BACHGRAD	–1.0215	0.1631	6.26
H_VG	0.2887	0.1063	2.72
H_GOOD	0.5700	0.1030	5.53
H_FAIR	0.8898	0.1141	7.79
H_POOR	1.1136	0.1330	8.37
LOGY	–0.0642	0.0329	1.95
FULLPT	0.0399	0.0884	0.45
CIG TAX	–0.4066	0.1026	3.96
BEERTAX	0.0014	0.0167	0.08
Drink Only			
ONE	–1.8888	0.1955	9.66
AGE	0.0015	0.0053	0.28
AGE^2	–0.0002	0.0001	2.78
BLACK	–0.6944	0.0503	13.82
HISP	–0.3796	0.0566	6.70
SPOUSE	0.1227	0.0354	3.46
SOMEHS	0.5034	0.1009	4.99
HIGHSCH	0.8791	0.0884	9.94
SOMECOLL	1.2317	0.0895	13.75
BACHGRAD	1.3524	0.0933	14.49
H_VG	–0.0537	0.0436	1.23
H_GOOD	–0.2641	0.0469	5.63
H_FAIR	–0.5074	0.0632	8.03
H_POOR	–1.0626	0.0996	10.67
LOGY	0.1721	0.0176	9.79
FULLPT	0.2705	0.0526	5.14
CIG TAX	0.2895	0.0537	5.39
BEERTAX	–0.1255	0.0100	12.52
Drugs Only			
ONE	–5.5262	1.4058	3.93
AGE	–0.0315	0.0355	0.89
AGE^2	0.0002	0.0003	0.57
BLACK	–0.4442	0.3795	1.17
HISP	0.5194	0.3332	1.56
SPOUSE	0.1345	0.2590	0.52
SOMEHS	1.2428	0.5735	2.17
HIGHSCH	1.1377	0.5450	2.09
SOMECOLL	0.1768	0.6239	0.28
BACHGRAD	1.2263	0.6027	2.03
H_VG	0.4056	0.3687	1.10

(segue)

	Coefficient	Std. Error	*t*-ratio
H_GOOD	–0.0784	0.4247	0.18
H_FAIR	0.8928	0.4176	2.14
H_POOR	1.3286	0.4649	2.86
LOGY	0.0331	0.1288	0.26
FULLPT	0.0060	0.3564	0.02
CIG TAX	0.1953	0.3771	0.52
BEERTAX	0.0292	0.0624	0.47
Smoke/Drink			
ONE	–3.3450	0.2692	12.43
AGE	0.0768	0.0084	9.18
AGE^2	–0.0013	0.0001	13.87
BLACK	–1.1698	0.0715	16.35
HISP	–1.0350	0.0826	12.53
SPOUSE	–0.2817	0.0472	5.97
SOMEHS	0.8789	0.1408	6.24
HIGHSCH	0.7425	0.1314	5.65
SOMECOLL	0.7385	0.1331	5.55
BACHGRAD	0.0497	0.1416	0.35
H_VG	0.2987	0.0603	4.95
H_GOOD	0.4310	0.0634	6.80
H_FAIR	0.3670	0.0845	4.34
H_POOR	0.2307	0.1235	1.87
LOGY	0.1668	0.0241	6.93
FULLPT	0.3416	0.0743	4.60
CIG TAX	–0.0507	0.0734	0.69
BEERTAX	–0.1022	0.0137	7.47
Smoke/Drugs			
ONE	–1.6645	1.3699	1.21
AGE	–0.0011	0.0436	0.03
AGE^2	–0.0003	0.0004	0.67
BLACK	–0.3627	0.3949	0.92
HISP	–1.5966	0.6469	2.47
SPOUSE	–0.2467	0.3246	0.76
SOMEHS	–0.1028	0.5158	0.20
HIGHSCH	–0.4026	0.4797	0.84
SOMECOLL	–1.3344	0.5846	2.28
BACHGRAD	–2.7460	1.0803	2.54
H_VG	0.1022	0.4800	0.21
H_GOOD	0.2074	0.4755	0.44
H_FAIR	0.5484	0.5240	1.05
H_POOR	1.2699	0.5706	2.23
LOGY	–0.2122	0.1333	1.59
FULLPT	0.3676	0.4236	0.87
CIG TAX	0.2002	0.4720	0.42
BEERTAX	–0.0998	0.0863	1.16
Drink/Drugs			
ONE	–4.1047	0.8795	4.67
AGE	–0.0668	0.0211	3.16
AGE^2	0.0001	0.0002	0.60
BLACK	–0.8707	0.1711	5.09
HISP	–0.6995	0.1888	3.70
SPOUSE	–0.2376	0.1163	2.04
SOMEHS	1.8519	0.7311	2.53
HIGHSCH	1.7307	0.7159	2.42

(segue)

	Coefficient	Std. Error	*t*-ratio
SOMECOLL	2.4077	0.7125	3.38
BACHGRAD	2.3189	0.7190	3.22
H_VG	0.3226	0.1305	2.47
H_GOOD	0.1291	0.1570	0.82
H_FAIR	0.3521	0.2205	1.60
H_POOR	–0.1646	0.4467	0.37
LOGY	0.0940	0.0548	1.72
FULLPT	0.8735	0.2446	3.57
CIG TAX	0.6000	0.1717	3.49
BEERTAX	–0.0801	0.0326	2.45
All 3			
ONE	–4.0471	0.6454	6.27
AGE	–0.0369	0.0205	1.80
AGE^2	–0.0006	0.0003	2.38
BLACK	–1.2195	0.1393	8.75
HISP	–1.3571	0.1698	7.99
SPOUSE	–0.4212	0.0959	4.39
SOMEHS	1.7190	0.4731	3.63
HIGHSCH	1.5429	0.4647	3.32
SOMECOLL	1.7230	0.4648	3.71
BACHGRAD	0.8495	0.4796	1.77
H_VG	0.6510	0.1218	5.34
H_GOOD	0.9758	0.1273	7.67
H_FAIR	1.1464	0.1676	6.84
H_POOR	1.4390	0.2445	5.89
LOGY	0.2102	0.0472	4.46
FULLPT	0.4883	0.1696	2.88
CIG TAX	0.5260	0.1395	3.77
BEERTAX	–0.0605	0.0254	2.38

