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RESEARCH ARTICLE

Longitudinal Analysis of Changes in Illicit Drug Use and Health Services Utilization

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Objective. To analyze the relationships between illicit drug use and three types of health services utilization: emergency room utilization, hospitalization, and medical attention required due to injury(s).
Data. Waves 1 and 2 (11,253 males and 13,059 females) from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC).
Study Design. We derive benchmark estimates by employing standard cross-sectional data models to pooled waves of NESARC data. To control for potential bias due to time-invariant unobserved individual heterogeneity, we reestimate the relationships with fixed-effects models.
Principal Findings. The cross-sectional data models suggest that illicit drug use is positively and significantly related to health services utilization in almost all specifications. Conversely, the only significant ($p < .05$) relationships in the fixed-effects models are the odds of receiving medical attention for an injury and the number of injuries requiring medical attention for men, and the number of times hospitalized for men and women.
Conclusions. Failing to control for time-invariant individual heterogeneity could lead to biased coefficients when estimating the effects of illicit drug use on health services utilization. Moreover, it is important to distinguish between types of drug user (casual versus heavy) and estimate gender-specific models.

Key Words. Illicit drug use, health services utilization, fixed-effects analysis

Numerous studies have shown that illicit drug use is associated with cardiovascular disease, stroke, HIV/AIDS, hepatitis, lung disease, injuries, mental health problems, and other health consequences (Cornish and O'Brien 1996; Falck et al. 2000; Gowing et al. 2002). It is less apparent, however, whether these higher risks of adverse outcomes actually lead to a greater use of medical care resources by drug users relative to nondrug users. Some studies have found that active drug users underutilize preventive and routine medical care but overutilize hospital care and emergency room (ER) facilities for acute and chronic conditions (Mor et al. 1992; Polen et al. 1993; Cherpitel 1999, 2003; French et al. 2000a; McGeary and French 2000; Kushel et al. 2002; Masson et al. 2004). A common explanation for this behavior is that many drug users, to escape scrutiny of their drug use, intentionally avoid the mainstream medical care system for health promotion and wellness services (Chitwood et al. 1999; Sterk, Theall, and Elifson 2002). This practice eventually leads to serious and costly health problems that must be treated in the ER or hospital. Some individuals are still active drug users when they seek emergency care for a serious health problem, while others address health problems as part of their recovery (Armstrong, Midanik, and Klatsky 1998; Rice et al. 2000; Hunkeler et al. 2001).

Because theory, intuition, and direct evidence are not united, it is important to use longitudinal data and advanced statistical techniques to properly sort out the direction and magnitude of the relationships between illicit drug use and health services utilization. Contact with the health care system could serve as a fruitful intervention opportunity for active drug users. If drug users tend to avoid health care providers, interventions must be initiated elsewhere. Moreover, from a cost-of-illness perspective, it is vital to know whether drug users burden the health care system to the same extent that they burden the criminal justice system (Spunt et al. 1995; Nurco 1998; French et al. 2000b; Farabee, Joshi, and Anglin 2001). Policy makers are interested in the total cost of drug abuse to society, but past estimations of medical care costs have been imprecise (Harwood, Fountain, and Livermore 1998; Cartwright 1999; Cohen 1999; Reuter 1999). Finally, the estimation techniques we present in this paper could be applied to other behaviors, outcomes, and settings.

The inconclusiveness of the literature in this area may be traced to estimation bias associated with unobserved heterogeneity. That is, important unobserved personal characteristics of respondents (e.g., maturity, discipline, organizational skills, time preferences) may significantly relate to both illicit drug use and health services utilization. These factors appear in the residual of the regression equation, thus introducing bias in the coefficient estimates (Wooldridge 2002). A priori, the direction of bias will probably lead to inflated

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effects because drug use is likely positively correlated with unobserved risky behaviors. But the bias could occur in either direction. Fixed-effects estimation with panel data can effectively control for time-invariant (but not time-varying) unobserved heterogeneity, thereby improving the precision of the estimation results (Wooldridge 2002; Greene 2007). Very few studies in the drug-abuse literature have employed fixed-effects techniques, most likely because large panel datasets with good measures for health services utilization, drug use, and other key variables are rare.

To improve on the existing literature on drug use and health services utilization, we first create an analysis file of all participants in the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) who completed interviews in Waves 1 and 2. Second, we pool data from Waves 1 and 2 and estimate gender-specific regression models for each of our health services utilization measures. Although these regression estimates are prone to bias due to unobserved heterogeneity, we present these benchmark results for comparison with the existing literature, which typically employs similar approaches. Third, we estimate and present results from fixed-effects models to control for unobserved time-invariant individual heterogeneity. Finally, we compare and contrast findings from both estimation strategies to help rectify the literature's lack of consistency and to examine the potential bias emerging from uncontrolled individual heterogeneity.

Conceptual Framework

Our standard economic framework is based on the premise that individuals do not consume health care for immediate pleasure but rather for the effect that health care has on health status and, consequently, on overall utility or well-being (Grossman 1999; Phelps 2002). Illicit drug use is expected to affect health care utilization by causing increased health problems (see previous section), which would normally lead to increased demand for health care (e.g., Mor et al. 1992; Polen et al. 1993; Cherpitel 1999, 2003; French et al. 2000a; McGeary and French 2000; Kushel et al. 2002; Masson et al. 2004). Under this framework, the derived demand for health care is given by

$$HC = \mathrm{f}(H(D, X), X) \tag{1}$$

where HC is a measure of health care utilization (e.g., ER visits, inpatient hospital days), H denotes health problems, D refers to illicit drug use, and X captures individual characteristics that affect the consumption of health care both directly and indirectly (e.g., health insurance; socioeconomic status; personal characteristics such as age, gender, race, and marital status; and behavioral characteristics such as alcohol and tobacco use). We expect illicit drug use to increase health problems and thus lead to a higher demand for health care services.

A parallel argument posits that substance abusers delay or decrease their use of preventive or ambulatory health care to avoid scrutiny of their substance use (Chitwood et al. 1999; Sterk, Theall, and Elifson 2002). In addition, financial barriers and difficulties navigating the health care system could further impede substance abusers' use of formal health care. These consumers may not seek medical attention until their health problems become acute and they need urgent care. As a consequence, they are more likely to go to the ER or be admitted to a hospital. The demand function above can be modified slightly to reflect this additional pathway:

$$HC = \mathrm{f}(H(D, X),\ D,\ X) \tag{2}$$

In Equation (2), $H(D, X)$ captures not only the higher risks of morbidity associated with illicit drug use but also the detrimental effects of delaying care on health. Moreover, given a particular health profile, illicit drug users may be willing to substitute acute care for more predictable and less costly preventive/ambulatory care to avoid scrutiny. The second D in Equation (2) captures this substitution effect.

The estimation of Equation (2) is empirically daunting without imposing strong and questionable structural assumptions on the model. For this reason, we propose to estimate the following reduced-form health care demand equation:

$$HC = \mathrm{f}(D, X) \tag{3}$$

Although reduced-form estimates cannot isolate the direct effect of illicit drug use on health, the effects of delayed care, or the substitution of acute for preventive services, they can identify the full consequences of illicit drug use on health care use.

In terms of the differential effects by types of drugs, all illicit drugs can cause harmful effects on physical and mental health. The duration of use and quantity of drugs consumed determine the degree to which these harmful effects occur (Han, Gfroerer, and Colliver 2010). Thus, we expect to see higher rates of injuries, ER utilization, and hospitalizations among heavy drug users compared with light or casual drug users. Heavy drug users are more likely to experience serious health problems and to substitute emergency care for preventive or routine care.

Methods

Data

We analyze data from Waves 1 and 2 of the NESARC to examine the impact of illicit drug use on health services utilization. The NESARC dataset is ideally suited for our analysis because it provides current, comprehensive, and nationally representative data on illicit drug use and health services utilization over time. Wave 1 of the NESARC was administered in 2001–2002, and Wave 2 was completed in 2004–2005. Respondents answered numerous pertinent questions about their substance use, health services utilization, demographics, current health status, chronic conditions, health insurance coverage, employment status, and living arrangements.

The U.S. Bureau of the Census conducted fieldwork for Wave 1 of the NESARC on behalf of the National Institute on Alcoholism and Alcohol Abuse (NIAAA). Wave 1 recruited a representative sample of the U.S. population, including both citizens and noncitizens. A total of 43,093 respondents were interviewed using a computer-assisted personal interviewing technique. The target population of the NESARC was the civilian noninstitutionalized population aged 18 and older and residing in the United States and the District of Columbia, including Alaska and Hawaii. The overall survey response rate was 81 percent, which is comparable with other national comorbidity surveys (Division of Health Interview Statistics, National Center for Health Statistics 2004).

In Wave 2 of the NESARC, 34,093 of the respondents who participated in Wave 1 were located and reinterviewed (see Grant et al. 2003, 2009; Dawson, Goldstein, and Grant 2007; Ruan et al. 2008 for additional information on the sampling frame, instrumentation, and main findings from Waves 1 and 2). Because our longitudinal analysis employs individual fixed-effects models of changes in drug use and health services utilization over time, we include in the analysis sample only those respondents who were interviewed in both waves. After we excluded pregnant women, the elderly, and those respondents who did not provide valid responses for many of the key variables in each wave, the final analysis sample amounted to 24,312 respondents between the ages of 18 and 60 in Wave 1 (11,253 males and 13,059 females).

Health Services Utilization Measures

Our dependent variables convey both intensive and extensive measures of health care utilization. First, we explore the extensive margin (who receives care) by creating three binary health services utilization measures: (1) any overnight hospitalization, (2) any ER visit, and (3) any injury that caused respondents to seek professional medical attention and/or alter their usual activities for more than half a day. All measures correspond to health care utilization that occurred during the previous 12 months. Second, we determine the intensity of services used in the past 12 months by constructing the following count measures: (1) number of times hospitalized, (2) number of ER visits, and (3) number of times seriously injured. While the distributions of these count measures are highly skewed with a small number of extreme values and an abundance of zeros, the change scores between waves are more normally distributed. We had intended to include at least one measure of routine outpatient care in a doctor's office, but the NESARC does not provide this information.

Illicit Drug Use Measures

The NESARC survey asks about the number of days the respondent used each of 10 distinct illicit drugs during the past 12 months. From this information, we construct an aggregate measure of drug use that sums the total number of drug-specific days of use for the different drugs distinguished in the survey. This aggregate measure captures not only the frequency of drug use in the past 12 months but also the number of different drugs consumed. While the frequency of drug use cannot exceed 365 days for any single drug, a small number of individuals in our sample (271 men and 192 women) had more than 365 total drug-specific days of use in Waves 1 or 2. We recognize that this measure is somewhat unconventional, but it enables us to distinguish casual use from heavy use while incorporating different types of drugs.

Our key explanatory variables are three gender-specific dummy categories based on this measure of total number of drug-specific days of use. The first category includes individuals who do not use illicit drugs (nondrug users), the second category includes drug users with a total number of drug-specific days of use below the gender-specific sample median (casual drug users), and the third category represents individuals with a total number of drug-specific days of use equal to or above the gender-specific sample median (heavy drug users). In our analysis sample, the conditional median is 12 days of drug use for women and 30 days of drug use for men. The 90th percentile begins at 365 total drug-specific days of use for both genders, and the maximum values are 810 for men and 730 for women.

We also constructed drug-specific measures of use to further investigate the relationships, but sample sizes were too small for sufficient power, especially for the fixed-effects models that require for identification changes in drug use over time.

Statistical Analysis

Our empirical approach has two stages. First, we pool both waves of the NESARC and estimate multivariate regression models with health services utilization as a function of illicit drug use and a long list of predisposing, enabling, and need characteristics (Aday and Andersen 1974). Predisposing characteristics include age, race (white, black, Latino, and other race), place of birth (U.S.-born versus foreign), marital status (married, widowed/divorced/separated, and never married), interview season (summer, fall, winter, and spring), Metropolitan Statistical Area (MSA), U.S. census region (Northeast, Midwest, South, and West), smoking status, and average daily alcohol consumption (ounces of ethanol). Among the enabling factors, we consider household income, household size, education, working status in the past 12 months, current employment status (employed, unemployed, and out of labor force), disability status, retirement status, student status, homemaker status, and health insurance (private insurance, Medicare, Medicaid, and military insurance). Finally, our set of need measures considers the SF-12 general health score, the SF-12 mental health score, self-reported health status, and indicators of select chronic diseases (hypertension, gastritis, arthritis, and heart disease). We use logistic regression for the binary measures of utilization and negative binomial for the count measures. All specifications include dummy variables for region of residence in Wave 1 and season of the interview as well as a wave-specific dummy variable.[1] The aim is to produce estimates that may be directly compared with the existing literature, most of which estimates similar models for a single year or pools cross-sectional data (Mor et al. 1992; McGeary and French 2000; Nietert et al. 2004). Another goal is to establish a benchmark set of estimates that we could contrast with the fixed-effects estimates that constitute the core of our analysis. If unobserved individual heterogeneity is correlated with the drug use measures, thereby causing bias in the logistic (negative binomial) models with pooled panel data, the estimated odds ratios (ORs) (incident rate ratios [IRRs]) from the fixed-effects models should deviate in direction, magnitude, and/or significance from the benchmark regression estimates.

The second stage involves estimating the conditional fixed-effects logit or negative binomial models, depending on the dichotomous or count nature of the dependent variable. As noted above, unobserved individual heterogeneity is a concern in most analyses with a behavioral choice measure, such as illicit drug use, as the key explanatory variable. The health economics literature favors instrumental variables (IV) models to address potential bias from unobserved heterogeneity (French and Popovici in press). Unfortunately, reliable IVs for substance use measures are elusive, and the pitfalls of using weak instruments are well documented (Murray 2006; Angrist and Pischke 2009; French and Popovici in press). Despite an exhaustive internal and external search, we were unable to find theoretically appealing and statistically strong IVs for our illicit drug use measures.

As an alternative to IV estimation, we take advantage of the longitudinal data in the NESARC and estimate conditional fixed-effects logit and negative binomial models (Wooldridge 2002). In addition to our three categories of illicit drug use (no drug use is the excluded category), the specifications include all other time-varying measures from the multivariate regression models with the pooled data. All observed (e.g., race, ethnicity, education) and unobserved (e.g., self control, time preference, discipline, genetic factors) time-invariant effects drop out of the model and are no longer a potential source of bias. Of course, any important and unobserved time-varying factors (e.g., new living arrangements, employment changes, health shocks) are a source of remaining bias. Although fixed-effects models are not a panacea, they are a significant improvement over standard regression models with cross-sectional data and no correction for unobserved individual heterogeneity (Wooldridge 2002).

RESULTS

Descriptive Statistics

Table 1 presents descriptive statistics for the analysis sample segmented by gender and survey wave for all the variables. For males, the mean probability of any hospitalization in the past 12 months is 6.4 percent in Wave 1 and 9.2 percent in Wave 2. For females, the mean probability of hospitalization is 8.7 percent in Wave 1 and 10.7 percent in Wave 2. Thus, between Waves 1 and 2, the average probability of hospitalization increased by 44 percent for men ($p < .01$) and 23 percent for women ($p < .01$), an effect that corresponds primarily to the aging of our sample (respondents are 5 years older in Wave 2).[2] Regarding ER utilization, 18.1 percent (20.3 percent) of male respondents visited the ER at least once in the past 12 months at Wave 1 (Wave 2). The percentage of female respondents who visited the ER in the past 12 months was slightly higher than that of male respondents in both waves. Yet men were more likely than women to suffer an injury that required medical attention and/or disrupted normal activities. The proportions increased from Wave 1 to Wave 2 for both genders.

The drug use measures also displayed gender differences, with males consistently showing a greater participation rate and frequency of use than

Table 1: Mean Values for Analysis Variables

	Males (N= 10,983)		*Females (N= 12,760)*	
*Variable**	*Wave 1*	*Wave 2*	*Wave 1*	*Wave 2*
Health services utilization past 12 months				
Any hospitalization (binary)	0.064	0.092	0.087	0.107
Times hospitalized	0.102	0.149	0.131	0.171
	(0.674)	(0.801)	(0.554)	(0.752)
Any ER visit (binary)	0.181	0.203	0.201	0.229
Number of ER visits	0.280	0.325	0.373	0.429
	(0.970)	(0.995)	(1.774)	(1.355)
Any serious injury (binary)[†]	0.196	0.216	0.159	0.190
Number of times seriously injured[†]	0.282	0.327	0.261	0.297
	(0.942)	(1.276)	(1.691)	(1.423)
Drug use past 12 months				
Total number of drug-specific days of use[‡]	9.894	10.435	5.792	5.391
	(58.828)	(59.172)	(48.017)	(44.858)
Not a drug user	0.915	0.899	0.947	0.942
Casual drug user (total days of use < median)[§]	0.040	0.048	0.022	0.028
Heavy drug user (total days of use $\geq$ median)[§]	0.045	0.052	0.031	0.030
Demographics and other variables				
Age (18–60 in Wave 1)	39.415	42.505	40.714	43.815
	(11.374)	(11.352)	(11.034)	(11.011)
White	0.590	0.590	0.540	0.540
Black	0.160	0.160	0.222	0.222
Latino	0.200	0.200	0.191	0.191
Other race	0.050	0.050	0.046	0.046
Foreign born	0.169	0.169	0.158	0.158
Married	0.580	0.612	0.529	0.538
Widowed, divorced, or separated	0.148	0.156	0.239	0.255
Never married	0.272	0.232	0.232	0.207
Household size	2.723	2.892	2.738	2.856
	(1.520)	(1.542)	(1.473)	(1.471)
Household income	59,883	67,915	51,443	57,279
	(50,301)	(56,698)	(46,678)	(50,600)
Household income imputed (binary)	0.096	0.059	0.097	0.065
Education (school years)	13.547	13.656	13.465	13.604
	(3.199)	(3.236)	(3.114)	(3.168)
Private insurance	0.713	0.729	0.687	0.7037618
Medicare	0.035	0.042	0.041	0.052
Medicaid	0.036	0.045	0.080	0.088
Military insurance	0.038	0.043	0.022	0.026
Employed during the past 12 months	0.929	0.906	0.820	0.800
Currently employed	0.854	0.843	0.739	0.726
Currently unemployed	0.043	0.042	0.039	0.042

continued

Table 1. *Continued*

	Males (N= 10,983)		Females (N= 12,760)	
*Variable**	*Wave 1*	*Wave 2*	*Wave 1*	*Wave 2*
Currently out of labor force	0.104	0.117	0.223	0.234
Disabled	0.034	0.041	0.044	0.055
Retired	0.030	0.054	0.026	0.051
Currently in school	0.043	0.026	0.044	0.031
Homemaker	0.006	0.005	0.150	0.137
Other nonwork activity	0.020	0.015	0.024	0.025
Live in an MSA	0.814	0.839	0.819	0.840
Northeast	0.183	0.176	0.184	0.174
Midwest	0.224	0.190	0.212	0.188
South	0.356	0.381	0.379	0.379
West	0.237	0.254	0.225	0.260
Interviewed in summer	0.416	0.236	0.405	0.264
Interviewed in fall	0.443	0.565	0.459	0.561
Interviewed in winter	0.138	0.166	0.134	0.145
Interviewed in spring	0.004	0.033	0.002	0.030
SF-12 general health score	52.370	51.121	50.856	49.716
(max = 62)	(10.918)	(11.089)	(11.830)	(11.897)
SF-12 mental health score (max = 65)	53.050	52.850	50.637	50.272
	(9.882)	(9.794)	(10.791)	(10.897)
Hypertension	0.143	0.203	0.162	0.221
Gastritis	0.051	0.031	0.072	0.054
Arthritis	0.123	0.118	0.185	0.198
Heart disease	0.021	0.022	0.020	0.023
Current smoker	0.352	0.310	0.244	0.219
Daily ethanol consumption (oz)	0.608	0.594	0.195	0.193
	(1.482)	(1.539)	(0.729)	(0.620)

*Standard deviations are reported in parentheses for continuous variables.

†For the purposes of this analysis, a serious injury is one that caused respondents to seek professional medical attention and/or alter their usual activities for more than half a day.

‡This measure is computed by summing the total number of days of use for each of 10 specific types. Values can exceed 365 if individuals were heavy users and consumed multiple drugs on some days.

§The median value for total number of drug-specific days of use is computed from the distribution of drug users only. The median value for men is 30 days, and the median value for women is 12 days.

females. Four percent of men were casual drug users at Wave 1 and 4.5 percent were heavy drug users. These rates rose slightly to 4.8 and 5.2 percent, respectively, at Wave 2. The usage rates were considerably lower for women than for men at Wave 1, with casual users comprising 2.2 percent of the sample and heavy users coming in at 3.1 percent. These rates remained fairly stable for women at Wave 2. While not reported in Table 1, cannabis is the most common illicit substance used by either gender, a finding that has been well

Table 2: Changes in Health Services Utilization and Illicit Drug Use from Wave 1 to Wave 2

	Men		*Women*	
	N	%	*N*	%
Changes in health services utilization				
Any hospitalization (binary)	1,395	12.70	1,914	15.00
Times hospitalized	1,477	13.45	2,066	16.19
Any ER visit (binary)	2,848	25.93	3,467	27.17
Number of ER visits	3,198	29.12	4,065	31.86
Any serious injury (binary)	3,176	28.92	3,294	25.82
Number of times seriously injured	3,482	31.70	3,548	27.81
Changes in illicit drug use				
Total number of drug-specific days of use	1,505	13.70	1,150	9.01
Drug use categories (three categories)	1,221	11.12	1,019	7.99
Not a drug user → casual drug user (days < median)	337	3.07	261	2.05
Casual drug user (days < median) → not a drug user	249	2.27	206	1.61
Not a drug user → heavy drug user (days ≥ median)	286	2.60	244	1.91
Heavy drug user (days ≥ median) → not a drug user	200	1.82	231	1.81
Casual drug user (days < median) → heavy drug user (days ≥ median)	71	0.65	27	0.21
Heavy drug user (days ≥ median) → casual drug user (days < median)	78	0.71	50	0.39

documented in other national surveys (SAMHSA 2009). About 5 percent of men and 2 percent of women used cannabis exclusively in each wave. A relatively small fraction of respondents—2 percent of men and 1 percent of women—used multiple drugs in both waves.[3]

As noted earlier, we control for a long list of predisposing, enabling, and need variables in the logistic and negative binomial regression models. We report mean values for all these control variables in Table 1.

Identification in conditional fixed-effects models relies on the number of people changing the likelihood and/or intensity of health services utilization and shifting across the drug use categories from one wave to the other. Table 2 displays changes in our health services utilization and drug use measures from Wave 1 to Wave 2. Number of hospitalizations changed between the two waves for 13 percent of men ($N = 1{,}477$) and 16 percent of women ($N = 2{,}066$); number of ER visits changed for 29 percent of men ($N = 3{,}198$) and 32 percent of women ($N = 4{,}065$); and number of serious injuries requiring medical attention changed for 32 percent of men ($N = 3{,}842$) and 28 percent of women ($N = 3{,}548$). In terms of drug use, 14 percent of men (1,505) and

9 percent of women (1,150) had a different number of drug-specific days of use in Waves 1 and 2. Moreover, 11 percent of men (1,221) and 8 percent of women (1,019) changed drug use categories between waves (i.e., no use, casual use, heavy use). Taken as a whole, these proportions are respectable (i.e., 8–32 percent of the sample for various measures of health services utilization and drug use), but identification would be further enhanced with more changers. We return to this issue later in the paper.

Logistic and Conditional Fixed-Effects Logit Models

Table 3 presents selected estimation results by gender when binary measures of health care utilization are the dependent variables. The key explanatory variables are dummies for casual drug users and heavy drug users, with no drug use as the reference condition. The pooled panel estimation (logistic regression) in columns (1) and (3) shows that heavy drug use is positively and significantly ($p<.05$) related to all three health services utilization measures (i.e., OR$>$1) for both men and women. The estimated ORs for casual drug users are also greater than one in almost all cases, but only significant ($p<.05$) for any ER use for women and any serious injury for men. The effect sizes are relatively large with ORs in the range of 1.22–1.50. These pooled panel results suggest that illicit drug users, particularly heavy users, are about 25–50 percent more likely to consume these health services than nondrug users. However, this conclusion would be misguided because the fixed-effects estimates tell a somewhat different story.

Columns (2) and (4) of Table 3 present estimates after controlling for unobserved individual heterogeneity using a fixed-effects estimator (conditional fixed-effects logit). For men (column (2)), both casual and heavy drug use continues to have a significant effect ($p<.05$) on the likelihood of experiencing a serious injury (similar effect sizes), but the estimates are no longer significant for any hospitalization and ER visit. None of the fixed-effects conditional logit estimates are statistically significant for women (column (4)), but the effect of heavy drug use on any ER visit is approaching significance ($p<.10$).

Negative Binomial and Conditional Fixed-Effects Negative Binomial Models

Table 4 presents estimation results for count measures of health services utilization. The key statistic in our negative binomial models is the IRR, or the exponentiated coefficient.[4] As with the ORs in Table 3, the majority of the IRRs in Table 4 are significantly ($p<.05$) different from one when we apply negative binomial models to the pooled panel data (columns (1) and (3)). The effect sizes indicate that drug users have about a 30 percent higher rate of

Table 3: Selected Estimation Results for Binary Measures of Health Services Utilization

	Men		*Women*	
	Logistic Regression (Pooled Panel)	*Conditional Fixed-Effects Logit*	*Logistic Regression (Pooled Panel)*	*Conditional Fixed-Effects Logit*
Specification 1: any hospitalization				
Sample size (*N*)	21,966	2,790	25,520	3,828
Not a drug user (reference)				
Casual drug user				
Coefficient estimate	−0.05	0.09	0.06	< 0.01
Standard error	(0.14)	(0.24)	(0.15)	(0.23)
Odds ratio	[0.95]	[1.10]	[1.07]	[1.00]
Heavy drug user				
Coefficient estimate	0.41***	0.35*	0.25**	0.34
Standard error	(0.11)	(0.21)	(0.12)	(0.21)
Odds ratio	[1.50]	[1.42]	[1.28]	[1.41]
Specification 2: any ER visit				
Sample size (*N*)	21,966	5,696	25,520	6,934
Not a drug user (reference)				
Casual drug user				
Coefficient estimate	0.15*	0.03	0.20**	0.19
Standard error	(0.08)	(0.15)	(0.10)	(0.16)
Odds ratio	[1.16]	[1.03]	[1.22]	[1.21]
Heavy drug user				
Coefficient estimate	0.29***	0.17	0.32***	0.28*
Standard error	(0.08)	(0.15)	(0.09)	(0.16)
Odds ratio	[1.33]	[1.18]	[1.37]	[1.32]
Specification 3: any serious injury				
Sample size (*N*)	21,966	6,352	25,520	6,588
Not a drug user (reference)				
Casual drug user				
Coefficient estimate	0.22***	0.29**	0.16*	0.12
Standard error	(0.08)	(0.14)	(0.10)	(0.16)
Odds ratio	[1.25]	[1.33]	[1.17]	[1.13]
Heavy drug user				
Coefficient estimate	0.36***	0.29**	0.32***	0.12
Standard error	(0.08)	(0.15)	(0.09)	(0.15)
Odds ratio	[1.44]	[1.34]	[1.37]	[1.12]

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

utilization of these services than nondrug users. Turning to the conditional fixed-effects negative binomial results (columns (2) and (4)), some of the IRRs are no longer significant. The four effects that remain significant are heavy

Table 4: Selected Estimation Results for Count Measures of Health Services Utilization

	Men		*Women*	
	Negative Binomial (Pooled Panel)	*Conditional Fixed-Effects Negative Binomial*	*Negative Binomial (Pooled Panel)*	*Conditional Fixed-Effects Negative Binomial*
Specification 4: number of times hospitalized				
Sample size (*N*)	21,966	3,118	25,520	4,386
Not a drug user (reference)				
Casual drug user				
Coefficient estimate	0.018	0.23	0.02	– 0.01
Standard error	(0.18)	(0.20)	(0.15)	(0.18)
Incident rate ratio	[1.02]	[1.25]	[1.02]	[0.99]
Heavy drug user				
Coefficient estimate	0.31**	0.37**	0.23**	0.37**
Standard error	(0.13)	(0.18)	(0.12)	(0.17)
Incident rate ratio (IRR)†	[1.36]	[1.45]	[1.26]	[1.44]
Specification 5: number of ER visits				
Sample size (*N*)	21,966	7,060	25,520	8,948
Not a drug user (reference)				
Casual drug user				
Coefficient estimate	0.10	0.12	0.16	0.10
Standard error	(0.09)	(0.11)	(0.11)	(0.11)
Incident rate ratio	[1.11]	[1.13]	[1.17]	[1.11]
Heavy drug user				
Coefficient estimate	0.27***	0.12	0.21**	0.10
Standard error	(0.08)	(0.10)	(0.09)	(0.10)
Incident rate ratio (IRR)†	[1.32]	[1.13]	[1.24]	[1.10]
Specification 6: number of times seriously injured				
Sample size (*N*)	21,966	7,700	25,520	7,750
Not a drug user (reference)				
Casual drug user				
Coefficient estimate	0.16**	0.21**	0.27**	0.09
Standard error	(0.08)	(0.10)	(0.13)	(0.13)
Incident rate ratio	[1.18]	[1.23]	[1.31]	[1.10]
Heavy drug user				
Coefficient estimate	0.32***	0.20**	0.25***	0.16
Standard error	(0.10)	(0.10)	(0.10)	(0.12)
Incident rate ratio (IRR)†	[1.38]	[1.22]	[1.28]	[1.17]

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

†Incident rate ratios (IRRs) are the exponentiated coefficients and represent the difference in the rate of utilization (i.e., hospitalizations, ER visits, or serious injuries) predicted by the model when the variable of interest is increased by one unit above its mean value while all other variables are kept constant at their means. A value greater than one indicates a positive relationship between the rate of utilization and the particular regressor, and a value less than one indicates the opposite.

drug use affecting the number of times hospitalized for both men and women and both casual and heavy drug use affecting the number of times seriously injured for men only. Except for heavy drug use's effect on injuries, the other significant estimates are higher in magnitude than those resulting from the pooled sample estimation.

Our results indicate that unobserved individual heterogeneity is not an important source of bias when estimating the effects of illicit drug use on serious injuries for men. This is also the case when estimating the effects of heavy drug use on the number of times hospitalized (intensive margin) for both genders. However, all of the other estimated ORs and IRRs are either nonsignificant throughout ($p < .05$) or become nonsignificant after we control for unobserved individual heterogeneity.

Sensitivity Analysis 1: Excluding Health Status Controls

The core results discussed above include a set of health status measures (i.e., SF-12 physical health score; SF-12 mental health score; dummy variables for arthritis, gastritis, heart disease, and hypertension) and other substance use variables (tobacco and alcohol) as controls. One potential problem with this approach is that the health status measures and substance use variables are contemporaneous and thus potentially endogenous to the drug use and health care utilization variables. Specifically, the effects of drug use on health care utilization could work through certain chronic health conditions or be diluted by the comorbid use of alcohol or tobacco. If our measures of health status and substance use behaviors do not predate the decision to use illicit drugs, we may overcontrol when adjusting for these measures.

To analyze how sensitive our results are to the inclusion of these controls, we reran all models excluding the six health status and two substance use variables from the core models presented in Tables 3 and 4. For both genders, ORs and IRRs from the fixed-effects models are generally larger (i.e., further away from 1) and more significant than those in the core models. In particular, female heavy drug users now have higher odds of being hospitalized ($p < .05$). These results suggest that the use of other substances and poor health status could mediate the effects of drug use on health care utilization.

Sensitivity Analysis 2: Analysis by Health Insurance Status

The marginal cost of care (i.e., price) for the consumer is one of the most important variables in a health care demand relationship. In the health care market, most patients do not directly respond to the true marginal cost of care because they are insured. Thus, insurance type, coverage parameters, and plan flexibility are often more important for consumers than health care prices per se. The NESARC does not include comprehensive measures of insurance features, but it does contain information on whether a person is covered by public (i.e., Medicaid, Medicare, VA) or private insurance or is uninsured. With these distinctions, we can explore how drug use's effects on health care utilization vary by type of insurance. Conditional fixed-effects results (available upon request) show a positive and statistically significant association ($p<.05$) between drug use and the number of visits to the ER for uninsured men, but not for men with private or public insurance. In addition, drug use is associated with a higher likelihood of serious injuries for privately insured men and a higher number of injuries for uninsured men. For women, drug use is associated with a higher number of times in the hospital ($p<.05$), but only among those with public health insurance. These subgroup analyses should be viewed with caution, however. Because fixed-effects estimates are identified by those individuals who change health care utilization and drug consumption over time, the sample sizes become quite small when running separate models by insurance type. Thus, some nonsignificant estimates could be influenced more by a lack of statistical power than by a weak relationship.

Sensitivity Analysis 3: Analysis by Age

To investigate the presence of age-specific effects, we divided the male and female samples into two groups (age 35 and younger, and older than age 35). As with the insurance type analysis reported above, identification and statistical power is a concern for some of the specifications. With this caveat in mind, findings indicate that older females (age >35) who are heavy drug users have a higher probability of entering a hospital and a greater number of hospital visits. None of the estimates are significant for men at the 5 percent level or better. These results are available upon request.

Sensitivity Analysis 4: Total Number of Drug-Specific Days of Use

In our core analyses, we divide drug users into two groups (casual and heavy users) to minimize the influence of extreme outliers. To explore the effects of a continuous measure of drug use on health care utilization, we replaced our two categories with the total number of drug-specific days of use. Findings from the fixed-effects models confirm a positive and significant effect of drug use on the number of hospitalizations for men. In contrast to the core analysis, the fixed-effects models demonstrate no evidence of an effect of drug use on serious injuries. However, they do show a positive and significant effect of drug use on the likelihood and number of ER visits for men, which were not detected in the categorical analysis. For women, the measure of drug-specific days of use is not statistically significant in any of the fixed-effects specifications.

Sensitivity Analysis 5: Interactions between Illicit Drug Use and Alcohol Use

The literature has firmly established that illicit drug users, especially heavy users, are often alcohol users as well. Thus, illicit drug users who also consume alcohol may disproportionately use health care services relative to those who use alcohol or illicit drugs only. To explore this relationship while also preserving statistical power, we reestimated models with five substance use variables (casual drug use, heavy drug use, ounces of ethanol consumed, and the two drug/alcohol interactions) and the standard set of controls. Given that all of our fixed-effects specifications are nonlinear (i.e., conditional fixed-effects logit and negative binomial), interpreting interaction terms is more complicated than simply assessing the statistical significance (Ai and Norton 2003). Following the advice of Norton (2004), we employed linear fixed-effects regression (e.g., linear probability models instead of logit) to the conditional samples because computations for interactions in nonlinear fixed-effects models with more than one interaction term are currently not available in *STATA* or other statistical packages (Norton, Wang, and Ai 2004). Although linear estimation of binary and count variables is not preferable, the advantage here is that the effect sizes and associated standard errors for interaction terms are easy to interpret. These estimates are available upon request.

With three health services utilization measures, two margins (intensive and extensive), and two genders, we estimated a total of 12 specifications with drug/alcohol interactions. For males, the interactions of both drug use variables (casual and heavy) with alcohol use are positive and statistically significant ($p < .05$) in the specification for the number of times hospitalized. This suggests that drug-using males who also consume alcohol are being admitted to a hospital more often than their drug-using counterparts who do not use alcohol. None of the other drug/alcohol interactions in the remaining 11 specifications are statistically significant at the 5 percent level or better.

Discussion and Conclusion

The primary objective of this investigation is to reexamine the relationships between illicit drug use and health services utilization by using longitudinal data and advanced statistical techniques. Our findings suggest that heavy drug use by men is associated with a greater number of hospitalizations relative to nondrug users. Both casual and heavy drug use by men is significantly related to the probability of a serious injury as well as the number of times injured. The only significant relationship for women is the effect of heavy drug use on the number of times admitted to a hospital. For most specifications, the conditional fixed-effects estimates are similar in magnitude yet less significant relative to the estimates derived from the pooled panel data. These changes in significance of the estimates suggest that the pooled panel analysis fails to account for some time-invariant omitted variables that are significantly correlated with illicit drug use such as risk preferences, sensation-seeking personalities, or self-control. Alternatively, attenuation bias due to measurement error could force the estimates toward zero. Fixed-effects specifications magnify measurement error biases, a problem that could be particularly severe in the case of women, whose variations over time in drug use and health services utilization are relatively small. Another potential explanation may be the loss of sample power due to fewer observations used in the conditional fixed-effects estimation, especially for women, who show lower consumption rates than men.

Overall, our analysis clearly indicates a positive association between any amount of illicit drug use and serious injuries for men and heavy drug use and hospital admissions for both genders. The effect of illicit drug use on hospitalizations seems to be stronger at the intensive margin, while its effect on injuries for men works both at the intensive and the extensive margin. The use of fixed-effects methods improves upon much of the previous literature, which fails to account for omitted variable bias when estimating the health care consequences of illicit drug use. In fact, we are not aware of any published study using fixed-effects estimation to address this topic.

Our sensitivity analyses and robustness checks support in general our core findings, but we acknowledge some data limitations. First, it would be interesting to estimate whether illicit drug use is significantly related to outpatient visits for preventive services and urgent care visits for acute services, two variables that are not available in the NESARC. Second, small sample sizes coupled with identification requirements prevented us from applying conditional fixed-effects models to some interesting subgroups (e.g., multiple age groups, race/ethnicity groups, drug-specific users). Third, time-varying unobserved individual heterogeneity is a potential source of remaining bias due to a shortage of detailed data on personal characteristics and behaviors. Finally, we cannot dismiss some spurious correlation in our estimates due to changes in underlying trends across waves (e.g., economy-wide income effects or a generalized deterioration in the population's health) that are associated with both health services utilization and illicit drug use.

In summary, health care providers, insurance companies, policy makers, taxpayers, and other stakeholders are generally uninformed about the effects of illicit drug use on health services utilization and associated costs. Much of the existing literature is mixed, adding to the ambiguity in this area. Findings from the present study suggest that, after accounting for unobserved individual heterogeneity, illicit drug use is positively and significantly associated with some types of costly health care use, but certainly not with all. We encourage future studies to employ similar estimation techniques with larger panel datasets spanning more than two waves along with credible measures of outpatient care to see whether the present findings endure.

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NOTES

1. State of residence was not available in Wave 2.
2. Individuals aged 18–29 show the highest levels of health services utilization, conditional on other covariates, followed by individuals aged 45–65. While this general age pattern is the same in Waves 1 and 2, the differences in health services utilization across age groups decrease in Wave 2. Thus, the changes we observe in the rates of health services utilization between Wave 1 and Wave 2 correspond to the aging of the population (more people in the 45–65 group) as well as to a smaller difference in the use of services between those aged 30 and older relative to those in the lower age ranks in Wave 2.

3. Rates of illicit drug use among NESARC respondents tend to be lower than those observed among respondents to other recent surveys (SAMHSA 2009). While self-reporting bias is a potential concern, the published literature on this topic indicates that self-reported substance use suffers less from misreporting when closed questions are utilized, as in the NESARC (Lintonen, Ahlstrom, and Metso 2004). Given that self-reporting of recent alcohol and illicit drug use is a reliable method used by the NIAAA and other national surveys (e.g., NHIS, NHANES, NHSDA), we have confidence in the estimated relationships. To the extent that they exist, discrepancies across surveys in usage rates are probably due to different populations sampled by each survey.
4. IRRs represent the difference in the rate of utilization (i.e., hospitalizations, ER visits, or serious injuries) predicted by the model when the variable of interest is increased by one unit above its mean value while all other variables are kept constant at their means. A value greater than one indicates a positive relationship between the rate of utilization and the particular regressor, and a value less than one indicates the opposite.

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