Health Insurance and Teenage Substance Abuse

Seth Kerstein[1]

Pomona College

Abstract

The theory of moral hazard suggests that health insurance coverage will lead to increased substance abuse by reducing incentives to avoid risky behaviors. We use data from the 2003 National Survey of Drug Use and Health to analyze the relationship between health insurance coverage and the use of cocaine and inhalants among teenagers. Although we do find significant associations between use of these drugs and various social and demographic variables, we do not find evidence of moral hazard.

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[1] 425 N. College Ave., Claremont, CA, 91711. Phone: (909) 621-8118. Email: seth.kerstein@pomona.edu.

Introduction

Insurance markets have peculiar characteristics that make them especially interesting objects of study for economists. Most of those peculiarities arise from uncertainty and information asymmetries. One such phenomenon, moral hazard, occurs when insurance alters the behavior of insured persons. Since insurance coverage reduces the costs associated with bad outcomes, insured individuals have a diminished incentive to engage in costly activities in order to avoid those outcomes. Meier (1999) develops a model of health insurance in which the insurer cannot observe some component of preventive care. The probability of becoming ill, $p(e)$, is a function of the quantity of costly preventive care e. Illness is associated with curative cost K. If the insurance coverage reduces K, then it reduces the marginal benefit of engaging in the preventive behavior. If the insurance company offers no additional incentive for prevention, the insured individual maximizes utility by reducing e. In this case, any positive level of coverage for curative care will reduce the amount of costly unobservable prevention.

Numerous empirical studies have confirmed the presence of moral hazard in insurance markets. Campolieti (2002) examines the relationship between disability benefits and the occurrence of hard-to-diagnose musculoskeletal conditions. She finds that more generous benefits contribute to the increased incidence of such conditions on the disability rolls. Lundin (2000) studies the relationship between patients' out-of-pocket drug costs and physicians' prescription decisions. He finds that patients whose costs are reimbursed are more likely to receive prescriptions for relatively expensive name-brand drugs than patients who face large out-of-pocket costs.

There is some empirical evidence that medical insurance coverage leads to increased health care demand. Riphahn, Wambach, and Million (2002) study the determinants of health care demand among German households between 1984 and 1995. They find that, taking into account sex differences in self-employment, self-employed adults visited doctors much less frequently than did other adults. During the studied period, Germany fully insured employees for wage losses due to illness, but self-employed workers were not insured in this way. Riphahn, Wambach, and Million find evidence of a similar effect among mothers of small children, whose opportunity cost of health care demand is also relatively high. These results are consistent with the theory of moral hazard.

Since the incidence of moral hazard depends upon asymmetric information, it is sometimes possible for insurers to structure their coverage in a way that reduces opportunistic behavior. For example, Richaudeau (1999) does not observe moral hazard in the French automobile insurance market, which relies upon a rating system. The rating system takes into account car and driver characteristics as well as the driver's record. Richaudeau attributes the lack of moral hazard to the rating system, which helps insurers eliminate information asymmetries by identifying risky drivers.

While the theory of moral hazard relies heavily upon the idea of preventive behavior, this behavior tends to be loosely defined. In practical terms, prevention can take a variety of forms. Some kinds of prevention involve actively taking precautionary measures. For example, an individual can reduce the likelihood of needing curative dental care by maintaining good oral hygiene. Alternatively, prevention can entail refraining from behaviors that pose health risks. For example, an individual might refrain from skateboarding in order to reduce the likelihood of injury. If, all else being equal, the individual would prefer to engage in the risky behavior, than refraining from doing so is a form of costly prevention.

In this study, we examine the second type of prevention. We study teenagers' decisions to abuse drugs at the risk of damaging their short-term health. We focus on teenagers for two reasons. First, adolescence is the period of greatest risk of initiating substance abuse (Fields, 1992; Bachman et al, 1997), so this question is most relevant for that age group. Second, it is unlikely that minors meaningfully participate in insurance purchasing decisions. For this reason, our model of their behavior can treat insurance coverage as exogenous, eliminating opportunities for adverse selection. This way, we can more confidently attribute an empirical relationship between insurance coverage and drug use to moral hazard.

In order for current health insurance coverage to have an impact on preventive behavior, at least some of the benefits of prevention must be immediate or close to immediate. The moral hazard effect occurs because of the decreased cost of risky behavior, so the individual must be insured both when he or she engages in the behavior and when the health consequences of the behavior materialize. For this reason, we will restrict our study to two drugs associated with short-term health risks: cocaine and inhalants.

Cocaine use increases the short-term risk of heart attacks and strokes (Bellenir, 1996). It can also lead to nausea, seizures, or respiratory failure (*Ibid.*). Cocaine is also associated with other medical problems that vary depending upon how the drug is taken (*Ibid.*).

Inhalant use can lead to heart arrhythmia and increase the risk of heart failure (Bellenir, 1996). Less serious side effects include nasal irritation and nosebleeds (*Ibid.*). The decreased coordination and impaired judgment arising from inhalant use commonly lead to physical injury (*Ibid.*). Additionally, certain methods of inhalant intake can cause suffocation (*Ibid.*).

In order to determine the effect of health insurance on drug abuse, we need to take into account the other factors that could influence the individual's drug use decision. These factors include family structure (Hoffman & Johnson, 1998), age (Elliott, Huizinga, & Menard, 1989; Bachman et al., 1997), mental health (Elliott, Huizinga, & Menard, 1989), sex (Saffer & Chaloupka, 1999), income (Saffer & Chaloupka, 1999), race (Saffer & Chaloupka, 1999), parents' education (Sickles & Taubman, 1991), and a number of other family and peer influences (Fields, 1992).

Among adolescents, the likelihood of substance abuse tends to increase with age (Elliott, Huizinga, & Menard, 1989). Cocaine use, which is most common among people in their early twenties (Bachman et al., 1997), follows this pattern. However, inhalant use does not. Adolescent inhalant use tends to peak around eighth grade (Bellenir, 1996).

Hoffman and Johnson (1998) find that, ceterus paribus, adolescents who live in households with two parents are less likely to abuse drugs than adolescents who live in single-parent households. They observe a greater risk increase for single-father households than for single-mother households. Saffer and Chaloupka (1999) study the relationship between race, sex, and the demand for cocaine. They find that women are less likely to use cocaine than men, and that Hispanics and Asians are less likely to use cocaine than people of other races. Although they do not find a statistically significant association between income and cocaine participation in the full sample, they do find such a relationship among Blacks and Native Americans.

A popular theory suggests that substances like tobacco, alcohol, and marijuana serve as “gateway” drugs. According to this theory, an individual’s previous use of gateway drugs increases the likelihood that he or she will use “harder,” more immediately risky drugs. Pudney (2003) uses survey data to measure these relationships. Although he finds significant associations between previous use of gateway drugs and further substance use, he claims that a set of confounding variables, consisting of unobserved personal characteristics, is responsible for the observed associations. After he controls for said characteristics, the magnitudes of the observed gateway effects become considerably smaller.

Does health insurance coverage make insured teenagers more likely to abuse drugs? In this study, we examine data from the 2003 National Survey on Drug Use and Health in order to see whether such a moral hazard effect exists.

Data

The U.S. government’s Substance Abuse and Mental Health Administration conducts a large annual survey called the National Survey on Drug Use and Health. The survey’s sampling frame consists of the entire U.S. noninstitutionalized population age 12 and older. The survey responses provide information on a wide variety of drug use behaviors as well as demographic information about respondents. That demographic information includes responses to questions about income and health insurance coverage. For respondents 17 years of age and younger, the survey includes responses to additional questions about the respondent's experiences in school, at home, and elsewhere. We conduct our analysis using data from the 2003 NSDUH.

Since so many variables describe the NSDUH data, we can control for some of them by including them in our model. Doing so helps us isolate the relationships between health insurance coverage and the drug use response variables. In Table 1, we present definitions for all of the variables we incorporate into our analysis.

We weight the sample using the analytic weights that accompany the data set. These weights are designed to compensate for the estimated sampling biases of the survey.

Although the survey gives us detailed information about respondents' drug use in the twelve months prior to survey participation, it does not tell us as much about previous drug use. However, it does include the year in which the respondent claims to have first tried each drug. This information allows us to determine whether a respondent's initial use of one drug unambiguously preceded his or her initial use of another drug. In doing so, we can capture some of the "gateway" effect conventionally associated with popular recreational drugs. We generate dummy variables that represent previous drug use as follows:

X = 1 if respondent used [explanatory drug] before 2003 and if the respondent's first [explanatory drug] use preceded his/her first [response drug] use; 0 else. If the respondent has never used the response drug, we consider any pre-2003 use of the explanatory drug to constitute "previous use." This conservative definition of previous use assigns zeroes to ambiguous cases. Our analysis includes such variables for previous use of cigarettes, alcohol, and marijuana.

Instead of precisely measuring family income, the NSDUH places each respondent into one of seven disjoint family income categories. For example, if the respondent's annul family income falls between $10,000 and $19,999 (inclusive), the NSDUH codes the respondent's family income as 2. In order to measure the effect of income as precisely as possible, we divide income up into six dummy variables, excluding the lowest income bracket (see Table 1).

Since the literature contains evidence of interactions between race and drug use, we include dummy variables indicating whether the respondent is black, Native American, Asian/Pacific Islander, Hispanic, or multiracial. We also create a dummy for sex.

The NSDUH includes a dummy variable that indicates whether the respondent has had any drug education in school. Since this variable has an intuitive causal relationship with drug use that does not suffer from serious codetermination issues, we include it in our analysis.

Incentives, demographics, and previous use of other drugs are not the only determinants of substance abuse. Numerous social and psychological factors can alter an individual's use of drugs (Fields, 1992). Unfortunately, the direction of causation between such variables and drug use tends to be quite unclear. Most of the social and psychological variables measured by the NSDUH suffer from this codetermination problem. Our analysis includes one notable exception: a variable representing social isolation. This variable attempts to measure the strength of the respondent's social support networks. It is coded based upon the response to the following question: "If you wanted to talk to someone about a serious problem, which of the following people would you turn to?" The list of potential responses includes friends, significant others, various family members, and "nobody." Since strong social support networks reduce the risk of substance abuse (Fields, 1992), we predict that the response "nobody" will be associated with increased drug use. In order to test this hypothesis, we include an appropriate dummy variable in our empirical analysis.

Limiting our study to 12- to 17-year-olds gives us a sample size of 8,954. After further restricting our sample to those individuals for whom every relevant variable has a meaningful value, we are left with 7,791 observations with which to perform our analysis. We present weighted summary statistics for these observations in Table 2.

Empirical Strategy

We analyze the relationships between drug use and the explanatory variables using a Tobit regression model. We use a Tobit model because the distribution of our response variable is extremely skewed. In particular, the response variable is censored from below at the value Y = 0, since it is impossible for a respondent to have used the response drug on fewer than zero days in the previous twelve months. Tobin (1958) developed the Tobit model to study exactly this kind of data. A benefit of the Tobit model is that, for relatively rare behaviors that vary significantly in magnitude, the analysis takes into account both participation (nonzero values) and magnitude (McDonald and Moffitt, 1980).

The behaviors we are studying are rare. The proportion of respondents who report more than zero days of inhalant use is 4.3%; for cocaine, the proportion is 1.6%. However, among those who report some use, the number of days ranges from 1 to 342 for inhalants and from 1 to 328 for cocaine. The rarity of nonzero values, combined with the wide range of degrees of use, suggests a Tobit model.

We set up two equations: one for cocaine and one for inhalants. We specify each equation as follows:

$$Y = \alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \beta_7X_7 + \beta_8X_8 + \beta_9X_9 + \beta_{10}X_{10} + \beta_{11}X_{11} + \beta_{12}X_{12} + \beta_{13}X_{13} + \beta_{14}X_{14} + \beta_{15}X_{15} + \beta_{16}X_{16} + \beta_{17}X_{17} \quad (1)$$

$$W = 0 \quad (\text{if } Y - \varepsilon < 0)$$
$$W = Y - \varepsilon \quad (\text{if } Y - \varepsilon \geq 0) \quad (2)$$

W = # of days used response drug in past 12 months
X_1 = Age (years)
X_2 = Race (1 if white, 0 else)
X_3 = Sex (1 if female, 0 else)
X_4 = Mother in Household (1 if mother lives in household, 0 else)
X_5 = Father in Household (1 if father lives in household, 0 else)
X_6- X_{11} = Family income dummies in ascending order, with lowest income bracket excluded (1 if respondent's family income falls into the given bracket, 0 else)
X_{12} = Drug Education (1 for any drug education, 0 else)
X_{13} = Social Isolation (1 if respondent answered "nobody," 0 else)
X_{14} = Previous cigarette use (1 for previous use, 0 else)
X_{15} = Previous alcohol use (1 for previous use, 0 else)
X_{16} = Previous marijuana use (1 for previous use, 0 else)
X_{17} = Health insurance coverage (1 if covered, 0 else)

We omit the variable "BLACK" from the cocaine regression because none of the black respondents report cocaine use in the past 12 months.

Results

We report coefficients for cocaine in Table 3 and coefficients for inhalants in Table 4. In the cocaine model, the coefficients for age, sex, drug education, social isolation, previous cigarette use, and previous marijuana use are all significant, and they all have the expected signs. Being multiracial is also significant and associated with decreased cocaine use, which is not a result predicted by the literature. The pseudo R-Squared of 0.1653 indicates that our model is incomplete. However, the model does explain enough to provide us with insight into the factors that contribute to cocaine use.

In the inhalants model, the coefficients for social isolation and previous cigarette use are significant and have the expected signs. Additionally, being black, Native American, or multiracial is associated with decreased inhalant use. With a pseudo R-Squared of 0.0202, the inhalant regression does a poor job of explaining inhalant use. Although some of the significant coefficients represent associations of considerable magnitude, the low pseudo R-Squared implies that those associations are not reliable predictors of inhalant use.

Discussion and Conclusions

Our finding that cocaine use increases with age is consistent with the literature (Elliott, Huizinga, & Menard, 1989; Bachman et al., 1997). Similarly, our finding that cocaine use is higher for men than for women is expected (Saffer & Chaloupka, 1999). It is curious that we do not find an association between sex and inhalant use, since the substance abuse literature so consistently indicates that males engage in substance abuse to a greater extent than females. This finding could have something to do with the difference in age effects. Although we do not find a significant negative association between age and inhalant use, the combination of our fairly low p-value (0.089) and the findings of the previous literature (Bellenir, 1996) suggest that we might have committed a Type II error. Among adolescents, sex differences might have something to do with age differences; if they do, then the difference in age effects might influence the difference in sex effects. In future studies, it might be worthwhile to examine the interaction between age and sex in determining substance abuse behaviors.

Our findings regarding social isolation are consistent with the literature (Fields, 1992). The significance of this coefficient in both models attests to the considerable influence of social and psychological factors on substance use decisions. It is unfortunate that codetermination issues prevented us from further exploring this dimension of substance abuse in this study.

The coefficients for previous substance use are consistent with the literature. Since we did not attempt to correct for the unobservable characteristics discussed by Pudney (2003), it is unclear whether these empirical findings represent causal gateway effects.

It is difficult to theoretically justify the finding that, *ceterus paribus*, blacks and Native Americans have lower levels of inhalant use. However, no theory is necessary to see the consequences of this relationship: inhalant use is not as pressing a problem among blacks and Native Americans as it is among other groups. Since the respondents not assigned a dummy variable were overwhelmingly white, it follows that white teenagers face a relatively high risk of increased inhalant use.

Due to the dearth of literature on the association between multiracial identity and drug use, it is somewhat surprising to find that it is so significantly associated with decreased use of both drugs studied. It is not immediately clear why we observe these relationships. Multiracial teens obviously come from less racially homogenous families than do other teens. This racial heterogeneity might also apply to the communities in which they live. Since we were unable to directly measure the characteristics of the surrounding community in this study, they might be the driving force behind the observed racial differences in drug use. Further research in this area is warranted.

There are two intuitive explanations for our finding that drug education has a significant effect on cocaine use but not on inhalant use. The first is that education about cocaine is simply a more effective deterrent to use than education about inhalants. Another possibility is that drug education curricula place more emphasis on cocaine than on inhalants. Since inhalant use is both popular among adolescents and potentially dangerous, drug education programs should strive to address it effectively.

The coefficient for health insurance coverage is not significantly different from zero in the cocaine regression (p-value = 0.308). Similarly, the results of the inhalant regression do not allow us to reject the null hypothesis that the health insurance coefficient is zero (p-value = 0.350). Since we do not find any association between health insurance coverage and use of cocaine or inhalants, our results do not provide evidence of moral hazard.

While our analysis does not yield results consistent with the theory of moral hazard, it is quite possible that these results occurred due to the limitations of the data set rather than flaws in the theory. However, in light of our results, it is not unreasonable to question whether the moral hazard relationship exists in this instance. Alternative theories posit different relationships between health insurance and substance abuse. Rollnick and Boycott (2002) suggest that access to primary health care can reduce the risk of substance abuse or help patients decrease their existing use. If both this effect and the moral hazard coexist, their combined effect might make the coefficient for health insurance statistically indistinguishable from zero.

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Table 1: Variable Definitions

Variable	Definition
COCYRTOT	The number of days in the past twelve months on which the respondent used cocaine
INHYRTOT	The number of days in the past twelve months on which the respondent used inhalants
AGE	The respondent's age (in years)
IRSEX	1 if female, 0 if male
BLACK	1 if respondent is Black; 0 else
NATIVAM	1 if respondent is Native American; 0 else
ASIANPA	1 if respondent is Asian or Pacific Islander; 0 else
HISPANIC	1 if respondent is Hispanic; 0 else
MULTRACE	1 if respondent is multiracial; 0 else
IMOTHER	1 if the respondent lives with his/her mother; 0 else
IFATHER	1 if the respondent lives with his/her father; 0 else
INCOME2	1 if the respondent's annual family income falls in the interval [$10,000, $19,999]; 0 else
INCOME3	1 if the respondent's annual family income falls in the interval [$20,000, $29,999]; 0 else
INCOME4	1 if the respondent's annual family income falls in the interval [$30,000, $39,999]; 0 else
INCOME5	1 if the respondent's annual family income falls in the interval [$40,000, $49,999]; 0 else
INCOME6	1 if the respondent's annual family income falls in the interval [$50,000, $74,999]; 0 else
INCOME7	1 if the respondent's annual family income is $75,000 or more; 0 else
ANYEDUC3	1 if the respondent reports having had any drug education in school; 0 else
YETLKNON	1 if respondent reports having nobody to talk to about serious problems; 0 else
CIGB4COC	1 for previous cigarette use (relative to cocaine); 0 else
ALCB4COC	1 for previous alcohol use (relative to cocaine); 0 else
MJB4COC	1 for previous marijuana use (relative to cocaine); 0 else
CIGB4INH	1 for previous cigarette use (relative to inhalants; 0 else
ALCB4INH	1 for previous alcohol use (relative to inhalants); 0 else
MJB4INH	1 for previous marijuana use (relative to inhalants); 0 else
ANYHLTI2	1 if respondent is covered by any type of health insurance; 0 else

Table 2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
COCYRTOT	7791	0.4237	8.2630	0	328
INHYRTOT	7791	0.8199	9.4477	0	342
AGE	7791	14.5351	1.6858	12	17
IRSEX	7791	0.5035	0.5000	0	1
BLACK	7791	0.1395	0.3465	0	1
NATIVAM	7791	0.0055	0.0738	0	1
ASIANPA	7791	0.0316	0.1749	0	1
HISPANIC	7791	0.1532	0.3602	0	1
MULTRACE	7791	0.0199	0.1397	0	1
IMOTHER	7791	0.9187	0.2734	0	1
IFATHER	7791	0.7348	0.4415	0	1
INCOME2	7791	0.1107	0.3138	0	1
INCOME3	7791	0.1177	0.3222	0	1
INCOME4	7791	0.1159	0.3202	0	1
INCOME5	7791	0.1097	0.3126	0	1
INCOME6	7791	0.1886	0.3912	0	1
INCOME7	7791	0.3026	0.4594	0	1
ANYEDUC3	7791	0.7838	0.4117	0	1
YETLKNON	7791	0.0376	0.1902	0	1
CIGB4COC	7791	0.3123	0.4634	0	1
ALCB4COC	7791	0.4199	0.4936	0	1
MJB4COC	7791	0.1916	0.3936	0	1
CIGB4INH	7791	0.2858	0.4518	0	1
ALCB4INH	7791	0.3850	0.4866	0	1
MJB4INH	7791	0.1712	0.3767	0	1
ANYHLTI2	7791	0.9335	0.2492	0	1

Table 3: Model Summary and Coefficients (Cocaine)

Number of obs = 7791
LR chi2(20) = 515.99
Prob > chi2 = 0.0000
Log likelihood = -1302.4618
Pseudo R2 = 0.1653

COCYRTOT	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
AGE	24.6381	4.7134	5.23	0.000	15.3987	33.8775
IRSEX	-26.9873	10.0437	-2.69	0.007	-46.6756	-7.2990
NATIVAM	-43.6691	47.1723	-0.93	0.355	-136.1396	48.8013
ASIANPA	28.6856	32.3400	0.89	0.375	-34.7095	92.0807
HISPANIC	15.0809	13.6915	1.10	0.271	-11.7580	41.9199
MULTRACE	-129.5414	42.6818	-3.04	0.002	-213.2091	-45.8736
IMOTHER	25.1916	17.4495	1.44	0.149	-9.0141	59.3972
IFATHER	7.5684	12.0693	0.63	0.531	-16.0906	31.2274
INCOME2	-4.1825	25.7353	-0.16	0.871	-54.6306	46.2655
INCOME3	25.0265	23.9619	1.04	0.296	-21.9453	71.9982
INCOME4	-17.1614	25.4875	-0.67	0.501	-67.1237	32.8010
INCOME5	-20.5023	26.6278	-0.77	0.441	-72.6999	31.6953
INCOME6	-6.1962	24.6654	-0.25	0.802	-54.5469	42.1546
INCOME7	-7.0253	24.9422	-0.28	0.778	-55.9187	41.8681
ANYEDUC3	-20.9655	10.6655	-1.97	0.049	-41.8727	-0.0583
YETLKNON	96.7118	16.9427	5.71	0.000	63.4996	129.9239
CIGB4COC	101.2301	18.2344	5.55	0.000	65.4859	136.9744
ALCB4COC	33.3228	17.3462	1.92	0.055	-0.6804	67.3260
MJB4COC	88.8429	14.1611	6.27	0.000	61.0834	116.6024
ANYHLTI2	20.9132	20.5332	1.02	0.308	-19.3374	61.1638
_cons	-788.1139	97.2777	-8.10	0.000	-978.8042	-597.4235

Table 4: Model Summary and Coefficients (Inhalants)

Number of obs = 7791
LR chi2(21) = 131.03
Prob > chi2 = 0.0000
Log likelihood = -3182.015
Pseudo R2 = 0.0202

INHYRTOT	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
AGE	-2.2690	1.3339	-1.70	0.089	-4.8838	0.3458
IRSEX	-0.0887	3.9081	-0.02	0.982	-7.7496	7.5721
BLACK	-27.0812	8.1317	-3.33	0.001	-43.0216	-11.1408
NATIVAM	-83.7919	30.4056	-2.76	0.006	-143.3951	-24.1887
ASIANPA	2.5360	12.2554	0.21	0.836	-21.4880	26.5599
HISPANIC	-1.3165	6.2223	-0.21	0.832	-13.5139	10.8808
MULTRACE	-68.7769	17.2794	-3.98	0.000	-102.6491	-34.9046
IMOTHER	0.0360	7.2919	0.00	0.996	-14.2581	14.3301
IFATHER	-2.0783	5.1890	-0.40	0.689	-12.2502	8.0935
INCOME2	-2.8705	10.8637	-0.26	0.792	-24.1662	18.4253
INCOME3	-12.8997	11.1396	-1.16	0.247	-34.7363	8.9369
INCOME4	-4.8989	10.9098	-0.45	0.653	-26.2851	16.4874
INCOME5	-0.6297	10.8615	-0.06	0.954	-21.9212	20.6618
INCOME6	0.5202	10.4609	0.05	0.960	-19.9859	21.0263
INCOME7	15.0000	10.3498	1.45	0.147	-5.2884	35.2885
ANYEDUC3	0.9890	4.7949	0.21	0.837	-8.4102	10.3883
YETLKNON	39.2437	7.8442	5.00	0.000	23.8669	54.6204
CIGB4INH	24.3593	5.2934	4.60	0.000	13.9829	34.7358
ALCB4INH	3.2474	4.8425	0.67	0.502	-6.2452	12.7401
MJB4INH	4.4720	5.7750	0.77	0.439	-6.8486	15.7926
ANYHLTI2	8.7214	9.3268	0.94	0.350	-9.5615	27.0044
_cons	-106.5531	24.6637	-4.32	0.000	-154.9007	-58.2056