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ESTIMATING ADDICTS' PRICE RESPONSE OF HEROIN: A PANEL DATA APPROACH BASED ON A RE-INTERVIEWED SAMPLE

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ESTIMATING ADDICTS= PRICE RESPONSE OF HEROIN: A PANEL DATA APPROACH BASED ON A RE-INTERVIEWED SAMPLE

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Abstract

Drug abuse inflicts considerable harm on users, non-using persons and on society, and a variety of means to curtail consumption of illegal drugs have been adopted. The consumption of drugs differ from consumption of most other goods in that it involves addiction. Inter-temporal models are needed to encompass this aspect. The data for this study have been collected through interviews with heroin injectors attending a needle exchange service in Oslo, and the respondents have undergone a second interview about one year after the first. Four regression models will be considered: two are static panel data models and two are cross-section models with lagged or leaded drug consumption as additional regressors. Each model comes in two versions, one for non-dealers and one for dealers of heroin. Despite our relatively small sample, we obtain negative and statistically significant price responses and positive and significant income responses for nearly all the models and specifications applied. The results from the two classes of models reflect the same picture although the absolute values of the elasticities vary. For the price elasticity, dealers obtain values in the range of [-0.25, -1.55] and non-dealers in the range of [-0.72, -1.83]. Somewhat surprisingly, we obtain low estimates for the habit component in the panel data model, but higher for non-dealers than for dealers.

1. Introduction

Drug use inflicts considerable harm on society and on non-using persons. In efforts to counteract this, a variety of means to curtail consumption of illegal drugs have been adopted. Since many drug policy interventions will increase the full price of drug consumption, knowledge of how drug users respond to price changes is of vital importance to evaluate and increase efficiency of the means applied. Lack of relevant data has however resulted in few studies including estimates of price and income elasticities of illegal drugs. A basic aim of the present study is to estimate such elasticities by using a two-wave panel data set collected from heroin injectors in Oslo.

Drug consumption differs from consumption of most other goods in that it involves an addiction. No generally accepted definition of the term exists (Elster and Skog 1999), but most authors agree that an important feature is the increase in current consumption resulting from an increase in past consumption of the said good. Consumption history influences current consumption through reinforcement and tolerance. An inter-temporal model is thus needed to encompass the addiction aspects. Panel data provide this opportunity, one reason being that panel data make it possible to distinguish between individual (inter-individual) (co)variation in the variables involved from their within individual (intra-individual) (co)variation.

Previous studies of price elasticities of illicit drugs can be classified according to the types of models applied: The first type consists of models based on cross-sectional data in which the consumption of drugs is treated as any other commodity and in which the special features of addiction are excluded. Examples here are Nisbet and Vakil (1972), who estimate the price elasticity of marijuana demand based on an anonymous mail survey of students; Silverman and Spruill (1977), who indirectly estimated the price elasticity of heroin from the relationship between crime and the price of heroin in a monthly time series of 41 neighbourhoods in Detroit; and Bretteville-Jensen (1999), in which the price and income elasticity of males and females were estimated on the basis on interviews with heroin injectors in Oslo during the period 1993-1997. The second type are models which take account of consumption history but do not fully anticipate future changes (so-called Amyopic≅ models). A recent example of a model which includes previous consumption is van Ours= (1995) study of opium demand in the Dutch East

Indies from 1923-38. The third type of models are Arational≅ models based on Becker and Murphy=s (1988) theory of rational addiction in which the agents are supposed to fully anticipate both previous and future economic variables when deciding on current consumption. Empirical testing of the theory in the nineties has resulted in studies of cocaine and marijuana addiction (Grossman and Chaloupka 1998; Grossman et al. 1998a); as well as cigarette addiction (Chaloupka 1991; Keeler et al. 1993; Becker et al. 1994); and alcohol addiction (Grossman et al. 1998b).

The data for this study have been collected among heroin injectors who use a needle exchange service in Oslo. The respondents were interviewed a second time about one year after the first. The panel data set includes detailed information on the consumption of legal and illegal substances in addition to reported income from various legal and illegal sources. The data set is unique firstly, in that it contains information on heavy heroin users= consumption and income at different points in time, and secondly, in that we are able to apply self-reported price data and thus do not have to rely on aggregated price series generated in enforcement agency reports. We will allow for the influence of previous consumption on present consumption thus explicitly allowing for the possible influence of addiction. Both random and fixed effects static models are applied in estimating price and income elasticities in addition to models with lagged and leaded response in consumption.

The rest of the paper is organised as follows: Section 2 outlines the empirical model and the specifications we want to test. Section 3 contains a description of the data set and an outline of the sampling procedure and contents of the questionnaire. Section 4 presents the results from the different model specifications before the results are discussed in the concluding section 5.

2. Models

Physical and psychological Astocks of habits≅ accumulated by previous heroin consumption are potentially important factors when attempting to explain observed heroin consumption. This habit effect may be considered an additional effect to standard observable economic factors like observed income, prices, sociodemographic variables, etc. In a dynamic model of individual behaviour, the addiction towards heroin may be represented by a *time-dependent* variable incorporating the Astock of habits≅ determined by each individual's past heroin consumption (cf. Grossman and Chaloupka, 1998). Unobserved habit effects can alternatively be considered as individual Aproperties≅, represented, within a static model, as (components in) *individual specific*, i.e., time invariant, latent variables. The latter approach may be the most convenient when individual data in the form of short panels from a sample of individuals are available. We consider both approaches in this paper.

Modelling addiction towards heroin as latent individual heterogeneity is interesting since we can expect that a large part of the variability of the individual effect for this commodity in due to variations in the degree of addiction. It should be recalled, however, that our estimates of the variation in the latent heterogeneity will also represent variations in genetic dispositions, attitudes towards health risks, and other valid explanatory variables not specified in the model. Why are genuine panel data essential for this kind of investigation? It is well-known that unobserved individual effects, whether they are treated as random or fixed, cannot be identified from cross-section data. In the random effects situation, when only one observation of each individual is available, such effects cannot be separated from the pure disturbance of the equation since only one time period is represented for each individual, and hence the relative variation of the latent individual effect and the genuine disturbance cannot be identified. Repeated observations of the individuals should be available.

Let y_{it} denote the heroin consumption of individual i reported in observation t; i=1,...,N; t=1,2. It is explained by three kinds of variables. The first, x_{it}, is a vector of variables which vary across individuals and observation number, e.g., income and price. The second, z_i, is a vector of variables which vary only across individuals, e.g., gender, including a one belonging to the intercept term of the equation. Third, α_i is an additive latent variable specific to individual i; it contains, inter alia, the psychological stock of habits attached to the drug and affects all observations of individual i's consumption of the drug. We assume that the realizations of α_i for the N individuals in the panel are either drawn from a distribution with zero expectation and variance σ_α^2 or completely unknown and unstructured.

Addiction can alternatively be represented by including lagged and/or leaded heroin consumption among the regressors. Following Grossman and Chaloupka (1998), whose point of departure is the rational addiction model (Becker and Murphy 1988), current drug consumption is affected by previous and future consumption in addition to current drug prices and individual characteristics. A positive and significant estimate of the consumption coefficients (λ_i) indicate that the drug in question is addictive, and in particular, a positive and significant estimate for the lead consumption coefficient indicates that the addicts also are rational or foresighted. Including both previous and future consumption in the same equation would however cause an identification problem in this analysis, since only two observations of each individual are available. In all models, the genuine disturbance, u_{it}, is assumed to have standard properties.

Four regression models are considered; two are static panel data models and two are cross-section models with lagged or leaded drug consumption as additional regressors. Each model has one version for non-dealers of heroin and one version for dealers, the different coefficients representing differences following from the divergent behaviour of the two types of drug users. As dealers in this sample both are suppliers and consumers, any price change of heroin will have two mutually conflicting effects on their consumption. This necessitate separate estimation for the two groups, but splitting the sample in this manner may give rise to self-selection bias. A switching regression model (SRM), aimed to take account of the problem, was applied in another study to a cross-sectional data set consisting of 1370 observations of drug users in Oslo and the analyses were conducted on the basis of an identical questionnaire as used here (Bretteville-Jensen 1999). The regression results indicated that although the estimated covariances between the error terms in the consumption equations and the probit equation representing the selection mechanism, were significantly different from zero (indicating that there is a scope for self selection bias), the estimated price and income elasticities from the SRM did only, on average, deviate by 10 percent from the corresponding ordinary least squares (OLS) results.

A person is defined as a dealer if he/she reported some income from dealing in the month leading up to the interview. The splitting of the sample gives eight model versions to be estimated. The four models are:

A. Random effects, static panel data model

$$(1) \qquad y_{it} = x_{it}\beta + z_i\gamma + \alpha_i + u_{it} \qquad \alpha_i \sim IDD(0,\sigma^2), u_{it} \sim IDD(0,\sigma^2), i = 1,...,N, t = 1,2$$

B. Fixed effect, static panel data model

$$(2) \qquad y_{it} = x_{it}\beta + z_i\gamma + \alpha_i + u_{it} \qquad \alpha_i \text{ is fixed}, u_{it} \sim IDD(0,\sigma^2), i = 1,...,N, t = 1,2$$

C. Cross section model with a one-period lag

$$(3) \qquad y_{i2} = x_{i2}\delta_2 + z_i\mu_2 + y_{i1}\lambda_2 + u_{i2} \qquad u_{i2} \sim IDD(0,\sigma^2), \quad i = 1,...,N$$

D. Cross section model with a one-period lead

$$(4) \qquad y_{i1} = x_{i1}\delta_1 + z_i\mu_1 + y_{i2}\lambda_1 + u_{i1} \qquad u_{i1} \sim IDD(0,\sigma^2), \quad i = 1,...,N$$

Models A-D express the habit formation vis-à-vis the drug in different ways: Models A and B by including a time invariant latent "explanatory" variable, α_i, Models C and D by including observed consumption of the drug in the immediately preceeding or succeeding year as regressors with unknown coefficients. λ_1 is assumed to equal λ_2 times a discount factor as the rational individuals discount future consumption (see Grossman and Chaloupka 1998, section 3). Since the data variation in Models C and D applies only across individuals, the inclusion of an individual effect, as in Model A, would have no consequence, as α_i would be captured by the genuine disturbances u_{i2} and u_{i1}. In Model A, we assume that α_i and u_{it} are mutually uncorrelated and uncorrelated with the regressors.

If we modify the random effects model (Model A) by allowing for correlation between the individual effects and the regressors, using Ordinary Least Squares (OLS) or Generalized Least Squares (GLS) regression, the method essentially boils down to using the fixed effects Model B, which is equivalent to OLS with individual dummies; see Hsiao (1986, section 3.4).

The estimation methods we consider are: OLS and GLS for Model A, OLS with individual dummies for Model B, and Two Stage Least Squares (2SLS) for Models C and D. A variant of the estimation method for Model B, which gives the same result, is to use OLS after having measured all variables from their individual means and thus eliminating α_i and z_i. Another variant (which can be related both to Model A and Model B) is to use OLS after having added the two observations to remove the within individual variation and represent the between variation only. The latter estimator can to some extent reduce the effect of measurement errors. The 2SLS method for Model C and D is applied because previous and future consumption, y_{i1} and y_{i2}, may be correlated with z_i through the optimizing behaviour and because the unobserved variables that affects utility in each period are likely to be serially correlated. An OLS approach could thus lead to biased estimates of the parameters of interest.

In all models, y_{it} denotes the logarithm of the heroin consumption; z_i = (1, male, age, education, debut), and we let x_{it} = [ln(income), ln(heroin price), a-length, alcohol, cannabis, pills]. Our reason for transforming the heroin consumption, the heroin price, and the income variable to logarithms are on the one hand our interest in estimating elasticities, on the other hand the fact that adding an additive disturbance with constant variance to a logarithmic equation is a way of representing multiplicative heteroskedasticity in the corresponding equation in levels. The variables are defined and described in Table 1. The instrumental variables we use to take account of the endogeneity of the lagged/leaded consumption in Models C and D are w_{it} = [ln(heroin price)$_{it}$, ln(income)$_{it}$] where t=1 for Model C and t=2 for Model D. Thus, again following Grossman and Chaloupka (1998), we assume perfect foresight and apply actual future prices and income as instruments for future consumption.

Whether the income variable can be treated as exogenous in relation to drug consumption has been a topic for discussion in the literature. In line with what was concluded in Bretteville-Jensen (1999), which is partly based on the same data set as this study, we will treat income as an exogenous variable.

3. Data

The initial interviews took place in the vicinity of the needle exchange service (NES) in the centre of Oslo in 1997. The interviews were part of an ongoing quarterly data collection which has been conducted since June 1993 (see Bretteville-Jensen 1999 for more details about the data collecting). These interviews are normally anonymous but we had obtained permission from the National Data Inspectorate to register name, address and time of birth of a limited number of people. Most of the persons who were interviewed in March, June and September were asked if they would consent to being re-interviewed with the same questionnaire in about one year's time. Those who agreed to do so were asked to identify themselves so that they could be contacted by the interviewer twelve months ahead. Out of a total of 286 persons interviewed during March to September 171 agreed to participate in the panel data study.

The NES in Oslo is the only one of its kind in the south-eastern part of Norway and it hands out free-of-charge hypodermic syringes and condoms as a HIV-preventive measure. It was chosen as the place to recruit interviewees for several reasons. We wanted to follow a group of heavy drug users who preferably used heroin as their main drug. Heroin abusers in Norway normally inject the drug. The NES registered more than 103.000 individual visits in 1997 (113,000 visits in 1998) and they handed out more than 1.5 millions syringes (1.8 mill. in 1998). The estimated number of drug injectors in the Oslo area is 4,000-5,000 (Bretteville-Jensen and Ødegård 1999). Thus, it may be assumed that a large proportion of the drug injectors in and around Oslo visit the NES on a regular basis, which means that we probably could obtain the required number of respondents there. Furthermore, as we wanted to follow active drug users, abusers now in treatment or in prisons were not of current interest.

The representativeness of the quarterly data collection has been discussed in more detail in Bretteville-Jensen and Sutton (1996). Based on some indicators like the age and sex distribution of the sample compared to what is commonly known about the group, the high number of visits to the NES, and the close agreement fit between what is reported to be sold by the user-dealers and the quantity reported to be consumed by the users, it has been assumed that the sample of quarterly data collection is fairly representative of drug injectors in the Oslo area. However, there is a possibility that those who agreed to participate in the panel data study could differ, for various reasons, from those who declined to take part. As it happens, this does not seem to be the case. When comparing the 171 drug users in the panel data sample with the 115 who only took part in the first regular quarterly data collection, we find a very similar distribution among variables such as age, gender, education, age at first injection, number of stops in drug career, income, amount of heroin per injection, and total amount of heroin consumed in the previous month. The hypothesis of equality of the two distributions were tested with a non-parametric Mann-Whitney test (Siegel and Castellan 1988, p 128) and not rejected at the 1 per cent level.

The final sample

Drug injectors constitute an unstable group with respect to where they live, how much and what types of drugs they consume, how they obtain money and so on. They often report poor housing conditions as many live in the streets, provisionally with a friend or in single-room apartment blocks. They are often in prison, in treatment institutions or in hospitals. Thus, drug injectors are generally very hard to trace for a re-interview. So even though we had their address at the time of the initial interview, we spent a great deal of time searching for the ones who had agreed to participate. First, we sent a letter to which only a few responded (they were not offered money or any other compensation for participating in the study). Next we tried to phone them or contact their social security officer. We also phoned prisons, hospitals, etc. in order to get in touch. As we regained contact with our sample, we began to re-interview those who were interviewed in

March 1997 in March the following year, and by the end of 1998 138 of the 171 drug users had been traced (retrieval rate of 81 per cent) and re-interviewed. Among the group of 138 only 84 persons (61 per cent) were still active drug users. Fourteen persons (10 per cent) were in prison; 11 persons (8.0 per cent) were in residential treatment institutions; 10 were dead (7 per cent); 10 did not want to give a second interview; 8 (6 per cent) had stopped consuming illegal drugs; and one person was in hospital.

Injection is the most common route of heroin administration in Norway whereas amphetamine users more often prefer other ways of consuming the drug. For reasons of representativeness, the following analyses are confined to heroin users only. Of the initial sample of 171 drug injectors 156 reported that they mainly consume heroin and 78 out of the 84 re-interviewed reported the same. The final analyses are thus confined to the group of 78 heroin injectors. Comparisons of those who were active heroin injectors both in 1997 and 1998 to those who injected heroin only in 1997 show that there are few differences between the groups regarding the variables we are able to control for. When comparing age, gender, education, age at first injection, number of stops in drug career, income, amount of heroin per injection and total amount of heroin consumed in the previous month we find by applying a Mann-Whitney test that only age is significantly different at a 1 per cent level. The group that was active also in 1998 is older on average in 1997 than the other heroin users interviewed that year (34.9 versus 30.4 years).

The questionnaire

The same questionnaire was applied in both interview periods. Interviewees were asked detailed questions about their levels and sources of monthly income, levels of drug consumption, and the prices they had paid for different types and quantities of drugs. Respondents were asked how much money they had obtained from six possible income sources: work, state benefit, theft, sale of drugs, prostitution, and Aother≅ sources. A detailed consumption measure is derived by multiplying the reported amount of heroin in the latest injection by the number of injections-per-day and the number of injecting-days per month to obtain the monthly heroin consumption in units.

Consumption of other drugs also affects the consumption of heroin. The data corroborate that heroin injectors are multi-drug users. Thus, the consumption of alcohol, cannabis, and pills may influence the intake of heroin. Information on the number of drug-using days in the previous month was available for alcohol and cannabis both for 1997 (T1) and 1998 (T2) whereas this data was only available for pills in T2. We have constructed a dummy variable for each of the three drugs. They are set to unity in cases of 20 or more using days per month since we assume that this consumption frequency is needed in order to classify a potential substitute or complementary good, to heroin.

To the authors= knowledge, this is the first panel data study to apply self-reported prices and thus does not have to rely on aggregated price series generated in, e.g., enforcement agency reports. Self-reported data will better represent the heterogeneity of prices within the market and reflect the price discount available to buyers who regularly frequent the same dealer. Also bulk-buy discount is available and is accounted for in the unit price employed. Bulk-buy discount may create an endogeneity bias in the analysis, but when balancing this potential problem against the alternative approach of using aggregated price series (which may also cause measurement error problems), we assumed that self-reported prices would better serve the aim of the paper.

Main properties of the data

Table 1 presents means, standard deviations, skewness, and kurtosis for the dependent and the independent variables. There are significant differences between dealers and non-dealers with respect to the mean values of monthly heroin consumption, income, and heroin price. Dealers report consuming more heroin and paying less per unit in addition to obtaining more money in the month prior to the interview. There seem to be more heavy alcohol and pill users among the non-dealers. The kurtosis for dealers= heroin price is fairly high, and both the skewness and kurtosis are substantially higher than for non-dealers. The form of the sample distributions of the two price variables thus depart substantially (cf. the skewness and the kurtosis), which may notbe very surprising. The mean age of both dealers and non-dealers is 34.9 years. The income of dealers is substantially higher than for non-dealers, 54,000 NOK vs. 38,000 NOK, and 77 per cent of the dealers and 67 per cent of the non-dealers are males.

Table 1. Description and definition of variables

Dealers

Variable	**Mean**	**S.D**	**Skew.**	**Kurt.**	**Definition**
Hercon	284.3	276.5	1.66	5.23	number of heroin units consumed per month
Income	53529	39644	1.24	4.33	total income in Norwegian kroner, per month
PriceH	171.1	72.5	2.8	15.8	price of heroin in Norwegian kroner
Male	0.77	0.42	-1.28	2.63	dummy; 1= male
Age	34.9	7.1	-0.52	2.22	age in years
Educ.	2.3	2.1	0.6	2.49	number of years schooling after the age of 15
Debut	16.9	5.1	1.71	6.27	age at first injection
A-length	15.8	7.7	-0.1	2.06	number of abusing years
Alcohol	0.09	0.29	2.77	8.68	dummy; 1=number of alcohol using days ∃ 20
Cannabis	0.18	0.38	1.68	3.82	dummy; 1=number of cannabis using days ∃ 20
Pills	0.44	0.5	0.25	1.04	dummy; 1=number of pill using days ∃ 20

Non-dealers

Variable	**Mean**	**S.D**	**Skew.**	**Kurt.**	**Definition**
Hercon	226.5	238.1	1.48	4.48	number of heroin units consumed per month
Income	38157	27099	1.08	3.97	total income in Norwegian kroner, per month
PriceH	213.3	79.8	1.49	3.81	price of heroin in Norwegian kroner
Male	0.67	0.47	-0.7	1.48	dummy; 1= male
Age	34.9	7.3	0.04	2.4	age in years

Educ.	2.1	1.8	0.69	2.77	number of years schooling after the age of 15
Debut	18.1	5.2	1.7	6.39	age at first injection
A-length	13.8	7.9	0.37	2.49	number of abusing years
Alcohol	0.16	0.38	1.78	4.13	dummy; 1=number of alcohol-using days ∃ 20
Cannabis	0.15	0.36	1.94	4.76	dummy; 1=number of cannabis-using days ∃ 20
Pills	0.57	0.5	-0.26	1.03	dummy; 1=number of pill-using days ∃ 20

Since our data are panel data, a decomposition of the variation of the primary variables of our study into between individual and within indivdual components may be informative. The outcome of such a decomposition, for heroin consumption, income, and heroin price (not transformed to logarithms), is given in Table 2.

Table 2. Shares of total variation representing between individual variation (B) and within individual variation (W) and two components ANOVA decomposition of total variation into share of variance representing variation between individuals (σ_a^2) and other variation (σ_c^2)

	Dealers		**Non-dealers**		**Dealers**		**Non-dealers**	
	B	**W**	**B**	**W**	**σ_a^2 share**	**σ_c^2 share**	**σ_a^2 share**	**σ_c^2 share**
Heroin cons.	0.6178	0.3822	0.6113	0.3887	0.2455	0.7545	0.2387	0.7613
Income	0.5485	0.4515	0.8776	0.1224	0.1074	0.8924	0.7625	0.2375
Heroin price	0.4768	0.5232	0.4405	0.5595	-0.036	1.0338	-0.1023	1.1023

The shares of the total variation, i.e., the sum of squares of the observations measured from their global mean, which are between individual variation (B) and within individual variation (W), are given in columns 1-4. For both dealers and non-dealers, the between component of the heroin consumption dominates. The same is true for the income of non-dealers, where the between component accounts for as much as 88 per cent of the total. For the income of dealers and the price variables of both groups, the two components are more equal. There is thus a pronounced difference between the distributional properties of the incomes of dealers and non-dealers over individuals and years, which may reflect the fact the incomes of the former to some extent are affected by the heroin prices, for which the within component is relatively large.

In columns 5-8 of Table 2, we take this decomposition a step further. We assume - for data description purposes - that each of the three variables can be decomposed into an individual effect a_i, with constant expectation and variance σ_a^2 and a combined component c_{it}, with zero expectation and variance σ_c^2. Provided that all a_i's and c_{it}'s are uncorrelated, the variances in such a descriptive analysis of variance (ANOVA) can be estimated from the within and between variation as follows:

$$\frac{\hat{\sigma}_a^2}{\hat{\sigma}_a^2 + \hat{\sigma}_c^2}, \qquad \frac{\hat{\sigma}_c^2}{\hat{\sigma}_a^2 + \hat{\sigma}_c^2}$$

where

$$\hat{\sigma}_c^2 = \frac{W}{N(T-1)},$$

$$\hat{\sigma}_a^2 = \frac{B}{(N-1)T} - \frac{W}{N(T-1)T}$$

where T is the number of replications (T=2 in our case), (see Searle et al. (1992, p. 59)). These estimates are unbiased.

For heroin consumption, the variance of the individual component is 24-25 per cent of the total variance for both dealers and non-dealers. For income, the variance of the individual component is 76 per cent for non-dealers and only 11 per cent for dealers. For the heroin price, the estimate of σ_a^2 is negative, reflecting that the negative term in the expression for the estimator dominates the positive one, which is a practical possibility when T is low, and the estimated variance ratio of the individual effect is -0.03 for dealers and -0.10 for non-dealers. Since a variance ratio cannot be negative, the practical interpretation of this finding is that no individual effect is detected in the heroin price.

4. Results

OLS and GLS estimates for Model A (random effects) and within (W) and between (B) individual estimates for Model B (fixed effects) are reported in Table 3. Both the OLS and the GLS estimator vectors can be interpreted as matrix weighted averages of the W and B estimator vectors (see Hsiao (1986, section 3.3.2)). The variance covariance matrices used in the GLS estimation are estimated from the OLS residuals, which are consistent under the assumptions made. The W estimator of the coefficient of the gender, age, education, and debut variables are undefined since these are individual-specific (age, education, and debut variables are set to their mean values in 1997 and 1998).

For both groups of drug users, the OLS and GLS estimates do not deviate very much. The income elasticity is, for all four estimation methods, between 0 and 1 and significantly positive at the 5 per cent level - except that the within estimate for non-dealers is negative (-0.122). Considered as a consumption good, heroin may thus be characterized as a "necessity good".

Of particular interest is the finding that the price elasticity estimates are all negative, in some cases exceeding one in absolute value, and most of them are significantly negative at the 5 per cent level. The effect of the male dummy is significantly negative for non-dealers, but insignificant for dealers. The estimated effect of age when using OLS, GLS, or the B estimators is positive, but insignificant. Finally, the alcohol dummy affects the OLS and the GLS estimates negatively, but the effect is not significant. Hence, heroin and alcohol bear some signs of being alternative goods in consumption. On the other hand, the effects of the cannabis and pills dummies are positive, which indicates that cannabis and pills are complementary to heroin in consumption.

Table 3. Ordinary least squares (OLS), Feasible Generalized Least Squares (GLS) estimates of random effects model, Within individual OLS (fixed effects OLS), and Between individuals OLS estimates for dealers (N=48, n=96) and non-dealers (N=30, n=60). Standard deviation estimates in parenthesis. Logged variables are marked with *.

	Dealers				**Non-dealers**			
	OLS	**GLS**	**W**	**B**	**OLS**	**GLS**	**W**	**B**
Constant	- 0.693 (2.267)	-0.357 (2.166)	---	-3.132	3.449 (4.644)	3.633 (4.306)	---	5.56
Income*	0.788 (0.115)	0.775 (0.109)	0.640	0.870	0.571 (0.224)	0.481 (0.213)	-0.122	0.811
Price*	-0.522 (0.265)	-0.556 (0.251)	-0.865	-0.248	-1.052 (0.558)	-0.938 (0.504)	-0.718	-1.830
Male	-0.135 (0.220)	-0.134 (0.222)	---	-0.130	-0.793 (0.359)	-0.861 (0.365)	---	-0.548
Age	0.007 (0.014)	0.007 (0.014)	---	0.011	0.036 (0.023)	0.040 (0.023)	---	0.023
Education	-0.059 (0.044)	-0.058 (0.044)	---	-0.062	-0.056 (0.101)	-0.039 (0.103)	---	-0.110
Alcohol	-0.001 (0.011)	-0.002 (0.011)	-0.013	0.0004	-0.029 (0.018)	-0.034 (0.018)	-0.059	-0.016
Cannabis	0.012 (0.009)	0.011 (0.009)	0.004	0.012	0.038 (0.020)	0.045 (0.019)	0.073	0.014
Pills	0.165 (0.181)	0.148 (0.173)	-0.058	0.262	0.570 (0.305)	0.559 (0.276)	0.477	0.621

σ^2	0.5828	1.0901
σ_α^2/σ^2	0.1200	0.2148

The number of non-dealers in Table 3 (N=30) includes only those who did not report income from dealing activities either at T1 or at T2. Among the group of dealers (N=48) there are Apure≅ dealers (reporting dealing income at both interviews) and those reporting dealing income either at T1 or at T2.

One of the most notable findings in Table 3 is the estimates in the bottom line, showing the ratio between the variance of the individual latent variable α_i and the sum of the variances of α_i and u_{it}. A priori, for such a commonly assumed addictive drug as heroin, one would expect this share to be large, indicating a large unobserved habit component not captured by the specified regressors. Somewhat surprisingly, we find that these estimates are as low as 21 per cent for non-dealers and 12 per cent for dealers. Both are, however, lower than the corresponding "marginal estimates" in the first row of Table 2 (25 and 24 per cent, respectively). When we condition on the covariates as we do when estimating the regression equation, we thus reduce the estimated degree of habit formation in heroin consumption to roughly one half for dealers and with about 10 per cent for non-dealers. In Section 5, some tentative explanations for these findings will be given.

The results from the estimation of Model C and D are reported in Table 4. The Amyopic≅ model with lagged heroin consumption indicates that heroin is addictive, as the estimate of its coefficient is positive both for dealers and non-dealers. However, it is not statistically significant at the 5 per cent level for either of the two groups. The absolute value for non-dealers is high both compared to the coefficient of lagged consumption of dealers and to the values for lead in consumption presented in the last two columns of Table 4. Also, the lead estimates are positive, although not significantly different from zero. A J-test indicated that the instrument variables for lagged and leaded consumption were valid ($p< 0.005$, Godfrey and Hutton 1994).

For both types of models we find, as for Model A and B in Table 3, a positive income elasticity and a negative price elasticity. Except for non-dealers= price response in Model D, all these estimates are significantly different from zero. Corresponding to the results reported in Table 3, the income elasticity both for dealers and non-dealers lies between 0 and 1 and the price elasticity is high and close to 1 or above in absolute value.

Table 4. 2SLS for dealers and non-dealers based on dealing status on T2 with a lagged heroin consumption variable and 2SLS for dealers and non-dealers based on dealing status on T1 with lead heroin consumption. Logged variables are marked with *.

	LAG		**LEAD**	
	Dealers	**Non-dealers**	**Dealers**	**Non-dealers**
Constant	5.432 (4.110)	5.087 (4.320)	9.983 (3.444)	-0.703 (7.073)
Income*	0.427 (0.233)	0.556 (0.189)	0.323 (0.116)	0.803 (0.340)
Price*	-0.087 (0.437)	-1.358 (0.707)	-1.549 (0.459)	-0.877 (0.732)
Male	-0.009 (0.302)	-0.390 (0.287)	0.331 (0.182)	-0.287 (0.308)
Age	-0.019 (0.017)	-0.005 (0.022)	-0.029 (0.014)	0.045 (0.021)
Education	0.096 (0.057)	-0.010 (0.076)	-0.026 (0.041)	-0.163 (0.091)
Alcohol	-0.166 (0.416)	-0.881 (0.507)	-0.608 (0.344)	-0.392 (0.468)
Cannabis	0.116 (0.350)	0.228 (0.294)	0.211 (0.206)	0.432 (0.385)
Pills	-0.085 (0.246)	0.350 (0.265)	---	---
Lagged H-cons.*	0.047 (0.088)	0.283 (0.234)	---	---
Leaded H-cons.*	---	---	0.111 (0.152)	0.157 (0.226)

adjusted R^2	0.223	0.456	0.428	0.555
σ_u	0.497	0.891	0.509	0.848
N	28	50	38	40

The groups of dealers and non-dealers in Model C are defined according to reported income sources at T2, and, correspondingly, the groups of dealers and non-dealers in Model D are defined according to reported income sources at T1.

In accordance with the findings in Bretteville-Jensen (1999), non-dealing males seem to consume less heroin than female counterparts, although the coefficients in Table 4 are not strongly significant. In Model D, age appears to have opposite influence as the significant coefficients are negative for dealers and positive for non-dealers. For all four specifications the age effect is small. The effect of education, measured as the number of years of schooling after the age of 15, is negative and the estimate came out as significantly different from zero in two of the four specifications in table 4 ($p<0.10$). In all cases, the effect of the alcohol dummy is negative and the dummies for heavy pills and cannabis consumption are positive, indicating, as the results in Table 3, that alcohol may be an alternative good, whereas pills and cannabis may be complementary goods to heroin. Since the consumption of these three drugs may be endogenous and determined jointly with the heroin consumption, there is a possibility that the estimates of the corresponding dummy coefficients may be affected by simultaneity bias. We have not made attempts to adjust for this potential problem, the main reason being that it seems difficult to find suitable instruments for these dummies among the variables recorded in the data set.

In addition to the individual characteristics gender, age, and education, the data set also offers information on the age at which the respondents started to inject drugs and the length of the drug career (defined as age at interview - age at debut - number of years (months) as a non-active injector). Tables 5 and 6 differ from tables 3 and 4 in that they include the Adebut≅ and Aa-length≅ as additional variables. Corresponding to what has been reported about the relationship of alcohol debut and later alcohol consumption (Pedersen and Skrondal 1998), we would expect the age of injection debut to be negatively correlated with the reported consumption of heroin. Also, if there is a strong element of tolerance associated with heroin consumption, we would expect a positive correlation between the length of the abusing career and current consumption.

Table 5. Ordinary least squares (OLS), Feasible Generalized Least Squares (GLS) estimates of random effects model, Within individual OLS (fixed effects OLS), and Between individuals OLS estimates for dealers (N=48, n=96) and non-dealers (N=30, n=60). Standard deviation estimates in parenthesis. Logged variables are marked with *.

	Dealers				**Non-dealers**			
	OLS	**GLS**	**W**	**B**	**OLS**	**GLS**	**W**	**B**
Constant	0.693 (2.329)	0.882 (2.205)	---	-1.685	3.659 (5.548)	4.056 (4.961)	---	6.829
Income*	0.711 (0.119)	0.709 (0.112)	0.641	0.68	0.563 (0.259)	0.464 (0.237)	-0.1	0.81
Price*	-0.520 (0.261)	-0.547 (0.246)	-0.881	-0.045	-1.069 (0.604)	-0.964 (0.529)	-0.662	-2.034
Male	-0.106 (0.224)	-0.102 (0.219)	---	-0.197	-0.799 (0.377)	-0.861 (0.376)	---	-0.606
Age	0.021 (0.033)	0.019 (0.031)	---	0.071	0.031 (0.044)	0.035 (0.040)	---	-0.019
Education	-0.055 (0.045)	-0.054 (0.044)	---	-0.064	-0.052 (0.107)	-0.033 (0.106)	---	-0.087
Debut	-0.051 (0.032)	-0.050 (0.031)	---	-0.095	0.002 (0.051)	-0.002 (0.049)	---	0.036
A-length	-0.015 (0.031)	-0.013 (0.029)	-0.01	-0.062	0.007 (0.045)	0.006 (0.040)	0.021	0.049
Alcohol	0.0009 (0.011)	0.0004 (0.011)	-0.013	0.007	-0.029 (0.020)	-0.033 (0.020)	-0.053	-0.013
Cannabis	0.012 (0.009)	0.011 (0.009)	0.004	0.017	0.037 (0.022)	0.044 (0.019)	0.073	0.006

Pills	0.111 (0.180)	0.099 (0.171)	-0.069	0.308	0.578 (0.318)	0.569 (0.287)	0.55	0.589
σ^2		0.5525				1.0904		
σ_α^2/σ^2		0.0777				0.2154		

Table 6. 2SLS for dealers and non-dealers based on dealing status on T2 with a lagged heroin consumption variable and 2SLS for dealers and non-dealers based on dealing status on T1 with lead heroin consumption. Logged variables are marked with *.

	LAG		**LEAD**	
	Dealers	**Non-dealers**	**Dealers**	**Non-dealers**
Constant	7.516 (3.753)	5.945 (4.383)	11.539 (3.717)	0.465 (7.976)
Income*	0.377 (0.217)	0.571 (0.187)	0.262 (0.128)	0.781 (0.365)
Price*	-1.093 (0.416)	-1.680 (0.726)	-1.507 (0.450)	-0.931 (0.822)
Male	-0.148 (0.284)	-0.602 (0.328)	0.394 (0.222)	-0.231 (0.303)
Age	0.012 (0.033)	-0.076 (0.034)	-0.044 (0.049)	0.069 (0.033)
Education	0.087 (0.060)	0.037 (0.075)	-0.014 (0.040)	-0.173 (0.087)
Debut	-0.074 (0.030)	0.088 (0.042)	-0.023 (0.065)	-0.045 (0.025)
A-length	-0.053 (0.030)	0.089 (0.038)	0.012 (0.051)	-0.027 (0.032)
Alcohol	-0.436 (0.441)	-0.976 (0.420)	-0.577 (0.402)	-0.461 (0.487)
Cannabis	0.294 (0.336)	0.028 (0.324)	0.174 (0.222)	0.466 (0.396)
Pills	-0.110 (0.245)	0.487 (0.242)	---	---

Lagged H-cons.*	0.109 (0.074)	0.336 (0.199)	---	---
Leaded H-cons.*	---	---	0.015 (0.194)	0.095 (0.226)
adjusted R^2	0.282	0.494	0.390	0.528
σ_u	0.450	0.847	0.507	0.844
N	26	48	38	40

Table 5 reveals that the estimated coefficients for the debut variable have the expected sign for dealers, although the estimates are not strictly significant. For non-dealers, however, two of the three estimates are positive and they all are insignificant and low in value. The a-length coefficient does not come out significantly for either dealers or non-dealers, but the length of drug career seems to have a negative influence on dealers= own consumption whereas it appears to influence positively non-dealers= heroin consumption. Except for the between estimates of price and income, the estimates of the remaining variables in the four specifications do not change to any large degree when the two additional variables are included. It is worth noting however, that the variance ratio of the latent individual effect drops from 12 per cent for dealers in Table 3 to 8 per cent in Table 5, whereas the corresponding ratio for non-dealers stays the same.

Table 6 reflects a similar picture as Table 4, and including the debut and a-length variables do not substantially change the other estimates. For two dealers and two non-dealers, we did not obtain all the information needed to construct the a-length variable at T2 and thus they were excluded from the analysis of model C. The debut coefficients have the expected negative sign in three of the four specifications. The estimated effect of the length of the injecting career is mixed, as both dealers and non-dealers obtain one positive as well as one negative coefficient. The effect of non-dealers= lagged consumption is here significant at the 10 per cent level, whereas the lead effect for both dealers and non-dealers and dealers= lagged consumption is insignificant. We confine the discussion in section 5 to Tables 3 and 4.

5. Discussion

Estimates of drug consumers= price and income elasticities indicate how drug users respond to changes in drug policy means and thus, should be of interest to policy-makers and others who deal with the drug problem. The legalization debate is an example where estimates of the consumers= price response may have an important role to play. De-criminalizing and/or legalizing consumption and sales of drugs that today are illegal will cause the full prices of the goods to fall, and for dealers, also income, and consumers= response will be of importance when evaluating the consequences on individuals and society by such a policy change.

Despite this study=s relatively small sample, we obtain negative and statistically significant price responses and positive and significant income responses for nearly all the models and specifications applied. The results from the two classes of models reflect by and large the same picture, although the absolute values of the elasticities vary. As expected, also the estimates of dealers and non-dealers= response to changes in economic variables differ. For the price elasticity, dealers obtain values in the range of [-0.25, -1.55] and non-dealers in the range of [-0.72, -1.83].

The results in this study are basically in line with previous estimates. Silverman and Spruill (1977) obtained, in an indirect manner, an estimated long-term price elasticity of heroin [-0.25], and van Our (1995) presented an estimate of -1.0 for the long-term price elasticity of opium demand in the Dutch East Indies. Saffer and Chaloupka (1999) estimated a participation price elasticity for heroin from a national household survey in the U.S., and by assuming that elasticity of demand roughly is twice that value, they obtained an estimate of [-1.60, -1.80]. Bretteville-Jensen (1999) estimated the price elasticity of heroin to -0.35 for dealers and -1.64 for non-dealers using a static cross-section model.

In the economic literature, the few studies of the price elasticity of heroin are supplemented by a number of studies which have estimated the price response for other addictive goods like cannabis, alcohol, and cigarettes. Many of the previous analyses have used either pure cross-section data, time series of (non-overlapping) cross sections, or panel data with aggregate entities, e.g. geographic regions, as observational units. There are at least two distinct advantages with having panel data for genuine micro units in analysing consumption of illegal drugs econometrically. First, micro data agree far more closely with the level of aggregation in the theory behind the analysis. Second, we can expect to get a far better empirical grasp on the habit component attached to a drug when we can follow the same sample of drug-using individuals over several periods. A researcher using, for instance, panel data for aggregate geographic regions, will automatically include observations on regressors covering both users and non-users of drugs. Moreover, the interpretation of the habit component in aggregate analyses easily becomes diffuse, since the number of drug addicts usually changes between the periods in the data set.

Admittedly, a limitation to our panel data set is that the length of the individual time series is the smallest possible, only two years, and the sample of individuals is not particularly large. More precise inferences might have been obtained if more than two observations of each individual and a larger number of individuals had been available. Our choice of data design was dictated mainly by practical considerations, in particular the problems of finding the heroin users the second time round and obtaining an interview comparable with the first; cf. Section 3.

The OLS and GLS estimates in Table 3 are unbiased and consistent only when the latent individual effects are uncorrelated with the specified regressors. These estimates utilize both the within and the between individual variations in the data. The within estimator (W) is more robust, as it is unbiased and consistent if the latent individual effects are correlated with (some of) the regressors (for instance age or education), by treating the effects as fixed (by conditioning on them). On the other hand, the within estimator takes no account of the between variation, and for some variables this part of the total variation is substantial (cf. Table 2). In fact, since this estimator is equivalent to using OLS with individual dummies, we spend one observation in estimating each of the N individual effects and therefore have only N effective observations for estimating the genuine regression coefficients, as against 2N when using OLS and GLS. The choice between the GLS - which is the Gauss-Markov estimator when the random effects specification in Model A is valid - and the W estimators therefore largely depends on whether we can accept to pay this price in order to increase the robustness to error specification.

We have found that the estimated relative "size" of the latent habit is not substantial, in the sense that the variance of the latent component α_i as a share of the variance of the sum of the latent component α_i and the genuine disturbance u_{it} is rather small, cf. Table 3, although larger for non-dealers than for dealers. The α_i variable, however, represents the effects of all individual variables which are not specified in the regression equation and hence are automatically treated as latent. Hence, α_i will not necessarily represent addiction or habit formation as an individual "property" in the narrow sense. Often the estimated relative variance of the latent component tends to decrease when more (observed) regressors are added to the equation. Still, considering that heroin is allegedly a strongly addictive good, this result is striking. Four explanations may, however, be given. First, our sample is rather small (N=48 dealers, N=30 non-dealers) in comparison with the number of regressors, and the estimates of this relative size may be imprecise. Second, the data on both heroin consumption and its specified explanatory variables may contain measurement errors which may lead to (negatively) biased estimates of this relative variance. Third, the habit component is estimated conditionally on a panel data set which only includes heroin addicts in both years; thus, in a sense, we are eliminating some part of the habit formation since most non-addicts tend to continue their careers as non-addicts. Finally, and maybe most importantly, heroin is a heavy drug which is not often subject to strong, continuous use over several years. Therefore, a one-year interval between the two observations may be large in relation to the usual Ahabit cycles≅ for this damaging drug. We might therefore expect that the estimated strength of the habit formation would have been larger if the drug addicts had been observed at, say, a monthly or quarterly interval.

Becker and Murphy=s (1988) theory of rational addiction has received much attention both theoretically and empirically in the last decade. The theory emphasises that even heavy drug addicts are rational in the sense that they are forward-looking utility maximisers who take possible future consequences into account when deciding on the optimal consumption level of the addictive good. Rational models of addiction, as well as Amyopic≅, stress that choices today depend on choices made in the past. AMyopic≅ models, however, frequently view preferences as endogenous whereas the rational addiction model presupposes stable preferences.

Several studies have tested the rational addiction theory for various addictive goods, and as they have obtained a positive estimate for the future consumption variable of the good in question, they have concluded that the theory holds. The results from this study do not offer the same support. The relevant estimates for the lead consumption are positive, as the theory presupposes, but they are very small in terms of absolute value and insignificant. Model D, does not however constitute a satisfactory framework for testing the rational addiction model as the model only incorporate future consumption without taking account of individuals= consumption history. Model C, which includes lagged consumption among the regressors, is more in line with traditional Amyopic≅ models. The estimates obtained here are positive, indicating that heroin is addictive. Grossman and Chaloupka (1998) include estimation results from a myopic version of their model and report that the price elasticities are larger for the myopic version than for the rational.

This study has offered several estimates of addicts consumption response to changes in economic variable. We have aimed at increasing the model=s explanatory power and avoiding possible bias. However, our estimates of the policy relevant price elasticity of heroin vary substantially between the model specifications and estimation methods applied and do not invite to fine-tuned policy measures. Still, it seems safe to conclude from our results that policy measures (e.g. de-criminalization or legalization) which can be expected to lower the full heroin price will tend to substantially increase the heroin users= consumption.

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