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ANNE LINE BRETTEVILLE-JENSEN AND ERIK BIØRN

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Department of Economics

UNIVERSITY OF BERGEN

DRUG INJECTION, DRUG DEALING, AND THE INFLUENCE OF ECONOMIC FACTORS: A TWO-DRUG MICRO-ECONOMETRIC ANALYSIS

by

ANNE LINE BRETTEVILLE-JENSEN[a)] **and ERIK BIØRN**[b)]

Abstract

An important question for policy makers is how drug users may respond to changes in economic factors. Based on a unique data set of almost 2,500 interviews with people attending a needle exchange service in Oslo, this paper aims at estimating the impact of economic factors on heroin and amphetamine injectors' drug consumption. Four econometric models versions are considered. The results include, in addition to estimates of price and income elasticities within switching regression models treating dealing/non-dealing as an endogenous decision, estimates of cross-price elasticities of the two drugs, and an examination of possible 'kinks' in the demand curve of heroin. One dynamic model version specifically aims at examining the issue of addiction. Lastly, we examine, by means of pseudo panel data models, the possible influence of various kinds of unobserved heterogeneity on estimated price and income responses. In many of the models, we obtain negative and significant price elasticities and positive and significant income elasticities, although the size of the estimates vary, depending on the model applied, on the main drug for injecting, and on whether the consumer also is a dealer.

Keywords: heroin, amphetamine, price response, drug dealing, cross-price elasticity
JEL classification: C21, C22, C23, D12

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a) Corresponding author: Norwegian Institute for Alcohol and Drug Research, and University of Bergen, Department of Economics. Address: P.O. Box 565 Sentrum, 0105 Oslo, Norway. E-mail: alb@sirus.no. Phone: +47 22 34 04 33. Fax: +47 22 34 04 01

b) University of Oslo, Department of Economics

1 Introduction

Both in North America and Europe the forces working for decriminalisation and/or legalization of illicit drugs have increased in impact. Some countries in southern Europe have decriminalized the use of cannabis and there is currently an experiment with cannabis decriminalisation going on in London. Canada is discussing the matter and has recently (August 2001) permitted medical use of this drug. In August, a survey published in *USA Today* revealed that the support for legalising cannabis in the US is at an 'all time high' (34 %). Portugal, as the first country in Europe, introduced in July 2001 a new law that removed penal sanctions for possession of small amounts of any kind of drugs. The changing attitudes towards drugs may also be exemplified by the fact that *The Economist*, in July 2001, had a number of articles arguing for legalization of all drugs. Thus, there seems to be a growing trend in most western societies and a discussion concerning relaxing the legal status of narcotic substances is on the political agenda. Among other things, a decriminalisation or legalization will most probably lead to a fall in drug prices. An interesting question therefore is how current and potential drug users will respond to such changes.

Following Becker and Murphy (1988), recent interest in the demand for illicit drugs has focused on inter-temporal aspects of consumption patterns and particularly on the development of an addictive stock and its impact on current consumption. This has tended to overshadow the controversy over the shape of the contemporaneous demand curve and its implications for policy intervention. The effects of the different means governments introduce to curtail consumption will depend heavily on whether the demand curve is vertical (indicating that drug users' demand is unresponsive to changes in drug prices), traditionally downward sloped, or has "kinks" (downward sloped with vertical segments).

It was originally proposed that drug consumption would be totally unaffected by increases in prices (Rottenberg 1968; Koch and Grupp, 1971, 1973). It was subsequently hypothesised that, for various reasons, consumers would be responsive. Bernard (1973) and Holahan (1973), for example, pointed out that illicit drug users could switch to substitute goods, enter treatment or reduce the frequency of their injections and tolerate the withdrawal effects. White and Luksetich (1983) suggested that demand would only be price-responsive at high-prices when the income-generating requirements for regular users would force them into the hands of either treatment or enforcement agencies. Blair and Vogel (1983), on the other hand, suggested that the price-elasticity was located in the low price interval, since decreases in price at low levels would induce occasional or experimental users to participate and increase the consumption of regular users. Combining these different hypotheses and relying on Blair and Vogel's notion of a maintenance dose, Wagstaff and Maynard proposed a "kinked" demand curve (Wagstaff and Maynard 1988), elastic at low and high price intervals but perfectly inelastic in a middle range. In their seminal article on the theory of rational addiction, Becker and Murphy (1988) strongly argue that drug users will respond to changes in prices, and, even more so, in the long run. Thus, the theory of Becker and Murphy goes against a vertical or a "kinked" curve as their contemporaneous demand curve will be a smoothly sloped demand curve for addictive goods.

In spite of the theoretical disagreement and the topic's relevance for the political discussions, such as the legalization debate, there have been relatively few empirical studies of how economic factors affect drug consumption. This dearth of research is primarily caused by lack of data. Occasionally, aggregated data have been employed (Silverman and Spruill 1977 [heroin]; van Ours 1995 [opium]; Liu et al. 1999 [opium]) and a few studies have applied individual consumption data for estimating price elasticities (Nisbet and Vakil 1972 [marijuana]; diNardo 1993 [cocaine]; Grossman and Chaloupka 1998 [cocaine]), Grossman et al. 1998 [cocaine and marijuana], Bretteville-Jensen 1999 [heroin], and Bretteville-Jensen and Biørn 2001 [heroin][1]). Not all the studies estimate income elasticities and only the latter two are based on individual observations on drug prices. There has been no empirical investigation of the proposed shifts in slope of Wagstaff and Maynard's demand curve and there is insufficient empirical basis in the literature to permit direct testing. Wagstaff and Maynard's demand curve has only a hypothetical scale and the arguments put forward to justify the shifts in slope do not directly translate into actual price values.

[1]Bretteville-Jensen and Biørn (2001) is based on a panel data set of 78 heroin injectors re-interviewed one year after the first interview.

The aim of this study is to empirically examine individual market behaviour by employing a unique data set of almost 2,500 interviews of drug injectors currently active on the drug scene in Oslo. Four econometric model versions, with focus on different aspects of the drug use, are specified. We estimate price and income elasticities for heroin and amphetamine as well as cross-price elasticities for the two. Moreover, we examine whether there are "kinks" in the demand curve for heroin. The possible separate impact of addiction on abusers' economic behaviour will also be dealt with, and lastly, by means of pseudo panel data models, the possible influence of various kinds of unobserved heterogeneity on estimated price and income responses are examined.

The article is organized as follows: Section 2 outlines the models and the econometric methods applied and Section 3 gives a description of the data set and the sampling procedure. The results are reported in Section 4 and discussed in the last section, Section 5, which includes some policy implications of the findings.

2 Models and methods

The purpose of this study is to estimate price and income responses for heroin and amphetamine users. A fact which should be reflected in the model, however, is that 46 per cent of the heroin users and 43 per cent of the amphetamine users in our data set report some income from dealing (see Table 1). The fact that drugs are bought at different prices thanks to the possibilities of bulk-buy discounts and other reasons, suggest that dealing/non-dealing decisions and drug consumption decisions should be modeled as interrelated decisions. There are several ways in which this could be done. One approach might be to put the piecewise linear budget constraint following from the existence of bulk discounting into the foreground and pick ideas from the 'econometrics of kinked budget constraints' literature. The latter has been done in analysing effects of tax reforms on labour supply (see, e.g., Burtless and Hausman 1978, and Moffitt 1990). We found, however, that the information on income, prices and consumption expenditures contained in our data set – inter alia, the lack of registrations of non-drug consumption – did not invite including kinked budget sets facing the drug consumers as a part of our formalised econometric models. Another, and far simpler, approach might be to specify separate selection models for dealers and non-dealers and criteria concerning their dealing status.

Rather than doing this, we wanted to formulate a framework which at least paid regard to the following: on the one hand, drug consumers may choose whether or not to become dealers. On the other hand, users who have decided to become dealers have a dual rôle as consumers and suppliers. This probably affects their response to changes in drug prices in a different way than for non-dealers, as any price change may affect own consumption both directly and via their income.

We now describe the four models considered. The first is a switching regression model, focusing on the selection mechanism for dealers and non-dealers. Second, as there are conflicting theories regarding the existence of kinks in the price responses, we reformulate the switching regression model into a model intended to examine whether there are diverging elasticities over different regions of the demand curves. Third, to account for the possible impact of addiction on the demand behaviour we formulate a dynamic model version in which lagged and leaded drug consumption are assumed to affect current consumption of the narcotic good. The data set for this model comprises time series of consumption, prices, etc., aggregated across individuals. Fourth, in order to specifically examine how various kinds of unobserved heterogeneity may affect the estimated price and income responses, pseudo panel data models have been constructed from the basic non-overlapping cross section data. We here pool the respondents according to their cohort, age, and observation year or quarter, respectively.

A switching regression model

Our first model is a switching regression model (SRM) containing an auxiliary equation for the dealing/non-dealing status and drug consumption equations for dealers and non-dealers, with normally distributed and correlated disturbances.

The auxiliary equation for the dealing decision of individual i is written as

$$Z_i^* = a_i + \gamma Y_i + e_i, \tag{1}$$

where Z_i^* is a latent variable, a_i is an intercept (which may be individual specific), Y_i is a vector of observable exogenous variables influencing the decision to deal, γ is a vector of coefficients, and e_i is a random error with zero mean and a scaled variance set to 1. We may interpret Z_i^* as the utility of becoming a dealer, as determined by Y_i. It is unobservable, but when its value exceeds a certain (unknown) threshold, ψ, the individual decides to deal. The corresponding observable variable, Z_i, is dichotomous and takes the value 1 if the consumer deals and 0 if it is a non-dealing person. The equation for drug demand is the following

$$C_i = \begin{cases} \alpha_{1i} + \beta_1 X_{1i} + u_{1i} & \text{iff} \quad Z_i^* > \psi, \\ \alpha_{2i} + \beta_2 X_{2i} + u_{2i} & \text{iff} \quad Z_i^* \leq \psi, \end{cases} \tag{2}$$

where C_i is the observed consumption of the drug, measured in logarithms, α_{1i} and α_{2i} are intercepts (which may also be individual specific), X_{1i} and X_{2i} are the vectors of independent variables for dealers and non-dealers, respectively, β_1 and β_2 are vectors of coefficients, and u_{1i} and u_{2i} are random errors with zero mean and variances σ_1^2 and σ_2^2. The covariance between u_{1i} and u_{2i} is set to zero, since the strict separation in the model implies that one 'regime' (dealer or non-dealer) is observed for each respondent. The two other covariances provide information about the nature of selectivity in each group. The vectors Y_i, X_{1i} and X_{2i} may have common elements. The error terms (u_{1i}, u_{2i}, e_i) are assumed to be independent across individuals and independent of (X_{1i}, X_{2i}, Y_i) and follow a trivariate normal distribution with zero means and covariance matrix

$$\begin{bmatrix} \sigma_1^2 & 0 & \rho_{1e}\sigma_1 \\ 0 & \sigma_2^2 & \rho_{2e}\sigma_2 \\ \rho_{1e}\sigma_1 & \rho_{2e}\sigma_2 & 1 \end{bmatrix},$$

where ρ_{1e} and ρ_{2e} are the correlation coefficients between u_{1i} and e_i and between u_{2i} and e_i, respectively. The possibility that e_i may be correlated with u_{1i} and u_{2i} is an essential argument for estimating (1) and (2) jointly.

It follows from (1) and (2) that (we here and in the following do not indicate conditioning with respect to (X_{1i}, Y_i) and (X_{2i}, Y_i))

$$E(C_i | Z_i^* > \psi) = \alpha_{1i} + \beta_1 X_{1i} + E(u_{1i} | e_i > \psi - a_i - \gamma Y_i),$$
$$E(C_i | Z_i^* \leq \psi) = \alpha_{2i} + \beta_2 X_{2i} + E(u_{2i} | e_i \leq \psi - a_i - \gamma Y_i).$$

Since (u_{1i}, e_i) and (u_{2i}, e_i) both follow binormal distributions marginally, the expected drug consumption given that the individual is a dealer and non-dealer, respectively, can be expressed as

$$E(C_i|Z_i = 1) = E(C_i|Z_i^* > \psi) = \alpha_{1i} + \beta_1 X_{1i} + \rho_{1e}\sigma_1\lambda_{1i}, \tag{3}$$

$$E(C_i|Z_i = 0) = E(C_i|Z_i^* \leq \psi) = \alpha_{2i} + \beta_2 X_{2i} + \rho_{2e}\sigma_2\lambda_{2i}, \tag{4}$$

where

$$\begin{aligned} \lambda_{1i} &= \frac{\phi(\psi - a_i - \gamma Y_i)}{1 - \Phi(\psi - a_i - \gamma Y_i)} = \frac{\phi(a_i + \gamma Y_i - \psi)}{\Phi(a_i + \gamma Y_i - \psi)}, \\ \lambda_{2i} &= -\frac{\phi(\psi - a_i - \gamma Y_i)}{\Phi(\psi - a_i - \gamma Y_i)} = -\frac{\phi(a_i + \gamma Y_i - \psi)}{1 - \Phi(a_i + \gamma Y_i - \psi)}, \end{aligned} \tag{5}$$

ϕ and Φ denoting the density function and the cumulative distribution function, respectively, of the standardised normal distribution, see, e.g., Gourieroux (2000, Appendix 7.2). Eqs. (3) – (5) clearly show why estimating β_1 and β_2 by regressing C_i on X_{1i} from the observations of dealers and regressing C_i on X_{2i} from the observations of non-dealers, separately, will give biased estimates when ρ_{1e} and ρ_{2e} are non-zero. We will then neglect that $E(C_i|Z_i = 1)$ and $E(C_i|Z_i = 0)$ depend on Y_i due to the selection mechanism.

The model is estimated by a stepwise procedure, using the Limdep 7 software (see, Greene, 1995, chapter 28.6). The values of the inverse Mills ratios λ_{1i} and λ_{2i}, given by (5), are computed as regressors in a first step probit estimation and inserted as regressors in the second step, with corresponding coefficients $\rho_{1e}\sigma_1$ and $\rho_{2e}\sigma_2$.

A spline function model

The second model is specifically constructed to investigate different forms of the relationship between drug prices and consumption by using a spline function (see Greene, 2000, section 8.2.6) in the SRM framework. This function reflects possible changes in the elasticity of different segments of the demand curve depending on the level of price. Since the literature offers no indication of the knot points of the price at which the slopes may change, changes in elasticity were tested for prices below the first quartile, the median, and third quartile, separately (assuming only one kink on the demand curve) and in both the bottom quartile and upper quartile jointly (two-kinks hypothesis). The spline functions used were versions of the following function, with appropriate zero restrictions on the μ coefficients:

$$(6) \qquad C_{ki} = \alpha_k + \beta_k P_{ki} + \mu_{1k}[D_{1k}(P_{ki} - P^*_{1k})] + \mu_{2k}[D_{2k}(P_{ki} - P^*_{2k})] + \mu_{3k}[D_{3k}(P_{ki} - P^*_{3k})] + \delta_k X_{ki} + \epsilon_{ki}, \qquad k = 1, 2,$$

where again i denotes individual, $k = 1$ and $k = 2$ denote dealer and non-dealer, respectively, C_{ki} is consumption, P_{ki} is the unit price of the drug, P^*_{ki} is the price of the drug at the j'th quartile ($j = 1, 2, 3$), X_{ki} is a vector of exogenous variables for dealers' and non-dealers' consumption, $D_{1k} = 1$ for $P_{ki} \geq P^*_{1k}$ and zero otherwise, $D_{2k} = 1$ for $P_{ki} \geq P^*_{2k}$ and zero otherwise, $D_{3k} = 1$ for $P_{ki} \geq P^*_{3k}$ and zero otherwise, and ϵ_{ki} is an error term. The price elasticity will then be β_k up to the first quartile, $\beta_k + \mu_{1k}$ between the first quartile and the median, $\beta_k + \mu_{1k} + \mu_{2k}$ between the median and the third quartile, and $\beta_k + \mu_{1k} + \mu_{2k} + \mu_{3k}$ above the third quartile.

The spline function (6) is combined with a SRM mechanism as in the previous model. It is only applied for heroin consumption as the number of observations was deemed too small to apply the model on amphetamine users.

A dynamic model applied to quarterly means

Third, as recent interest in demand for illicit drugs has focused on inter-temporal aspects, we wanted to take advantage of the fact that our data set of heroin consumption is collected over a period of 28 quarters (December 1993 to September 2000). By constructing averages of consumption, prices and income for dealers and non-dealers interviewed in each quarterly interview session we have obtained time series for the relevant variables, although not for the same individuals, since the basic data are non-overlapping cross sections. According to Becker and Murphy (1988), current heroin consumption (C_t) will be influenced by past (C_{t-1}) and future (C_{t+1}) consumption in addition to current heroin price (p_{Ht}), and other factors. We have also included income (I_t) and the amphetamine price (p_{At}). The theory presupposes that the higher the previous and future consumption of the addictive good is, the higher current consumption. The functional form in Becker and Murphy's model is, however, different from the one used here. Assuming that the underlying instantaneous utility function is quadratic, they use a linear demand function, whereas our demand function is log-linear.

This function, estimated for dealers and non-dealers separately, is

$$\sqrt{n_t}\bar{C}_t = \alpha\sqrt{n_t} + \beta_H\sqrt{n_t}\bar{p}_{Ht} + \beta_A\sqrt{n_t}\bar{p}_{At} + \beta_I\sqrt{n_t}\bar{I}_t + \gamma_{-1}\sqrt{n_t}\bar{C}_{t-1} + \gamma_{+1}\sqrt{n_t}\bar{C}_{t+1} + u_t, \tag{7}$$

where t denotes the quarter and the bars indicate quarter specific means. The weighting by the square root of the number of observations underlying each mean, $\sqrt{n_t}$, adjusts for disturbance heteroskedasticity, since we assume that the origin of (7) is an equation for a single consumer, so that u_t can be expected to be homoskedastic. We estimate (7) by a two-stage least squares (2SLS) method because past and future consumption may be correlated with the error term via the multiperiod optimization and because the unobserved variables that affect utility in each quarter are likely to be serially correlated, so that OLS would be biased. Instead we instrument $\bar{C}_{t-1}$ and $\bar{C}_{t+1}$ by using the predicted values obtained in a first step by regressing these two variables on income and drug prices in the corresponding quarters as instruments. The effective number of quarters in the estimation is thus 26.

Pseudo panel data models with heterogeneity

Our fourth model specifically focuses on the hypothesis that unobserved heterogeneity in preferences and experiences across the individuals may affect the consumption pattern for drugs. This issue may be analyzed at the individual level from genuine panel data; see Bretteville-Jensen and Biørn (2001) for a discussion of an empirical study based on a two-wave panel. However, heterogeneity may also be attached to other properties of the respondents. For instance, respondents belonging to the same cohort or having the same age may share the same experiences. There may also be unobserved heterogeneity associated with the period of observation.

In order to examine such effects and their potential impact on the estimated price and income responses, we have constructed from our data set of non-overlapping cross sections, four model versions in which all individuals (i) belonging to the same cohort (year of birth), (ii) having the same age (in the observation period), (iii) having been observed in the same year, and (iv) having been observed in the same quarter, respectively, are treated as 'similar'. We then proceed as if all realizations of the individuals of, say, the same cohort, cf. (i), are 'replications' of observations of one typical individual of that cohort. The number of such 'pseudo individuals' is thus the number of cohorts occurring in the data set, and the unobserved heterogeneity, whether represented as fixed effects or as random effects, is cohort specific. We do not, however, aggregate the individual observations up to the cohort level to get one set of time series for each cohort, as is commonly done in the 'pseudo panel data' literature (see, e.g., Verbeek 1996), since this data reduction would have reduced the variability of the data. We proceed in a similar way for (ii) – (iv). We then, formally, get four different unbalanced panel data sets. These four model versions are only estimated for heroin, by using the OLS and GLS routines for unbalanced panel data in the Limdep 7 software. In this model, the switching regression mechanism is omitted, and replaced by a dummy variable for the dealing status.

3 Data

The data set applied in this study was obtained in interviews which took place near the needle exchange service located at the centre of Oslo. The interviews were conducted from June 1993 to September 2000. The sessions were first held on a monthly basis, then quarterly from June 1994. A total of 3,039 questionnaires were completed. There were two to four interviewers working the 2-3 evening/nights of every data collecting session and people were approached after they had used the needle exchange service. As many as possible were asked to participate but asking everyone was not possible as they often came, and left, in groups. The interviews were anonymous, and it was not possible, therefore, to register the interviewees to help recognise them from one interview session to the next. Some individuals will have been interviewed more than once, but precautions were taken to prevent it from happening within the same interview session. The mean age for the whole sample was 31.6 years (29.6 for females and 32.5 for males). The youngest person to be interviewed was 16 years old, and the oldest 59. Females constituted 32 per cent of the sample.

The illegal nature of drug market participation implies that representativeness in data collection is difficult to ensure. The representativeness of the current sample can be discussed in two stages: First, whether the drug users attending the needle exchange service are representative of all drug injectors in the area; secondly, whether the individuals included in the sample are representative of the attendees.

Attendees versus the population of drug injectors in Oslo

The number of drug injectors in the Oslo area has increased in the nineties and is now estimated to be 4-5,000 people (Bretteville-Jensen and Ødegård 1999). The needle exchange service is the only of its kind in Oslo, and the number of visits has increased steadily since it opened in 1988. In 1993, the first year of data collecting, 48,600 visits were paid and 626,800 syringes were handed out. Seven years later, the corresponding numbers were 116,400 visits and 1.87 million syringes. Syringes may also be obtained, for a small fee, from pharmacies, and their share of the total number of syringes delivered to drug injectors seems to have decreased in the nineties (Annual Report 1997). Thus, the high number of visits and syringes handed out by the service indicates that a large proportion of the drug injectors in the Oslo area uses the service.

On individual visits only the visitor's gender and the requested number of syringes are registered by the service. The registered sex characteristics agree, however, well with other studies of the injecting population (Lauritzen et al. 1998; Skog 1990). In 1994, 1997, and 2000 the service asked every visitor in a certain week to participate in a survey and nearly all agreed to do so. The studies revealed that there are relatively few very young people (under the age of 20) visiting the service, which may suggest that the younger age group is under-represented. It may be that young people tend to get their needles through older friends or buy them at pharmacies, etc.

Respondents in the sample versus all attendees

Whether the current sample is representative of all attendees can be examined by comparing mean variables in this study with the three studies conducted by the needle exchange service. Comparisons of age, gender and age at first injection revealed no significant differences in the latter two variables between this study and the service's three surveys. The mean age of participants, however, was slightly higher in the service's studies (32.27 versus 31.24 years).

Persons with a deep-seated injection habit will be likely to attend the service more often than infrequent users, and an over-representation of the former is probable. However, frequent reasons for refusal to participate in the interview were that individuals had customers waiting or that withdrawal pains were bothering them. Therefore, heavier users at the needle-exchange may have been more likely to refuse to participate and over-representation may not be a problem.

All things considered, we regard the current sample as fairly representative of injectors in the Oslo area.

Contents of the questionnaire

Interviewees were asked detailed questions about their levels and sources of monthly income, levels of drug consumption, and the prices they had paid for the different types and quantities of drugs. Initially, concerns regarding the response rate in these outdoor interviews curtailed the feasible length of the questionnaire and only a few socio-economic variables (gender and age) were included. After some time, however, we decided to add questions like age at first injection, education, the number of occasions and total length of drug-free periods, housing conditions, experience with non-fatal overdoses etc. to the questionnaire.

Income: Respondents were asked about their revenues from six possible income sources: work, state benefit, theft, sale of drugs, prostitution, and "other" sources. The exercise was dealt with in two stages: individuals were asked to rank the six possible sources of income in terms of their contribution to total income; they were then asked to estimate the amount earned from each source. Besides social benefit, dealing and prostitution were the most frequently reported income sources for men and women, respectively.

Information on income was problematic to obtain. Most interviewees responded to the ranking exercise, but some refrained from giving an estimate of their monthly revenue from the different sources. To avoid possible biases due to this non-response, an imputation of the missing values has been undertaken. For example, an individual who reported drug dealing to be the second most important income source could be assumed to have raised the average amount reported by others who ranked dealing second. The imputation assigned an income value to 44 heroin users and 14 amphetamine users who only had responded to the ranking exercise. In addition, it increased monthly income for some who had not completed the amount of income question for all income sources they had ranked. The interpolation slightly raised the sample's average income (from NOK 38,000 to NOK 44,000 [US$ 4,900]).

Consumption: For heroin users, a combination of three variables was used to estimate monthly consumption: quantity of drugs in last injection; number of injections on previous day; number of injecting-days in previous month. The wide variation in the amount-per-injection was only recognised after some time into the interview period and an additional question was then included in the questionnaire. For amphetamine users, only the number of injections set during the previous day times the number of injecting-days in the previous month were used to sum up monthly consumption, as the variation in dosage per injection is assumed to be small and amount to roughly 1/4 of a gram. Both for heroin and amphetamine users the dealers reported to consume more of the injecting drug than their non-dealing counterparts (Table 1).

Most respondents also reported an extensive use of other intoxicants. The number of using days in the month leading up to the interview was available for alcohol and cannabis. We have constructed a dummy variable for each which is set to unity in cases of 20 or more using days since we assume that this consumption frequency is needed in order to classify a potential substitute or complementary good to heroin or amphetamine, respectively. For pills, we only have information on whether they were consumed or not in the previous month and the corresponding dummy variable is set to unity if the respondent reported consumption.

Prices: Price data were obtained by asking the respondents what they would have to pay for different types and quantities of drugs. Dealers were asked how much they had paid for the last quantity of drugs they bought (at least partially) for dealing. The number of units into which a gram of heroin was "cut", declined over the period and we have taken account of this trend in calculating equivalent unit prices for those who buy in grams. Both the heroin price and the amphetamine price decreased throughout the observation period. For heroin users not reporting any amphetamine price, we constructed a variable by assigning to each dealer and non-dealer the average price reported by amphetamine dealers and non-dealers in the corresponding interview session. The same procedure was followed for amphetamine users not reporting any heroin price.

The market purity of drugs could be an important determinant of the price-responsiveness of consumption, and trends in market prices should ideally have been presented in quality-adjusted terms to reflect the potentially important effects of purity changes on behaviour. Police seizures indicate large variation in heroin purity at the wholesale level and somewhat more stability at the retail level. The same is true for amphetamine. However, the purity is often unknown to the buyer at the time of purchase so quality-adjusted prices may not be very useful after all. In any case, it was not possible to collect any purity data for these drugs.

Independent variables used in regression analysis

Effectively, total income constructed as described above is assumed to be exogenous in relation to drug consumption in the econometric analyses. This characterisation conflicts with US studies of the role of heroin consumption in influencing the level of crime (one of the frequently cited sources of income used by drug-users) at the aggregate level (Benson et al. 1992). However, European, individual-level studies of income-generating activities and patterns of drug consumption have concluded that the 'causality chain' is basically that available resources influence the amount of drugs purchased and consumed, not that the causality link is the opposite: "The level of consumption of illegal drugs depends on the amount of money earned. In this sense junkies might be said to have a 'money' habit, or an 'activities' habit, rather than an 'unlimited' need for cocaine or heroin, or an unlimited willingness to do 'anything' to get it. There is little support in this study for the widespread notion that every junkie must steal to obtain his invariable daily dose of drugs" (Grapendaal, Leuw and Nelen 1993, p. 158).

To avoid the problem that income may be a possibly endogenous regressor, 'income' could have been instrumented. Unfortunately, the present data set is sparse and no single variable or set of variables emerge as an appropriate instrument. A simpler, but less satisfactory approach, has been to run estimations with and without the income variable and examine whether the size of the estimates for the other variables varies between the models. The other independent variables did not show substantial variation between the sets of estimates indicating that the income variable could well be exogenous. Income from dealing is treated as any other income even though, by applying the switching regression model, we take into account that dealing status is assumed to directly influence the consumption behaviour.

The assumption that income is exogenous may have influenced the estimates of the price elasticities. If the addicts respond to changes in prices by adjusting not only their consumption, but also their income, the estimated price elasticities will be biased upwards provided that the income elasiticity is positive. Estimates of the average income reported by dealers and non-dealers show that while dealers' income has fallen nominally by almost 20 per cent during the period 1993 – 2000, the income of non-dealers has been fairly stable when taking the period's rise in the consumer price level (15 per cent) into account. Even though other factors than price changes may have influenced the addicts' income level during the observation period, this could indicate that the estimate of dealers' price elasticity may be slightly more biased than the estimate obtained for non-dealers.

Drug prices are also treated as exogenous variables in the estimation. There are, however, substantial bulk-buy discounts available in the market for illegal drugs in Oslo. Bulk-buy discounts may imply that prices no longer are strictly exogenous as the consumer can 'choose' the price they pay for the good by varying the amount purchased. Bulk-buy discounts in the Norwegian drug market relate especially to heroin and are more pronounced for quantities in the lower segment, i.e. there is relatively more to save per unit when increasing the amount of drugs bought from the smallest unit (0.1 gram) to a one-gram buy than there is to save when increasing the purchased quantity from 1 gram to 5 grams or to 10 grams of heroin. We assume that all drug dealers are buying in gram units (from one gram and upwards). Among non-dealers, on the other hand, there is one group that usually buys the smallest quantity available in the market and another group buying both in small units and in grams. Thus, large bulk-buy discounts may be most problematic for estimation of price elasticities in the latter group. In the appendix we attempt to formalize this and examine the potential asymptotic bias in the OLS estimates of the price elasticity when the drug price is treated as if it were exogenous for both dealers and non-dealers. We find that the bias may go in both directions.

As the physiological impact of heroin and amphetamine is very distinct, we assumed that the groups reporting to mainly inject one of them would differ too. The differences were tested for by applying a non-parametric Mann-Whitney test (5 per cent significance level) (Siegel and Castellan 1988, p. 128). Table 1 illustrates these differences.

(Table 1 about here)

The share of males is higher among amphetamine users than we found in the heroin using group. Amphetamine users are also on average older, have a slightly longer education, and have started to inject somewhat later than the heroin injectors. More people in the amphetamine group drink alcohol, smoke cannabis, and use ecstasy and they have more using-days per month of these substances. Heroin injectors, on the other hand, report to consume cocaine and tablets more frequently than their amphetamine using counterparts. As expected, average income is higher for the heroin injectors and the relative importance of the various income sources differs between the two groups of injectors. Heroin injectors more often report income from theft, prostitution, and social security whereas amphetamine users more often obtain money from ordinary work. Dealing and 'other sources' are equally common for the two groups.

The final sample

Out of the total of 3,039 completed questionnaires 2,595 reported to mainly inject heroin and 299 to mainly inject amphetamine. The remaining group of 145 consisted of respondents who injected both drugs equally frequently, mainly injected other drugs (morphine, methadone, etc.), or who did not respond to this particular question. As already mentioned, some of the heroin injectors were not asked the more detailed question regarding the amount per injection and they were left out of the final sample (278). Some questionnaires were excluded due to missing observation of age, gender, ranking of income sources, or of prices of the drug they injected. The final samples for heroin and amphetamine injectors consist of 2,240 and 241 observations, respectively.

4 Results

The estimation of the probit equation corresponding to (1) for heroin injectors, given in the first column of Table 2, reveals that the probability of becoming a dealer is significantly influenced by age, type of additional income sources and the consumption of other drugs. Alcohol consumption makes a person less likely to deal, whereas cannabis consumption does the opposite. Males and persons in the middle age-range are more often dealers than females and very young or very old heroin users. ‘Number of newcomers’, a market indicator based on the number of persons registered for drug offences for the first time by the police, is not significant. Throughout, the significance level is set to 5 per cent.

(Table 2 about here)

Results from the switching regression equations (2) are reported in columns 2 and 3 of Table 2. The heroin consumption, heroin and amphetamine prices, and the income variables are in log-form. In agreement with previous results (Silverman and Spruill 1977, Bretteville-Jensen 1999), the price elasticity for heroin is negative and significant for both dealers and non-dealers, indicating that heroin consumption would increase substantially if the price of the drug decreased. Non-dealers are estimated to be more price responsive than dealers, with elasticities -1.20 and -0.61 respectively. The cross-price elasticity of the two injecting goods has not, to the authors’ knowledge, been previously estimated. Our results suggest that an increase in the price of amphetamine will have the opposite impact on the two groups of heroin users: dealers will reduce their heroin consumption, whereas non-dealers’ consumption will increase. The income elasticity estimates for the two groups do not differ significantly and is about 0.5.

Male dealers and male non-dealers are estimated to consume less heroin than their female counterparts. Age has a significant effect only on non-dealers’ consumption. The more dealers consume of other drugs (alcohol, cannabis and tablets), the less they tend to consume of heroin. Only the coefficient for alcohol, however, comes out significantly. Non-dealers, on the other hand, obtain significant coefficients for all three variables representing other drugs. Cannabis and pills appear to be complementary goods, whereas alcohol seems to be an alternative good to heroin. The variable ‘year’ was included to account for the fact that the data set had been collected over a seven year period, but its coefficient did not come out significantly.

The bottom parts of columns 2 and 3 contain results based on a sub-sample of respondents that had been asked more socio-economic questions than the other respondents

($n = 1311$). Both for dealers and non-dealers the results indicate that the longer a person has been a misuser the higher is his/her current heroin consumption, although the estimate is not significant. Education has a significantly negative effect on non-dealers' consumption whereas the response has the opposite sign for dealers. The age-of-injection-debut variable does not come out significantly. For both groups, however, the results suggest that the lower the debut age the higher is consumption of heroin at the time of interview. A similar relationship is found in studies of debut age and later consumption of alcohol (see e.g. Pedersen and Skrondal 1998).

For comparison, Table 2 also includes the corresponding estimates for dealers and non-dealers resulting from ordinary least squares (OLS) estimation. More variables, especially in dealers' consumption equation, obtain significant estimates with the OLS approach. As expected, only the coefficient estimates of variables appearing both in the probit and the two consumption equations of the switching regression model (SRM), show some discrepancy, although small, between this model and the estimates obtained by the OLS approach. The price and income elasticities, only appearing in the consumption equations of the SRM, are almost identical for the two approaches. Thus, the results seem robust. At the bottom of the table are given the estimated coefficients of the 'selection variables' λ_{i1} and λ_{i2}. The former is positive, although not significant, and the latter is significantly negative, which indicates [cf. eqs. (1) – (4)] that in the auxiliary equation determining the 'utility' of becoming a heroin dealer, the disturbance e_i is positively correlated with the disturbance in the heroin demand equation for dealers, u_{1i}, and is negatively correlated with the disturbance in the heroin demand equation for non-dealers, u_{2i}.

The results reported in Table 3 are based on information given by amphetamine injectors. Columns 1 – 3 are based on the SRM whereas column 4 and 5 contain standard OLS estimates. Compared with Table 2 there are fewer significant results, which may partly be explained by the much lower number of observations of the latter group (2,240 heroin injectors versus 241 amphetamine injectors). Also, due to the relatively low number of observations, fewer regressors have been included in the model.

(Table 3 about here)

The probit equation for amphetamine injectors indicates that males and persons in the middle age-range are more likely to become dealers and so are tablet users. Alcohol and cannabis use and other income sources like work, prostitution, and theft are negatively associated with dealing activity. Only the variables for work and alcohol and tablet use are significant however.

Both for amphetamine dealers and non-dealers the estimated price coefficient for the main injecting drug had the expected negative sign and also the cross-price elasticities were negative. Amphetamine dealers seem to be more price responsive than their non-dealing counterparts. Both groups of amphetamine users obtained positive and significant income elasticities, smaller, however, than those obtained for heroin injectors. Dealers were again more responsive to changes in economic factors than non-dealers. Gender appears to not be important for dealers' consumption as its coefficient is low and insignificant. Among non-dealers, however, and in line with the results for the heroin injectors, the estimates suggest that females consume more of the injecting drug than males. For both groups the results indicate that the higher consumption of alcohol and cannabis the lower is the consumption of amphetamine, although only the coefficient for non-dealers' alcohol consumption is significant. Consumption of pills, on the other hand, seems to be complementary to amphetamine as the coefficients for both dealers and non-dealers are positive.

The last two columns of Table 3 show the standard OLS estimates for amphetamine consumption. As only gender and age appear both in the probit and the two consumption equations in the SRM, it is these variables we would expect to differ when applying standard OLS; cf. the discussion of eqs. (3) – (5) in Section 2. As shown in Table 3, non-dealers estimates of these variables seem robust whereas dealers' estimates differ to a larger extent. That is also the case for the estimated own and cross price elasticities. The estimates for the income elasticities, however, do not vary substantially between the methods applied for either of the groups. Again, at the bottom of the table are given the estimated coefficients of the 'selection variables' λ_{i1} and λ_{i2}. The former is positive, and the latter is negative (both significant), which indicates that for amphetamine users, the disturbance in the 'utility of dealing equation', e_i, is positively correlated with the amphetamine demand disturbance for dealers, u_{1i}, and negatively correlated with the demand disturbance for dealers, u_{2i}. These sign conclusions are the same as for heroin.

The results from the spline function analysis of changes in the slope of the demand curve are summarised in Table 4. Each column of the table contains the price coefficients estimated in a switching regression model using five different price-response models. These models were described in Section 2 and relate to the following predicted shapes of the demand curve:

(i) no kinks in the demand curve, which is represented by a log-linear relationship between heroin consumption and price (similar to the model applied for Table 2);

(ii) significant difference between price-responsiveness above and below the lower quartile price;

(iii) significant difference between price-responsiveness above and below the median price;

(iv) significant difference between price-responsiveness above and below the upper quartile price;

(v) significant differences in price-responsiveness between the three sections of the curve relating to the regions below the lower quartile price, between the lower and upper quartile prices, and above the upper quartile price.

Assuming the lower and upper quartiles are the appropriate places for the 'kinks', the Wagstaff and Maynard hypothesis is a special case of model (v) in which price-responsiveness is greater in the upper and lower segments, and consumption is perfectly price-inelastic in the middle segment.

(Table 4 about here)

The estimates give no support to the Wagstaff-Maynard hypothesis. On the contrary, Table 4 shows that both dealers and non-dealers appear to be increasingly responsive with increasing heroin prices. There is no inelastic middle segment. For prices at and above the median price, dealers seem to respond even more to price changes than non-dealers, and dealers' elasticities in the different segments of the demand curve vary to larger extent. For both groups the income elasticity remains stable across the models whereas the cross-price elasticity fluctuates somewhat.

Table 5 reports the results for dealers and non-dealers of heroin employing the time series data on equation (7). Applying an OLS model here would have caused biased coefficients due to serial correlation in the data. Thus, separate ARIMA models were applied for the two groups of heroin users.

(Table 5 about here)

Again we find significant and negative price elasticities for heroin and again heroin dealers appear to be less price responsive than their non-dealing counterparts. The price coefficient for non-dealers has about the same size as the corresponding estimate in the switching regression model, whereas dealers' coefficient is slightly higher. The cross-price elasticities paint the same picture as the results in Table 2. According to the findings, amphetamine is a substitute for dealers and a complementary good for non-dealers. Dealers' income elasticity differs more from previous results than the results for non-dealers and, in contrast to the non-dealers' result, is insignificant at a 5 per cent level. However, the coefficients for both groups have the expected positive sign.

The coefficients of the lagged variables, on the other hand, did not have the expected signs. According to the theory of Becker and Murphy (1988) these coefficients were expected to be positive, indicating that current consumption is positively correlated with previous consumption of the addictive good. Only the estimate for non-dealers is significant, however. The estimates of the coefficients of the leaded consumption, indicating whether the consumers are rational addicts, according to Becker and Murphy, obtained the expected positive signs, although insignificant. In addition, the estimated size of dealers' leaded consumption was very low.

Tables 6A and 6B give the result of the pseudo panel analysis for (the log of) heroin consumption, described in Section 2. As regressors the models include, in addition to the logs of the income and the heroin price, dummies for male, dealer, alcohol consumption, and cannabis consumption, as well as (i) age and its square in the equation modelling cohort specific, year specific, and quarter specific heterogeneity, and (ii) cohort (birth year) in the equations modelling age-specific heterogeneity. We do not include the observation year in any of the regressions, as year is the sum of cohort and age and heterogeneity across years is one of the 'dimensions' we are investigating. The heterogeneity is modelled both as fixed effects and, more restrictively, as random effects (with zero expectations and constant variance), and the former is estimated by OLS, the latter by GLS, since random effects imply a non-scalar disturbance covariance matrix. For the sake of comparison, OLS estimates with no heterogeneity assumed are also included (columns 1 and 2 of Table 6A, column 1 of Table 6B). The random effects specifications are tested against the fixed effects specification by means of a Hausman test (see, for example, Baltagi 2001, section 4.3) and in no case is it rejected, all p values exceeding 0.75.

(Table 6 about here)

Somewhat surprisingly, we do not find evidence of cohort-specific heterogeneity. Testing for fixed and random heterogeneity gives a p value of 0.93 (F-test) and 0.11 (LM-test), respectively (bottom of Table 6A). The ρ value, which is the estimated ratio between the variance of the random effect and the sum of the variances of the random effect and the genuine disturbance, is as low as 0.017. There is thus little reason to pool all respondents born in the same year into one group and consider their observations as originating from one 'pseudo individual', even if they, to some extent, share the same experiences. On the other hand, there is evidence of age-specific and year-specific heterogeneity. The ρ values are 0.12 and 0.07, respectively, and the p values are 0.02 and 0.001 for fixed effects and 0.23 and 0.000 for random effects, respectively.

Overall, the coefficient estimates are very insensitive to the way in which heterogeneity is modelled. The income elasticity estimate is 0.51 with standard error estimates of about 0.03 in all alternatives. The estimates of the price elasticity vary between -1.05 and -0.99, with standard error estimates in the range 0.05-0.07. These estimates agree well with those in Table 2; hence we can conclude that these results are robust. The coefficient estimates of the male, dealer, and alcohol dummies are also very insensitive to how heterogeneity is modelled, and all estimates are significant at the 5 per cent level. The coefficient estimate of the age variables are almost the same when heterogeneity is attached to cohort as when it is attached to observation year or quarter, about 0.09-0.11 for the linear term and about -0.0013 for the square term (both significant), indicating that the heroin consumption attains its maximum at an age of approximately 38 years. The cohort variable and the cannabis dummy are insignificant, however.

5 Discussion

Drug taking is influenced by accessibility in a broad sense. Cultural, economical, physical, as well as legal accessibility will affect the amounts and the types of drugs consumed in society. Moreover, these factors are interrelated. A legalization will, for instance, lead to a fall in drug prices. A simultaneous introduction of drug taxation will probably not capture the profit gained by today's dealers - otherwise, the black market would re-emerge. Thus, a change in the legal status of currently illegal drugs will also change economic accessibility for drug users. In addition, such a change may affect physical accessibility, as well as, in a longer perspective, cultural accessibility.

People's attitudes towards drugs have changed over time. The "War on Drugs" does not receive as strong support as it did in the eighties. Both in North America and Europe the forces working for decriminalisation and/or legalization have multiplied. This trend influences the political agenda and the matter is being discussed in most Western societies. An important question for policy makers will be how current and potential drug users may respond to possible changes in prices.

Based on almost 2,500 interviews with people attending a needle exchange service in Oslo during a seven-year period we have been able to estimate price and income elasticities for heroin and amphetamine injectors separately. Empirical analyses regarding the impact of economic factors on illicit drug consumption based on data directly collected from the consumers are rare and, to our knowledge, we are the first ones to obtain and analyse economic data also for amphetamine users. Unlike some of the theoretical contributions mentioned in the introduction, our results suggest that people who use hard drugs extensively will respond according to standard economic theory to changes in prices and income. Across a wide range of models we obtained negative and significant price elasticities and positive and significant income elasticities. The size of the elasticities vary depending on the model applied, on whether the main drug for injection is heroin or amphetamine, and on whether the consumer also is a drug dealer. The models have given quite different estimates for dealers and non-dealers indicating that the separation of the two was a correct decision. The effect of self-selection to the groups seems to be smaller, however, as the SRM estimates and the OLS estimates do not vary for topical variables.

Heroin users seem to have a higher price elasticity than amphetamine users, which could be taken as evidence that amphetamine users are more addicted to the drug they inject. In the literature, however, heroin is described as causing more 'craving' and physical withdrawal pains. Also, heroin users in the present data set report a higher frequency of injections, with more injecting days per month and more injections per using day, than amphetamine users do. Amphetamine users, on the other hand, report a more extensive use of other intoxicants like alcohol, cannabis, ecstasy and LSD. An interpretation of the more intensive use of other intoxicants could be that amphetamine users have a larger set of substitutes than do heroin injectors. The higher use of tablets by heroin injectors can probably be explained by the fact that many of them use tablets containing flunitrazepam to increase the effect of heroin. Thus, the finding of heroin injectors being more price responsive than the amphetamine injectors is somewhat surprising.

The prices of heroin and amphetamine have declined throughout the period of data collecting. Would the elasticity estimates from the present data set have differed if prices instead had increased, i.e. are there asymmetric price responses in the market for injecting drugs? If the drug user experiences both heavy physical and psychological dependence he may have problems reducing consumption in response to a prices increase. Pekurinen (1989), applying a model by Young (1983) and using data for cigarette consumption in Finland, found that the response to falling prices was twice as large as the response to rising prices (-0.94 versus -0.49, respectively).

Due to most individuals' resistance against changing habits, a tendency of asymmetry in responses may, to some extent, be found for most goods, even though it is more likely for addictive goods like cigarettes and heroin. The exact impact, however, is difficult to assess. The physical tolerance that heroin users build up by consuming the drug (causing the addict to consume increasingly larger amounts to get 'high'), is rapidly weakened when consumption is terminated. After only three weeks it is almost gone completely. Follow-up studies of Norwegian heroin injectors have shown that drug users have frequent breaks from daily injecting routines. Heroin injectors are often in custody, in in-patient treatment or detoxification centres, or in a situation in which they, due to financial or health problems, must desist from drug injecting (Bretteville-Jensen and Biørn 2001). The physical tolerance, and also withdrawal pains, may be smaller for heroin addicts than is commonly assumed. Still, the estimated price elasticities are probably, to some extent, influenced by the declining trend in prices in the present data set.

Injecting is an extreme way of consumption. Even if other routes of administration, like sniffing and smoking, appear to be less dramatic, Norwegian heroin users seem to mainly prefer injection. Many amphetamine users, however, prefer tablets to injection. Heroin and amphetamine are by far the most popular drugs for injection in Norway, whereas methadone and opiate products other than heroin are less common. Among the interviewees a considerably group (43 %) reported to have injected both heroin and amphetamine within the month leading up to the interview. For most drug users, however, one injecting drug seems to be preferred to the others as measured by the frequency of injection.

It is interesting to see whether users mainly injecting heroin or amphetamine differ. Some differences regarding socio-economic variables, income sources and consumption patterns were tested for and are reported in Table 1. As mentioned, the groups also responded differently to economic changes. The estimates of the cross-price elasticity indicate that heroin users respond more to changes in amphetamine prices than vice versa. Except for non-dealers of heroin, the cross-price elasticities were negative both for heroin and amphetamine users, which suggest that the two injecting drugs are complements. Thus, in spite of the drugs' very distinct physiological effects and the differences reported in Table 1 and 2, the users do not stick strictly to either heroin or amphetamine for injecting. For many injectors an increase in consumption of one of the drugs may also lead to an increase in the use of the other. Thus, drug policies that successfully reduce the demand for either heroin or amphetamine may also reduce the consumption of the other.

In this paper, we tested for the existence of kinks in the demand curve for heroin. We introduced splines at the lower, median, and upper quartile prices (one-kink hypothesis) as well as at both the lower and the upper quartile (two-kink hypothesis). Interestingly, we found that the estimated price elasticity increased with increasing heroin prices both for dealers and non-dealers. Thus, at low heroin prices the relative response to a price change is less than it is at a higher price level. This is in line with White and Luksetich (1983) who argue that the higher income-generating requirements at high prices will make regular users more inclined to approach treatment agencies or likely to get arrested for carrying out crime for profit. Dealers appear to be even more price responsive than non-dealers at higher prices. This could be due to their dual role as consumers and suppliers. At very high prices their own consumption will be relatively more expensive, as they alternatively could make more money when selling it than they would do at lower prices. We found no indication of an inelastic segment of the demand curve in line with the hypothesis of Wagstaff and Maynard (1988).

One of the hypotheses of Becker and Murphy's theory (1988) suggests that previous and future consumption of the addictive good is positively correlated with current consumption due to 'adjacent complementary'. Our results do not unambiguously support this suggestion. The coefficients for previous consumption are, on the contrary, negative for both groups and highly significant for non-dealers, somewhat less significant for dealers. Future consumption comes out with a positive coefficient for both groups, but none of them are significant. Keeler et al. (1993) and Becker et al. (1994) have tested the Becker-Murphy theory with aggregate time series for cigarettes and Olekalns and Bardsley (1996) have applied aggregate data for coffee consumption. These studies, as well as some studies which have applied individual panel data for addictive goods, report support to the rational addiction theory, i.e. they report positive and significant coefficients for the leaded consumption variable.

Our results, especially the negative estimates for past consumption, are surprising. If there is an effect of previous consumption on current one would expect it to be positive. The above-mentioned work based on time series data has been criticised for not taking sufficiently into account the trend in the data and thereby causing possible spurious results (Skog 1999; Gruber and Köszegi 2001). By applying a version of an ARIMA model we have aimed at avoiding this pitfall and thus the result should not be driven by a spurious relationship between the variables. Another explanation for the diverging results could be that previous empirical testing of the theory have applied a function form for the demand equation derived from a quadratic utility function. Here, we have applied a semi-logged demand function. The choice of functional form should, however, not influence the results much. We cannot explain the findings of a negative relationship between past and present consumption other than claiming that aggregate data are not well suited to explain individual behaviour.

Our reported results regarding the price elasticities must, with respect to their policy implications, be applied with caution. One reason is that the models and estimation methods do not take into account possible changes in drug use caused by a change of legal status. This relates especially to how potential drug users will react to legalization. Also, as indicated in Table 4, the price elasticity seems to be smaller for lower prices. Hence, if legalization leads to large price cuts, the response by drug users would be smaller than suggested by our estimates based on a higher price level. A large price fall following in the wake of legalization may, however, in part be counteracted by taxation of the addicitve good. All possible future consequences, negative and positive, should be considered, however, for properly analyzing the full effects of legalization. Here, we are only arguing that making illegal drugs like heroin a legal commodity will cause the heroin price to fall, which, in turn, will increase the consumption of heroin among current users.

Table 1. Description and definition of variables. Standard deviations in parentheses.

Variables	Heroin injectors Dealers (n=1031)	Heroin injectors Non-dealers (n=1209)	Amphet. injectors Dealers (n=103)	Amphet. injectors Non-dealers (n=138)	Definitions
Gender	0.71 (0.45)	0.64 (0.48)	0.78 (0.42)	0.78 (0.41)	Dummy; 1 if male
Age	31.6 (6.4)	31.3 (6.92)	32.6 (6.9)	33.0 (7.4)	Age in years
Debut age	18.1 (5.2)	18.8 (5.8)	19.5 (6.0)	21.8 (7.3)	Age at first injection
Education	2.0 (2.0)	2.0 (2.1)	2.9 (2.3)	2.5 (2.3)	Number of years of education after the age of 16
Alcohol freq.	3.19 (6.79)	4.72 (8.75)	3.65 (7.80)	6.68 (9.69)	Numb. of days per month (all)
	9.11 (10.38)	7.06 (8.65)	11.82 (10.28)	7.83 (9.93)	Numb. of days per month (users only)
Cannabis freq.	8.77 (10.29)	7.13 (9.66)	11.24 (11.66)	9.68 (10.57)	Numb. of days per month (all)
	10.21 (10.11)	11.13 (10.39)	12.85 (10.37)	14.66 (11.28)	Numb. of days per month (users only)
Ecstasy freq.	0.28 (0.88)	0.36 (1.06)	0.76 (1.61)	0.49 (1.41)	Numb. of days per month (all)
	2.45 (1.61)	2.30 (1.29)	2.72 (2.23)	2.60 (2.04)	Numb. of days per month (users only)
Cocaine freq.	0.49 (2.23)	0.26 (1.71)	0.41 (1.20)	0.35 (1.79)	Numb. of days per month (all)
	3.63 (5.36)	4.47 (5.24)	3.20 (4.65)	2.47 (1.94)	Numb. of days per month (users only)
Tablet use	0.81 (0.39)	0.71 (0.45)	0.42 (0.50)	0.29 (0.46)	Dummy; 1 if pills are used last month
Income	54206 (41652)	36755 (29682)	43834 (55362)	22559 (20625)	Monthly income in NOK
Theft	0.25 (0.44)	0.33 (0.47)	0.18 (0.39)	0.22 (0.42)	Dummy; 1 if income from theft
Prostitution	0.10 (0.29)	0.24 (0.43)	0.03 (0.17)	0.04 (0.20)	Dummy; 1 if income from prostitution
Social security	0.88 (0.32)	0.85 (0.36)	0.76 (0.43)	0.77 (0.42)	Dummy; 1 if income from soc. sec.
Work	0.08 (0.27)	0.16 (0.37)	0.13 (0.33)	0.34 (0.48)	Dummy; 1 if income from work
Other sources	0.10 (0.29)	0.22 (0.41)	0.11 (0.31)	0.24 (0.43)	Dummy; 1 if income from other soruces
Heroin price	1700 (626)	2949 (1685)	1723 (535)	3351 (1475)	Price of heroin per gram
Amph. price	427 (119)	726 (134)	438 (203)	739 (255)	Price of amphetamine per gram
Heroin cons.	20.9 (19.9)	13.8 (15.2)	-	-	Monthly heroin consumption in grams
Amph. cons.	-	-	25.4 (23.0)	15.6 (15.9)	Monthly amphetamine cons. in grams

Table 2. Estimation results for heroin injectors using a switching regression model and ordinary least square. Standard deviations in parentheses. Heroin consumption, heroin price, amphetamine price, and income are in log form. n=2240

Variables	Switching regression model (SRM)			Ordinary least square (OLS)	
	Probit equation	Dealers' consumption	Non-dealers' consumption	Dealers' consumption	Non-dealers' consumption
Constant	-1.09 (0.46)	21.47 (70.47)	-109.35 (109.70)	-40.37 (72.16)	-103.36 (103.30)
Male	0.07 (0.07)	-0.235 (0.079)	-0.269 (0.075)	-0.141 (0.068)	-0.242 (0.068)
Age	0.07 (0.03)	-0.006 (0.042)	0.093 (0.035)	0.076 (0.034)	0.102 (0.033)
Age^2	-0.0011 (0.0004)	0.0002 (0.0007)	-0.0013 (0.0005)	-0.0010 (0.0005)	-0.0014 (0.0005)
Aquisitive crime (theft)	-0.43 (0.05)	-	-	-	-
Work	-0.58 (0.07)	-	-	-	-
Prostitution	-0.65 (0.08)	-	-	-	-
Alcohol frequency	-0.26 (0.07)	-0.016 (0.092)	-0.238 (0.083)	-0.297 (0.089)	-0.276 (0.081)
Cannabis frequency	0.20 (0.06)	-0.298 (0.073)	0.147 (0.069)	-0.177 (0.062)	0.170 (0.066)
Tablet use	0.37 (0.06)	-0.133 (0.085)	0.319 (0.080)	0.139 (0.078)	0.366 (0.070)
Number of newcomers	-0.0004 (0.0004)	-	-	-	-
Heroin price	-	-0.609 (0.103)	-1.196 (0.084)	-0.637 (0.105)	-1.195 (0.086)
Ampht. price	-	-0.514 (0.217)	1.079 (0.588)	-0.397 (0.231)	1.053 (0.526)
Income	-	0.531 (0.045)	0.511 (0.035)	0.481 (0.044)	0.491 (0.034)
Year	-	-0.008 (0.035)	0.053 (0.053)	0.022 (0.035)	0.051 (0.050)
Length of abuse*	-	0.018 (0.019)	0.015 (0.016)	-	-
Education*	-	0.018 (0.020)	-0.049 (0.020)	-	-
Age of inject. debut*	-	-0.012 (0.020)	-0.013 (0.015)	-	-
λ_{1i}, λ_{2i}	-	0.53 (0.14)	0.38 (0.18)	-	-
Selection mech. $\rho_{1\varepsilon}$, $\rho_{2\varepsilon}$	-	0.211 (0.175)	-0.871 (0.023)	-	-
Log likelihood	-	-4576.62**	-	-1409.92	-1781.85
Adjusted R^2	-	-	-	0.25	0.42

***Estimations based on a subsample of n=1311, ** Log likelihood for the whole SRM**

Table 3. Estimation results for amphetamine injectors using a switching regression model and an ordinary least square. Standard deviations in parentheses. Amphetamine consumption, heorin price, amphetamine price, and income are in log form. n=241

Variables	Switching regression model (SRM)			Ordinary Least Square (OLS)	
	Probit equation	Dealers' consumption	Non-dealers' consumption	Dealers' consumption	Non-dealers' consumption
Constant	-0.75 (1.86)	6.620 (3.709)	2.019 (3.346)	5.2437 (3.722)	3.144 (3.240)
Male	0.15 (0.25)	0.108 (0.376)	-0.673 (0.357)	0.305 (0.269)	-0.692 (0.271)
Age	0.04 (0.12)	-0.188 (0.152)	0.019 (0.143)	-0.043 (0.137)	0.003 (0.119)
Age^2	-0.0005 (0.0018)	0.003 (0.002)	-0.0006 (0.0022)	0.0005 (0.0021)	0.0003 (0.0018)
Aquisitive crime (theft)	-0.09 (0.16)	-	-	-	-
Work	-0.60 (0.19)	-	-	-	-
Prostitution	-0.01 (0.41)	-	-	-	-
Alcohol frequency	-0.48 (0.21)	-	-	-	-
Cannabis frequency	-0.03 (0.13	-	-	-	-
Tablet use	0.40 (0.20)	-	-	-	-
Heroin price	-	-0.069 (0.413)	-0.217 (0.304)	-0.558 (0.389)	-0.264 (0.295)
Ampht. price	-	-0.509 (0.263)	-0.222 (0.325)	-0.259 (0.227)	-0.284 (0.305)
Income	-	0.367 (0.139)	0.332 (0.127)	0.389 (0.129)	0.313 (0.124)
$\lambda_{1i}, \lambda_{2i}$	-	-0.992 (0.413)	0.898 (0.439)	-	-
Selection mech. $\rho_{1\varepsilon}, \rho_{2\varepsilon}$	-	0.571 (0.245)	-0.987 (0.016)	-	-
Log-likelihood	-	-516.00*	-	-154.57	-227.07
Adjusted R^2	-	-	-	0.08	0.08

* **Log likelihood for the whole selection model**

Table 4. Results from the spline functions estimations for heroin injectors based on a switching regression model. Only estimates for prices and income are shown here, the other regressors (corresponding to those reported in Table 2) are suppressed. Standard deviations in parentheses. n=2240.

DEALERS:

	Model (i)	Model (ii)	Model (iii)	Model (iv)	Model (v)
Heroin price	-0.61 (0.10)	-0.11 (0.21)	-0.28 (0.13)	-0.40 (0.12)	-0.26 (0.22)
Lower quartile (μ_{11})	-	-0.90 (0.29)	-	-	-0.31 (0.35)
Median (μ_{21})	-	-	-1.36 (0.28)	-	-
Upper quartile (μ_{31})	-	-	-	-1.47 (0.33)	-1.26 (0.39)
Amphet. price	-0.52 (0.22)	-0.49 (0.22)	-0.34 (0.22)	-0.36 (0.22)	-0.38 (0.22)
Income	0.53 (0.05)	0.52 (0.04)	0.54 (0.04)	0.54 (0.04)	0.54 (0.05)

NON-DEALERS:

	Model (i)	Model (ii)	Model (iii)	Model (iv)	Model (v)
Heroin price	-1.20 (0.08)	-0.48 (0.37)	-0.60 (0.28)	-1.07 (0.13)	-0.50 (0.38)
Lower quartile (μ_{12})	-	-0.80 (0.38)	-	-	-0.74 (0.43)
Median (μ_{22})	-	-	-0.73 (0.31)	-	-
Upper quartile (μ_{32})	-	-	-	-0.55 (0.35)	-0.14 (0.40)
Amphet. price	1.08 (0.59)	0.86 (0.60)	0.66 (0.61)	0.90 (0.61)	0.83 (0.61)
Income	0.51 (0.04)	0.51 (0.04)	0.51 (0.04)	0.51 (0.04)	0.51 (0.04)

Log likelihood	-4576.61	-4567.75	-4561.10	-4564.85	-4562.30

Table 5. Results from estimations based on time series data for heroin injectors. Number of interview sessions = 28. Standard deviations in parentheses.

Variables	Dealers	Non-dealers
Constant	7.381 (2.525)	-1.131 (3.899)
Heroin price	-0.794 (0.226)	-1.300 (0.426)
Amphetamine price	-0.349 (0.201)	1.034 (0.691)
Income	0.319 (0.196)	0.595 (0.260)
Lagged consumption	-0.652 (0.419)	-0.894 (0.181)
Leaded consumption	0.013 (0.081)	0.112 (0.121)
ARIMA	(1,0,1)	(1,1,1)

Table 6A: Pseudo panel models. Grouping by cohort and by age. LHS variable: log of heroin consumption. Standard error estimates in parenthesis. Intercepts not reported.

Variables	No heterogeneity		Pseudo panel Cohort spec. heterog. (N=40)		Pseudo panel Age spec. heterog. (N=39)	
	OLS	OLS	OLS, FE	GLS, RE	OLS, FE	GLS, RE
Heroin price	-1.0325 (0.0483)	-1.0475 (0.0485)	-0.9923 (0.0676)	-1.0280 (0.0494)	-0.9894 (0.0674)	-1.0339 (0.0520)
Income	0.5108 (0.0262)	0.5134 (0.0262)	0.5115 (0.0268)	0.5106 (0.0264)	0.5134 (0.0267)	0.5097 (0.0263)
Male	-0.2091 (0.0487)	-0.1960 (0.0486)	-0.2071 (0.0494)	-0.2081 (0.0491)	-0.2116 (0.0491)	-0.2028 (0.0488)
Age	0.0911 (0.0241)	-	0.1152 (0.0583)	0.0910 (0.0287)	-	-
Age^2	-0.0013 (0.0004)	-	-0.0015 (0.0009)	-0.0013 (0.0004)	-	-
Cohort	-	-0.0066 (0.0034)	-	-	0.0130 (0.0148)	0.0002 (0.0068)
Dealer	-0.1639 (0.0506)	-0.1627 (0.0509)	-0.1472 (0.0558)	-0.1641 (0.0512)	-0.1424 (0.0554)	-0.1627 (0.0515)
Alcohol	-0.2751 (0.0603)	-0.2652 (0.0604)	-0.2740 (0.0609)	-0.2773 (0.0606)	-0.2772 (0.0608)	-0.2763 (0.0606)
Cannabis	0.0026 (0.0461)	-0.0002 (0.0462)	0.0083 (0.0467)	0.0062 (0.0464)	-0.0001 (0.0463)	0.0010 (0.0462)
R^2	0.3833	0.3777	0.3890	0.3813	0.3942	0.3746
SER	1.0288	1.0316	1.0317	1.0403	1.0268	1.0954
	-	-	F(het)=0.692 P=0.929	-	F(het)=1.53 P=0.019	-
	-	-	-	Rho=0.0165	-	Rho=0.1212
	-	-	-	LM(het)=2.61 P=0.106	-	LM(het)=2.39 P=0.239

FE = Fixed effects, RE = Random effects, N = No. of groups,
F(het), LM(het)= F, LM statistics for testing for heterogeneity
Rho=variance of latent heterogeneity/Gross disturbance variance

Table 6B: Pseudo panel models. Grouping by year and by quarter. LHS variable: log of heroin consumption. Standard error estimates in parenthesis. Intercepts not reported.

Variables	No heterogeneity	Pseudo panel Year spec. heterog. (N=7)		Pseudo panel Quarter spec. heterog. (N=27)	
	OLS	OLS, FE	GLS, RE	OLS, FE	GLS, RE
Heroin price	-1.0325 (0.0483)	-1.0132 (0.0671)	-1.0146 (0.0657)	-1.0380 (0.0683)	-1.0292 (0.0520)
Income	0.5108 (0.0262)	0.5135 (0.0264)	0.5134 (0.0264)	0.5092 (0.0267)	0.5107 (0.0262)
Male	-0.2091 (0.0487)	-0.2181 (0.0487)	-0.2175 (0.0487)	-0.2267 (0.0490)	-0.2133 (0.0487)
Age	0.0911 (0.0241)	0.0934 (0.0241)	0.0933 (0.0241)	0.0952 (0.0243)	0.0924 (0.0241)
Age^2	-0.0013 (0.0004)	-0.0013 (0.0004)	-0.0013 (0.0004)	-0.0013 (0.0004)	-0.0013 (0.0004)
Dealer	-0.1639 (0.0506)	-0.1530 (0.0548)	-0.1537 (0.0544)	-0.1658 (0.0552)	-0.1628 (0.0513)
Alcohol	-0.2751 (0.0603)	-0.2844 (0.0602)	-0.2841 (0.0602)	-0.2822 (0.0606)	-0.2767 (0.0602)
Cannabis	0.0026 (0.0461)	0.0166 (0.0462)	0.0160 (0.0462)	-0.0187 (0.0466)	0.0064 (0.0461)
R^2	0.3833	0.3881	0.3812	0.3919	0.3812
SER	1.0288	1.0247	1.0681	1.0262	1.0283
	-	F(het)=3.55 P=0.001	-	F(het)=1.43 P=0.071	-
	-	-	Rho=0.0797	-	Rho=0.004
	-	-	LM(het)=16.14 P=0.000	-	LM(het)=0.85 P=0.356

FE = Fixed effects, RE = Random effects, N = No. of groups,
F(het), LM(het)= F, LM statistics for testing for heterogeneity
Rho=variance of latent heterogeneity/Gross disturbance variance

Appendix: A potential bias in the estimation of the demand price elasticity of a drug when the quantity is bought at bulk discounts

In this appendix, we discuss a potential bias in the estimation of a demand price elasticity of a drug when we open for bulk-buy discounts.

We examine first how the average price of the drug depends on the quantity bought in the presence of bulk discounts. Let X denote the quantity purchased and P its price per unit. Two stylized descriptions of the pattern of bulk discounts will be considered. In the first we assume that both the marginal and the average prices are gradually decreasing, as the price depends on the quantity according to the following rule: small quantities up to $X = X_0$ units are sold at the (high) price P_0, quantities between X_0 and X_1 units are sold at the (lower) price P_1, and quantities above X_1 units are sold at the (lowest) price P_2, where $P_2 < P_1 < P_0$. The value of the purchase is then

$$PX = \begin{cases} P_0 X, & \text{for } 0 < X \leq X_0, \\ P_0 X_0 + P_1(X - X_0), & \text{for } X_0 < X \leq X_1, \\ P_0 X_0 + P_1(X_1 - X_0) + P_2(X - X_1), & \text{for } X > X_1, \end{cases} \tag{A.1}$$

which implies that the *average price* at which the drug is bought can be written as

$$P = \begin{cases} P_0, & \text{for } 0 < X \leq X_0, \\ P_1 + (P_0 - P_1)\dfrac{X_0}{X}, & \text{for } X_0 < X \leq X_1, \\ P_2 + (P_1 - P_2)\dfrac{X_1}{X} + (P_0 - P_1)\dfrac{X_0}{X}, & \text{for } X > X_1. \end{cases} \tag{A.2}$$

The functions (A.1) and (A.2) are both continuous, but kinked at X_0 and X_1.

Since the *marginal price* is

$$\frac{\partial(PX)}{\partial X} = \begin{cases} P_0, & \text{for } 0 < X < X_0, \\ P_1, & \text{for } X_0 < X < X_1, \\ P_2, & \text{for } X > X_1, \end{cases}$$

the elasticity of the purchase value with respect to the quantity is

$$\frac{\partial(PX)}{\partial X}\frac{X}{(PX)} = \frac{\partial(PX)}{\partial X}\frac{1}{P} = \begin{cases} \dfrac{P_0}{P} = 1, & \text{for} \;\; 0 < X < X_0, \\ \dfrac{P_1}{P} < 1, & \text{for} \;\; X_0 < X < X_1, \\ \dfrac{P_2}{P} < 1, & \text{for} \;\; X > X_1. \end{cases}$$

Inserting for P from (A.2), we obtain the following expression for the *elasticity of the purchase price with respect to the quantity*

$$\text{(A.3)}\quad \frac{\partial P}{\partial X}\frac{X}{P} = \begin{cases} \dfrac{P_0}{P} - 1 = 0, & \text{for } 0 < X < X_0, \\ \dfrac{P_1}{P} - 1 = -\dfrac{(P_0 - P_1)X_0}{P_1X + (P_0 - P_1)X_0}, & \text{for } X_0 < X < X_1, \\ \dfrac{P_2}{P} - 1 = -\dfrac{(P_1 - P_2)X_1 + (P_0 - P_1)X_0}{P_2X + (P_1 - P_2)X_1 + (P_0 - P_1)X_0}, & \text{for } X > X_1. \end{cases}$$

This elasticity is zero for $X < X_0$, belongs to the interval $(-1, 0)$ for $X_0 < X < X_1$ and $X > X_1$, is undefined for $X = X_0$ and $X = X_1$, and goes to zero as X goes to infinity.

An alternative description of the discounting system may be that when the quantity purchased passes the thresholds X_0 and X_1, the *entire quantity* is sold to the lower price, subject to the restriction that $P_1X_1 > P_2X_1 > P_0X_0$. Instead of (A.1) and (A.2) we then get

$$\text{(A.4)}\qquad PX = \begin{cases} P_0X, & \text{for } 0 < X < X_0, \\ P_1X, & \text{for } X_0 < X < X_1, \\ P_2X, & \text{for } X > X_1, \end{cases}$$

and

$$\text{(A.5)}\qquad P = \begin{cases} P_0, & \text{for } 0 < X < X_0, \\ P_1, & \text{for } X_0 < X < X_1, \\ P_2, & \text{for } X > X_1. \end{cases}$$

The latter step function implies that the *elasticity of the purchase price with respect to the quantity* is zero except at the threshold values where it goes to minus infinity, so that (A.3) is replaced by

$$\text{(A.6)}\qquad \frac{\partial P}{\partial X}\frac{X}{P} = 0, \quad \text{for} \quad X \neq X_0, X_1.$$

The relative change in P divided by the relative change in X over finite X intervals is always non-positive, but its absolute value may exceed 1 on certain segments including X_0 or X_1. For small and large X, however, it is always zero.

With these two simplistic descriptions of bulk discounts is mind, let us examine how the existence of the price-quantity relationships (A.2) – (A.3) or (A.5) – (A.6) may lead to biased estimation of the demand price elasticity if the average drug price is treated as exogenous when estimating the demand equation for the drug by OLS. To make things simple we formulate the following, stylized two-equation model for joint determination of the quantity demanded by a drug user who is also a potential dealer, and the average price of the drug:

$$y = \alpha + \beta p + \gamma z + u, \tag{A.7}$$

$$p = \delta + \epsilon y + \phi q + v, \tag{A.8}$$

where y is the quantity consumed (which may differ from the quantity purchased), p is the average purchase price, z is an exogenous variable in the demand function, and q is an exogenous variable in the price function, all in logarithms. Eq. (A.7) is a simplified version of the log-linear demand function of the drug user, and (A.8) is a continuous approximation to the piecewise linear price function (A.2) or to the 'downward sloping' step function (A.5). If, for instance, q is the quantity sold to other consumers, then X, the quantity variable in (A.2), corresponds to $e^y + e^q$. The exogeneity assumption implies that z and q are both uncorrelated with u and v, and we additionally assume that u and v are mutually uncorrelated, with variances σ_{uu} and σ_{vv}. The above discussion implies that $\epsilon = 0$ for purchasers who buy small quantities without discounts or very large quantities with discounts, and negative and most likely less than one in absolute value for others.

It follows from the textbook formulae for OLS that the plims of the OLS estimators of β and γ are

$$\text{plim}(\widehat{\beta}_{OLS}) = \frac{c_{yp}c_{zz} - c_{yz}c_{pz}}{c_{pp}c_{zz} - c_{pz}^2} = \beta + \frac{c_{up}c_{zz}}{c_{pp}c_{zz} - c_{pz}^2}, \tag{A.9}$$

$$\text{plim}(\widehat{\gamma}_{OLS}) = \frac{c_{yz}c_{pp} - c_{yp}c_{pz}}{c_{pp}c_{zz} - c_{pz}^2} = \gamma - \frac{c_{up}c_{pz}}{c_{pp}c_{zz} - c_{pz}^2}, \tag{A.10}$$

where the c's denote theoretical covariances (or plims of empirical covariances) between the variables indicated by the subscripts.

Provided that $\beta\epsilon \neq 1$, the reduced form of (A.7) – (A.8) exists, and is

$$p = (1-\beta\epsilon)^{-1}(\delta + \epsilon\alpha + \epsilon\gamma z + \phi q) + (1-\beta\epsilon)^{-1}(\epsilon u + v), \tag{A.11}$$

$$y = (1-\beta\epsilon)^{-1}(\alpha + \beta\delta + \gamma z + \beta\phi q) + (1-\beta\epsilon)^{-1}(u + \beta v), \tag{A.12}$$

which we use to express the c's in (A.9) and (A.10) in terms of the coefficients in (A.7) and (A.8) and the second order moments of the disturbances and the exogenous variables. It follows that

$$\begin{aligned}
c_{yp} &= (1-\beta\epsilon)^{-2}[\epsilon\gamma^2 c_{zz} + \beta\phi^2 c_{qq} + (\epsilon\gamma\beta\phi + \gamma\phi)c_{zq} + (\epsilon\sigma_{uu} + \beta\sigma_{vv})],\\
c_{pp} &= (1-\beta\epsilon)^{-2}[\epsilon^2\gamma^2 c_{zz} + \phi^2 c_{qq} + 2\epsilon\gamma\phi c_{zq} + (\epsilon^2\sigma_{uu} + \sigma_{vv})],\\
c_{yz} &= (1-\beta\epsilon)^{-1}[\gamma c_{zz} + \beta\phi c_{zq}],\\
c_{pz} &= (1-\beta\epsilon)^{-1}[\epsilon\gamma c_{zz} + \phi c_{zq}],\\
c_{yu} &= (1-\beta\epsilon)^{-1}\sigma_{uu},\\
c_{pu} &= (1-\beta\epsilon)^{-1}\epsilon\sigma_{uu},
\end{aligned}$$

since $c_{zu} = c_{qu} = 0$, and hence

$$\begin{aligned}
(1-\beta\epsilon)^2(c_{yp}c_{zz} - c_{yz}c_{pz}) &= \beta\phi^2(c_{qq}c_{zz} - c_{zq}^2) + (\epsilon\sigma_{uu} + \beta\sigma_{vv})c_{zz},\\
(1-\beta\epsilon)^2(c_{pp}c_{zz} - c_{pz}^2) &= \phi^2(c_{qq}c_{zz} - c_{zq}^2) + (\epsilon^2\sigma_{uu} + \sigma_{vv})c_{zz},\\
(1-\beta\epsilon)^2 c_{up}c_{zz} &= (1-\beta\epsilon)\epsilon\sigma_{uu}c_{zz},\\
(1-\beta\epsilon)^2 c_{up}c_{pz} &= (\epsilon\gamma c_{zz} + \phi c_{zq})\epsilon\sigma_{uu}.
\end{aligned}$$

Inserting the latter expressions into (A.9) and (A.10) we obtain

$$\begin{aligned}
\operatorname{plim}(\widehat{\beta}_{OLS}) &= \beta + \frac{(1-\beta\epsilon)\epsilon\sigma_{uu}}{[\phi^2 c_{qq}(1-\rho_{zq}^2) + \sigma_{vv}] + \epsilon^2\sigma_{uu}}\\
&= \frac{\beta[\phi^2 c_{qq}(1-\rho_{zq}^2) + \sigma_{vv}] + \epsilon\sigma_{uu}}{[\phi^2 c_{qq}(1-\rho_{zq}^2) + \sigma_{vv}] + \epsilon^2\sigma_{uu}},
\end{aligned} \tag{A.13}$$

$$\begin{aligned}
\operatorname{plim}(\widehat{\gamma}_{OLS}) &= \gamma - \frac{\left(\gamma\epsilon + \phi\dfrac{c_{zq}}{c_{zz}}\right)\epsilon\sigma_{uu}}{[\phi^2 c_{qq}(1-\rho_{zq}^2) + \sigma_{vv}] + \epsilon^2\sigma_{uu}}\\
&= \frac{\gamma[\phi^2 c_{qq}(1-\rho_{zq}^2) + \sigma_{vv}] - \phi\epsilon\dfrac{c_{zq}}{c_{zz}}\sigma_{uu}}{[\phi^2 c_{qq}(1-\rho_{zq}^2) + \sigma_{vv}] + \epsilon^2\sigma_{uu}},
\end{aligned} \tag{A.14}$$

where $\rho_{zq} = c_{zq}/(c_{zz}c_{qq})^{1/2}$, i.e., the population correlation coefficient between the two exogenous variables. We see that the OLS estimator of the demand price elasticity β based on (A.7) is unbiased when $\epsilon = 0$ and otherwise converges in probability to a weighted average of the true demand price elasticity β and the inverse of the quantity elasticity in (A.8), $1/\epsilon$, with weights equal to $\phi^2 c_{qq}(1-\rho_{zq}^2)+\sigma_{vv}$ and $\epsilon^2\sigma_{uu}$, respectively. This means that $\widehat{\beta}_{OLS}$ is unbiased for non-dealers and approximately unbiased for dealers who trade very large quantities of the drug. For other dealers, $|\widehat{\beta}_{OLS}|$ has an upward (asymptotic) bias if $|1/\epsilon| > |\beta|$ and a downward bias if $|1/\epsilon| < |\beta|$. How large the latter bias will be, depends on the relative variances of the two disturbances and of the exogenous variable q in the price equation (A.8) as well as on the coefficient of correlation between the two exogenous variables. If $\phi^2 c_{qq}$ and σ_{vv} are large as compared with σ_{uu} and $|\rho_{zq}|$ is small, the bias tends to be small.

Similarly, the OLS estimator of γ in (A.7) is unbiased when $\epsilon = 0$ and otherwise converges in probability to a weighted average of γ and $-\ (\phi/\epsilon)(c_{zq}/c_{zz})$, with weights equal to $\phi^2 c_{qq}(1-\rho_{zq}^2)+\sigma_{vv}$ and $\epsilon^2\sigma_{uu}$, respectively. This means that $\widehat{\gamma}_{OLS}$ is unbiased for non-dealers and approximately unbiased for dealers who trade very large quantities of the drug. How large the latter bias will be, depends on the relative size of γ and $-\ (\phi/\epsilon)(c_{zq}/c_{zz})$, the relative variances of u, v, and q, as well as on the coefficient of correlation between the two exogenous variables.

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Department of Economics
University of Bergen
Fosswinckels gate 6
N-5007 Bergen, Norway
Phone: +47 55 58 92 00
Telefax: +47 55 58 92 10
http://www.svf.uib.no/econ