UNEMPLOYMENT AND DRUG TREATMENT[*]

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Abstract:

Background: The economic recession that hit most industrial countries since 2007 has raised the question of how economic hardship affects illicit drug users' decisions to enter into treatment. We analyze this question in this paper.
Methods: We test the hypothesis that an improvement in the employment prospects, as measured by a decline in unemployment, strengthens the intrinsic motivation of a drug user unemployed person to enter treatment. Our hypothesis is that the "payoff" of entering treatment increases when the unemployed drug user has a greater probability of finding a job. We first survey the literature on the subject and we find that there is considerable evidence substantiating this effect. We then test the hypothesis econometrically using two different data sets, one EU-wide and one German data set.
Results: Our main findings are that unemployment has a significant negative effect on the number of drug users entering treatment, i.e. when unemployment declines (increases) the number of drug clients increases (declines). We also find that *unemployed* drug users entering treatment are most sensitive to variations in the economy-wide unemployment rate. Employed drug users in contrast are not influenced by variations in the economy-wide unemployment rate in their decisions to enter treatment.
Conclusion: Our empirical results confirm that the creation of job prospects adds significantly to the willingness of unemployed drug users to enter treatment. This lends support to the idea that treatment programs should be embedded in programs aiming at improving the job prospects of drug users.

Keywords: Economic recession, unemployment, treatment, illicit drug use

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Introduction

Since the start of the financial crisis unemployment in the European Union has increased sharply. As the recession wears on, and the unemployed fail to find a job, they lose part of their human capital, making it more difficult for them to re-enter the labor market. They become structurally unemployed.

Unemployment has an important influence on drug use. It is useful to make a distinction between "being unemployed" at the individual level and the aggregate unemployment rate. There is a large literature studying the link between drug use and the individual employment situation. This literature finds that causation runs in two directions, i.e. lack of employment is a factor that leads individuals to more serious drug taking whereas more serious drug involvement works against more stable and/or better paying employment. While the link between individual employment situation and drug use has been very much researched, the question of how macroeconomic employment prospects as measured by the aggregate unemployment rate affects drug use has not been much researched. We are aware of only one published study (see Arkes(2007)). Even less is known about the effects of the aggregate unemployment rate on the probability that drug users enter treatment. This is the issue we want to analyze in this paper.

Brief survey of the literature

Most of the empirical research on the link between unemployment and drug use has concentrated on how individual employment and drug use are related. In these empirical studies individual employment is seen as one of the measures of social inclusion. Typical examples of these studies are (without attempting to be comprehensive): Eisenbach-Stangl et al (2009), Buchmueller and Zuyekas (1994), Zarkin et al (1988), MacDonald and Pudney (2000) Pollack at al. (2002), French at al. (2001), March at al. (2006) DeSimone (2002), Hoare (2009). On the whole these studies strongly suggest that causality runs both ways, i.e. poor individual employment prospects enhance drug use, and intense drug use significantly reduces employability. A study that stands out as finding little robust relation between drug use and employability is Van Ours(2006).

To our knowledge the only published study analyzing the relation between the macroeconomic employment conditions and drug use is Arkes (2007). The latter estimated the impact of the economic cycle on drug use among teenagers. He concludes that a weaker economy leads to greater teenage marijuana and “hard–drug” use. He also shows that teenagers are more likely to sell drugs in weaker economies, which acts as a mechanism counter-cyclical mechanism facilitating drug use in economic downwards.

Some studies have concentrated on how treatment affects “employability”, i.e. the probability of getting a job. Wickizer et al. (2000), confirms that treatment has a positive effect on employability. Meara(2006) and McCoy et al. (2007) find that treatment tends to improve the earning status of patients. In this connection, the selection problem should be mentioned. Individuals who are more confident of finding a job after treatment are more likely to enter treatment. This creates a selection bias tending to overestimate the effect of treatment per se. This problem can be overcome by using randomized sampling methods (see Heckman(1979)).

The reverse causality relation has also been analyzed. McIntosh, et al. (2008), Klee et al. (2002) and Room(1998). These studies stress that of the factors involved in sustaining recovery from drug dependency, the achievement of paid employment was probably one of the most important ones. Research has identified different ways through which having a paid job contributes to an individual’s ability to create and sustain a drug free life (Cebulla 2004). First, it enables drug user to fill time constructively and becoming independent. Second, it helps users to reintegrate into a wider network, facilitating the development of a set of drug-free social relationships. Third, it enhances individual’s self-esteem. Finally, it works as a symbol of the individual’s capacity to return to a more conventional lifestyle.

Several authors have stressed the importance of achieving a paid job, as a factor responsible for sustained recoveries from drug dependencies (Westermeyer 1989, Patt 1995, Room 1998, Klee et al. 2002, DeFulio, 2009). Wong and Silverman 2007 discussed extensively which kinds of treatment programs were more adequate to employment-based drugs users’ interventions.

Employment status is frequently used as an outcome in determining treatment efficacy (see, Hermalin at al., 1990). Some treatment includes employment counseling as part of the array of services provided to clients (Reif and al., 2004) or vocational rehabilitation courses (Platt, 1995).

Some theoretical considerations

The number of drug users entering treatment at a particular point in time is influenced by demand and supply factors. The demand factors originate from the drug user. The decision of a drug user to enter treatment is determined by an intrinsic motivation, i.e. a desire of the dependent person to free him/herself from a dependence that is perceived to reduce his/her quality of life. This intrinsic motivation can, however, also be influenced by external factors. According to EMCDDA (2010), most clients enter treatment on their own initiative or under the pressure of family and friends (43%); 27% go to drug treatment through health or social services, including other drug treatment centres; around 20% are referred to treatment by the criminal justice system, and the remaining through other referral sources.

In this paper we will focus on one such factor: that is the state of the economy, and more specifically the employment prospects for the dependent person. The hypothesis that we want to test is the following. An improvement in the employment prospects induced for example by a business cycle upturn, strengthens the intrinsic motivation of an dependent unemployed person to seek treatment. The reason is that the "payoff" of entering treatment increases when the unemployed drug user has a greater probability of finding a job after his treatment. There is a large literature substantiating this effect (see e.g. Biernacki 1986, Luchansky, et al. 2000, Cebulla, et al. 2004, McIntosh, et al. 2008). Paid employment contributes to an individual's ability to create a drug free life in several ways. It allows an individual to become economically independent, to integrate in a wider social network and to boost his self-esteem. All this makes it more attractive for an unemployed drug user to seek treatment when job prospects improve.

There are also supply factors affecting the number of drug users seeking treatment. We will focus here on the availability of treatment centers. The more centers that are available, the more drug users will seek treatment. The supply of treatment centers and treatment units is in turn influenced by the state of the economy. When the economy is booming government revenues increase, making it more likely that additional treatment centers become available (OECD(2009). When the economy is turning into a recession, budgetary restrictions may reduce the funding for treatment centers thereby negatively affecting the availability of treatment centers.

We now discuss these demand and supply factors in the framework of a simple model. We start with a definition. By definition one can write the number of individuals entering treatment in period t as follows:

$$T_t = \lambda_t N_t \tag{1}$$

where T_t is the number of individuals entering treatment in period t; λ_t is the fraction of drug users entering treatment in period t and N_t is the number of drug users in period t.

In this paper we focus on how the state of the economy and more particularly the employment prospects affect λ_t and N_t in equation (1). We will use the economy-wide unemployment rate as the indicator of these employment prospects. Thus we write that the fraction of drug users, λ_t, and the number of drug users, N_t, are a function of the economy-wide unemployment rate, U_t, i.e.

$$\lambda_t = \lambda(U_t) \tag{2}$$

$$N_t = N(U_t) \tag{3}$$

Thus we assume implicitly that the unemployment rate is the exogenous variable. There is of course also an influence of drug use on the probability that an individual becomes unemployed. Since U_t is the economy-wide unemployment rate, this reverse causality is very small. Substituting (2) and (3) into (1) and totally differentiating yields

$$dT_t = N_t \frac{\partial \lambda_t}{\partial U_t} dU_t + \lambda_t \frac{\partial N_t}{\partial U_t} dU_t \tag{4}$$

We now discuss the signs of the partial derivatives in equation (4).

The first term on the right hand side of (4) measures the impact of unemployment on the *fraction* of drug users, λ_t, seeking treatment. We will make a distinction between the unemployed drug users seeking treatment and those who are employed because we assume that incentives for the unemployed are different from those who are employed. More specifically, as indicated above, our assumption is that, if employment opportunities improve, unemployed drug users will have more incentives to seek treatment so that this fraction increases. We will call this the *incentive* effect. It is not a-priori clear how the employed drug users seeking treatment react to changes in economic conditions. It will depend on how they perceive the economic conditions to affect the probability of loosing their jobs. We will let the data decide here. Thus we assume that

$$\frac{\partial \lambda_{U\,t}}{\partial U_t} \leq 0$$

$$\frac{\partial \lambda_{E\,t}}{\partial U_t} \leq ?$$

where λ_{Ut} is the share of unemployed drug users seeking treatment, λ_{Et} is the share of employed drug users seeking treatment and $\lambda_{Ut} + \lambda_{Et} = \lambda_t$

There is a second potential mechanism whereby the state of the economy (as represented by the rate of unemployment) may affect λ_t. This is a *supply* effect created by the state of the economy. An improvement in the state of the economy also improves the government's budget, allowing for more spending on treatment centers and units. Thus when economic activity improves, the supply of treatment centers/units may increase. This increased supply may then lead to more drug users entering treatment.

Both the *incentive* and the *supply* effects work in the same direction, i.e. they tend to increase the number of drug clients when the state of the economy improves (unemployment declines).

The second term measures the impact of unemployment on the *number* of drug users. There is a general presumption that an increase in unemployment leads to more drug dependence. The literature, however, reveals that this sign depends upon several different factors, as the type of drug, the ingestion method, the dependence level or the quality of the available treatment (see section 2). So there is not a unique sign of the effect of unemployment on the number of drug users. An improvement of economic conditions and thus of job opportunities can increase or decrease the number of drug users.

We refer to the articles in this Special Issue for an example of the description of the different effects of the state of the economy on drug use (teenage use). Thus

$$\frac{\partial N_t}{\partial U_t} \leq 0 or \geq 0$$

We conclude that the effect of the state of the economy (as measured by the unemployment rate) on the number of drug users entering treatment is ambiguous. Determining the sign of this effect is thus an empirical issue.

In the empirical part we concentrate on measuring the effect of the state of the economy on the number of drug users entering into treatment. As argued before the incentives of employed and unemployed drug users entering into treatment are different. Therefore we will distinguish between these two types of drug users seeking treatment. This will also allow us to determine which of the four effects in equation (4) tends to dominate.

Description of the data

The treatment demand data published by the EMCDDA aims at providing comparable, reliable and anonymous information concerning the number and characteristics of people entering into treatment for their drug use in Europe. The drugs considered are opiates, cocaine, stimulants (amphetamines, MDMAand others), hypnotics and sedatives, hallucinogens, volatile inhalants and cannabis. Alcohol is only registered when it is used as a secondary drug (tobacco excluded as primary drug excluded).

This data set has the best available and harmonized information at the European level. In order to arrive to the current figures, much time has been devoted to set up a solid conceptual framework and there has been a convergence of the definitions used to collect data, thanks to the work done at the EMCDDA, in close collaboration with national authorities and different experts.

In this study, treatment data refers to the total number of clients who have started treatment during the year (2002-2007). It excludes those clients who had started their treatment before the beginning of the year. According to the EMCDDA protocol, the category “new clients” concerns those persons entering treatment during the calendar year regardless of having been treated before (during their lifetime) or not. In case multiple entrances occur this client is only counted once.

In this study, it was decided to take only into consideration the number of new clients benefiting from outpatient services of treatment. We excluded data on inpatient/residential services. We decided to do this because the series available are considerably longer and a larger number of countries report data. Additionally, most of the treatment provision occurs in outpatient centers.

These data have some limitations and comparability across countries is limited. The coverage of the target institutions differs between countries and the percentage of total clients accounted is not always the same. Furthermore, these data include mostly those clients who benefit from specialist treatment. As a result, they do not generally consider those who benefit from treatment given by non-specialists, e.g., hospital emergency rooms, general practitioners, other primary care or psychiatric services and low threshold facilities. These data are described in more detail in the Data Description Document of this article (see).

A general comment should be made here. The samples obtained from the different countries have different coverage, and are therefore not fully comparable. This could lead to biases in the econometric estimates. These biases arise if there are systematic errors in the sampling procedures. We have no way of knowing how systematic these errors are. This is an area where future research will have an important payoff.

Concerning the social–economic characteristics of the clients under drug-treatment, this study uses the EMCCDA available data. There clients are split into 6 main categories. They are “regular employment”, “pupil/student”, “economically inactive (pensioners, housewives/-men, invalids)”, “unemployed”, “other” and “not known”. The first category concerns those who have a regular employment.

It is important to note that the definition of “regular employed” was set quite broad in the standard protocol of the data collection (EMCDDA, 2000) comprising persons with a regular licit job, part-time, undeclared work, people working in the grey market and also those who benefit from public employment programs, even though there is specific guidance on the EMCDDA protocol (EMCDDA, 2000) to code those with irregular employment situations as “Other”. In practice this does not always apply, though.

In order to analyze whether the decision to enter into new treatment varies according to the primary drug used by new clients, this study used another EMCDDA dataset. This dataset reports the number of new clients entering into outpatient treatment, by country and by primary drug, annually (http://www.emcdda.europa.eu/stats10/tditab19a). However, it should be stressed that this dataset is not fully comparable with the previous one, because countries do not always report complete information either on the employment status or on the primary drug that a client has been receiving treatment for.

Data on national treatment units used to model the supply of drug treatment is obtained from the EMCDDA (2009). The number of units refers to all outpatient and inpatient treatment centers reported annually to the EMCDDA. There is a potential endogeneity problem, i.e. there is a two-way causality between the number of treatment centers and the number of drug users entering in new treatment. This will tend to introduce a bias in the estimation of the effect of the number of treatment centers on the number of drug users entering treatment. In order to correct for this bias, the number of treatment units is instrumented by the total health expenditure as a percentage of GDP and by the logarithm of the population of working age (more details in the Data Description Document ()).

The data about the rates of unemployment (both the structural and the cyclical components) in the different member countries are obtained from the AMECO data set of the European Commission. More information on this data set can be found in.

It has to be stressed that the different definitions of unemployment, employment and inactive population used in EMCDDA and AMECO databases are not always fully consistent. However, we do consider that this data set is the best possible available one at the present.

In a later section, we will test our results using another dataset. In order to have a comparable set of variables, we used German drug treatment data, published by the *IFT - Institut für Therapieforschung*, over the period 1988-2007. This dataset provides detailed information on the labor status of persons in treatment, who are grouped by the type of drug addiction. According to their labor status, persons in treatment are also cluster into 3 aggregate groups: employed, unemployed and inactive. We tried to harmonize the definitions of labor status used by the IFT with the ones of the Eurostat and the International Labor Organization (ILO). More information on the German data can be consulted from the Data Description Document ( ).

The empirical model and estimation results

In this section we analyze empirically how the state of the economy as measured by the economy wide unemployment rate affects the number of drug users entering outpatient treatment (drug clients). We first analyze the total number of drug clients and then we factor out two groups, the unemployed and the employed drug clients, from the total. Thus we obtain three econometric equations,

$$T_{it} = \alpha_i + \beta\, U_{it} + \varepsilon_{it} \tag{5}$$

$$TU_{it} = \alpha_i + \beta\, U_{it} + \varepsilon_{it} \tag{6}$$

$$TE_{it} = \gamma_i + \delta\, U_{it} + \eta_{it} \tag{7}$$

Where T_{it} is the total number of drug clients, TU_{it} is the number of unemployed drug clients and TE_{it} is the number of employed drug clients in country *i*, in period *t*. The three variables are expressed as a percentage of total population of working age in country *i*, in period *t*. We perform this normalization process because the explanatory variable, the unemployment rate, $U_{it,}$, is also a percentage (i.e. the number of unemployed as a percent of active population in country *i*, in period *t*). Thus, in what follows, $T_{it,}$ TU_{it} and TE_{it} are to be interpreted as fractions of total population. We will continue to use the shorthand "number of drug clients"

Equations (5), (6) and (7) have a panel data structure, i.e. they combine time series and cross section data. We estimated equations (5) , (6) and (7) using a fixed effect model: α_i

and γ_i are the fixed (country) effects. The term "fixed" should be interpreted as a country effect that does not vary over time. These fixed effects summarize the idiosyncratic effects originating from individual countries, e.g. cultural, social and political peculiarities of countries that affect individuals of these countries to enter treatment and that are unrelated to the other explanatory variables in the model. We checked the validity of the fixed effect model against a random effect model and we rejected the latter using the standard Hausmann-test.

It would have been interesting to check whether there are country effects that vary over time. For example, some countries saw a large increase in cocaine consumption during the sample period. We would have had to add country-time variables, but we decided not to do this because of too great a loss in degrees of freedom.

The results are shown in tables 1, 2 and 3. It should be noted that the results contained in table 1 (total number of clients) use a larger sample of countries than the results contained in tables 2 and 3. This has to do with the fact that there are fewer countries providing information on the occupation of the drug clients

We now interpret the results and concentrate first on table 1, where country fixed effects are presented. First, most of the variation in the number of drug clients is explained by country differences. This can be seen from the difference between the total R^2 and the R^2 obtained without the fixed country effects. These country differences can be due to many idiosyncratic factors differences between countries, i.e. differences in drug demand reduction and social policies, in treatment availability, in different stages of the epidemics, in different prevalence rates, in culture, in per capita income, in the age of population, etc. Second we find that the unemployment rate has a significant (at 10% level) negative effect on the total number of drug clients., i.e. when the unemployment increases (declines) the number of drug clients seeking treatment declines (increases).

Focusing on table 2, we find that the unemployment rate has a significant (at 10% level) negative effect on the number of unemployed drug clients seeking treatment (note that we do not show the country fixed effects; these are very similar as in the previous table). No such significant effect of the unemployment rate on the number of employed drug clients seeking treatment exists. Thus the effect of unemployment on the total number of drug clients seems to come from its effect on the unemployed drug clients, as hypothesized in the theoretical section.

These results can be interpreted as follows. A decline in unemployment increases the number of unemployed drug clients. This increase is the result of the *incentive* effect (unemployed drug users have better incentives to seek treatment when employment prospects improve) and of the *supply* effect (better economic conditions lead to an increase in the supply of treatment centers). We will analyze the supply effect explicitly at a later stage. The results of table 2 suggest that the *incentive* effect is probably the more important one. The reason is that if the *supply* effect were important we would also find that more <u>employed</u> drug users enter treatment when economic conditions improve. We do not find such an effect, though, leading us to conclude that the negative sign we find in table 1 most likely reflects the *incentive* effect. (See Edwards(2004) for an interesting analysis confirming this result. It is also consistent with the study of Cebulla, et al.(2004) showing that drug treatment service providers are viewed as a means to build trust between substance users and employment service providers).

It should be stressed that although the unemployment rate has a significant negative effect on the number of unemployed drug users entering treatment, the quantitative importance of the unemployment rate remains small. This can be seen from the low R^2 obtained when we exclude the country fixed effects. This suggests that there are other, probably stronger factors, determining the decision of drug users to seek treatment. For an analysis of these factors see e.g. Kemp and Neale (2005).

Table 1. Regression of drug clients on unemployment (equation (5))
(country fixed effects)

Table 2. Regression of unemployed drug clients on unemployment (equation (6)) and
regression of employed drug clients on unemployment (equation (7))
(country fixed effects)

The next step in our analysis consists in of splitting the unemployment rate into a structural and cyclical component. There are different ways to compute the structural and cyclical components of unemployment. We use the AMECO data set of the European Commission. The methodology used by the European Commission is to first compute the level of unemployment that is consistent with price and wage stability. This leads to an estimate of the NAWRU (the non-accelerating wage inflation rate of unemployment). This can be interpreted as the structural unemployment, i.e. as the level of unemployment that is due to rigidities in the labor market or other economic, regulatory or cultural impediments. The cyclical component of unemployment is then obtained by taking the difference between the observed unemployment rate and the NAWRU.

We show the estimation results in table 3. (We have omitted the estimations of the fixed effects as these are very similar to the ones shown in table 1). From table 3 we conclude that the negative effect of unemployment on the total number of drug clients comes exclusively from the structural component of unemployment. This is now significant at the 5% level. The cyclical component of unemployment has no significant effect on the total number drug clients. These results make sense: only when labor market conditions improve structurally, leading to an improved long-term employment outlook, do they give sufficient incentives to the drug users to seek treatment. These results also suggest that drug users are aware that durable employment prospects matter more than temporary ones in their decision to seek treatment.

Table 3 also confirms what the theory would suggest. The effect of unemployment on the total number of drug treatments is due to the fact that a low unemployment (better job opportunities) increases the number of unemployed drug users entering treatment, while leaving the number of employed drug users entering treatment unaffected. This can be seen from the fact that parameter of structural unemployment is significantly associated with the unemployed treatment clients while it is non-significant for employed treatment clients (compare columns 2 and 3).

Table 3: Estimation of equations (5)- (7) with structural and cyclical unemployment: (fixed effects)

The previous results did not distinguish the different types of drugs. We now distinguish between cocaine, cannabis, heroin and other drugs. Because of lack of data availability we could not, however, distinguish between unemployed and employed drug clients. This is an important drawback because, as we have shown earlier, the incentives of unemployed and employed drug users in seeking treatment may be very different. Nevertheless it may be useful to check for possibly different reactions of drug clients depending on the type of drug they are using.

Drug users are not a homogeneous group and it cannot be assumed that all groups share the same barriers or incentives when reacting to external factors, such as the rate of unemployment. French et al. (2001) have also shown that while chronic drug use was significantly negatively related to employment, non-chronic drug was not. In the case of treatment analyzed here there is a very high probability that all clients have some degree of dependency. However, its level varies according to the drug and the level of dependence. In order to have an even better insight on drug clients behavior, it would also be interesting to have information on their different dependence stages, and to take into account what other than the primary drug used are these clients using or are being treated for. However, the available dataset does not allow us to go this far.

The estimation results are shown in table 4. For cocaine and cannabis we find similar results as the ones obtained earlier, i.e. an improvement in labour market conditions (decline in unemployment) leads to an increase in drug clients. This effect comes mostly from the structural component of unemployment.

Table 4: Regression of total drug clients (by drug use) on cyclical and structural unemployment: (fixed effects)

The results for heroin, however, do not confirm the previous results. For heroin we find a positive and significant effect of unemployment on the number of drug clients. It may be related to the fact that heroin users are very dependent or problematic drug users for which the *incentive* effect is very weak, since the negative effect of drug use in more dependent users strongly reduces their ability to obtain and maintain regular employment (Cebulla, 2004). UKDPC (2008) stresses that there is a need to stabilize drug use, to treat physical and mental health problems, to build motivation and aspirations, to provide appropriate stable accommodations as minimal factors required before many problematic drug users will be in a position to participate in the formal job market. This is most likely coupled with the possibility that deteriorating economic conditions have a positive effect on the number of heroin users (the term N_{it} in equation (4)). The estimated coefficients for the new stimulants are negative but not significant. Again this may be due to the lack of disaggregation between unemployed and employed drug clients.

The theoretical discussion in section 3 also focused on the effect of supply factors. In particular when the supply of treatment centers increases this is likely to have a positive effect on the number of drug users entering treatment.

We test this hypothesis now. The equations to be estimated now become:

$$T_{it} = \alpha_i + \beta\, U_{it} + \beta_S S_{it} + \varepsilon_{it} \tag{8}$$

$$T_{it} = \alpha_i + \beta_C UC_{it} + \beta_N UN_{it} + \beta_S S_{it} + \varepsilon_{it} \tag{9}$$

$$TU_{it} = \alpha_i + \beta_C UC_{it} + \beta_N UN_{it} + \beta_S S_{it} + \upsilon_{it} \tag{10}$$

$$TE_{it} = \phi_i + \beta_C UC_{it} + \delta_N UN_{it} + \beta_S S_{it} + \psi_{it} \tag{11}$$

where S_{it} is the number of treatment centers in country i and period t. We instrument this variable using the share of government spending on health in country i and period t. Equation (12) regresses the number of treatment clients on the total unemployment rate (as we did in equation (5)); equation (13) regresses the number of treatment clients on the cyclical and structural components of the unemployment rate; and equations (14) and (15) do the same for the shares of unemployed and employed drug clients in the total population of working age. The results are shown in table 5.

An important econometric problem that arises here is the two-way causality between the number of treatment centers and the number of drug users entering in new treatment. We discuss this problem in the next section.

Causality issues

As a result of the two-way causality, a regression of the number of new drug clients on the number of treatment centers is not an appropriate procedure because the latter variable is not exogenous in such a regression. In order to take into account that the variable, which measures the supply of drug treatment, might be endogenous we have used the instrumental variable (IV) approach. We selected two instrumental variables. The first one is the log of country-wide population. This is based on the assumption that the number of inhabitants in a country does not influence the share of drug addicts, who demand treatment, directly but only through the amount of treatment centers in a country(Dranove and Wehner, 1994, Carlsen and Grytten, 1998). There is some evidence that the size of the youth cohort in a jurisdiction is positively related to marijuana consumption(Jacobson(2004). Since this increase in consumption could lead to an increase in the demand for outpatient treatment, this could reduce the quality of this instrument. Since out instrument is the *total* population in a country this effect is considerably reduced.

The second instrument included into regression equations is the total expenditure on health care as percentage of GDP (data obtained from the health statistics collected by the World Health Organization Regional Office for Europe). We use this variable as our instrument because it is correlated with the number of treatment centers (the independent variable, corr=-0.293) while it is little correlated with the number of drug clients (dependent variable, corr=-0.029). There are, of course, mechanisms that could lead to a correlation between the number of drug clients and health expenditure. We list a few here:

An increase in health spending may be positively correlated with the number of intensive treatment and detoxification slots available in hospital settings, which could influence the number of outpatient clients in non-hospital settings

An increase in health spending may be positively correlated with the number of inpatient beds available in non-hospital settings, which could influence the number of outpatient clients in non-hospital settings.

An increase in health spending may be positively correlated with an increase in drug prevention spending which can *reduce* use and thus demand for outpatient treatment.

An increase in health spending may be positively correlated with advertising and outreach activities (e.g., syringe exchange programs) intended to *increase* treatment entry.

The effects of these mechanisms, however, are not always clear, and the sign of the influences may go in opposite directions. That is why we found a low correlation between the number of drug clients and health expenditure.

We also tested for the statistical validity of instruments in two ways. First, following Dranove and Wehner, 1994, for an instrument to be valid the correlation between the residuals of the OLS estimation and the instrument has to be low and insignificant. In other words, a valid instrument does not improve the OLS model's fit if included into the equation. We found low correlations for both instruments: 0,139 for the population and 0,113 for the health expenditure. Second, the statistical validity of instruments can be checked by testing for over-identifying restrictions using the Hansen J-statistics. Note that this is a joint test on the validity of the instrumental variables. We found that instruments jointly pass the Hansen J test at the 5% significance level.

It should be admitted, though, that both population and health expenditure measures appear to be relatively weak instruments and thus give a biased estimate of the effect of the supply variable (Staiger and Stock,(1997), see also Angrist, and Krueger(2001)). At this stage we do not see how we can resolve this problem. This problem, however, does not bias the main estimation results concerning the relevance of the labor market conditions for the individuals' decision to demand drug treatment. The reason is that the general labour market conditions can safely be assumed to be exogenous with respect to the dependent variable, outpatient treatment, i.e. it is safe to assume that the number of outpatient treatments in a country does not influence general economic conditions in that country.

The results of the estimation using these instrumental variables are shown in table 5.

Table 5: Estimation results with supply of treatment centers

We find that the number of treatment centers has the expected positive effect on the number of drug clients and is highly significant. The unemployment rate has a significant negative effect on the total number of treatment clients. In contrast to our previous results, though, this negative effect comes mainly from the cyclical component of unemployment.

We performed two robustness checks of the obtained estimation results: (a) we modeled labor market conditions by the country-specific employment level and (b) ran additional regressions for the shares of unemployed *and* inactive drug clients in the total population of working age. The latter check was motivated by the unclear distinction between unemployed and inactive clients in treatment in the EMCDDA data. In both cases our results were consistent with the main findings.

Empirical analysis using German data

In this we use a German data set to test our main hypothesis. The advantage of this data set is that it has disaggregated information of treatment by type of drug. This allows us to find out whether the effect of unemployment on treatment differs for different types of drugs. The data are described in appendix.

We proceed in the same way as in the empirical analysis using EU-data, i.e. we first present regression results using the total treatment clients, and then the results using unemployed and employed drug clients. The equations we want to estimate are specified as follows:

$$T_{kt} = \alpha \; + \beta_{Ck} UC_t * D_k + \beta_{Nk} UN_t * D_k + \beta_S S_t + \varepsilon_{kt} \tag{8}$$

$$TU_{kt} = \gamma \; + \gamma_{Ck} UC_t * D_k + \gamma_{Nk} UN_t * D_k + \gamma_S S_t + \eta_{kt} \tag{9}$$

$$TE_{kt} = \delta \; + \delta_{Ck} UC_t * D_k + \delta_{Nk} UN_t * D_k + \delta_S S_t + \upsilon_{kt} \tag{10}$$

where T_{kt} = the total number of drug clients using drug k in period t, as percent of population of working age; TU_{kt} is the unemployed number of drug clients; TE_{kt} is the employed number of drug clients; UC_t and UN_t are the cyclical and structural components of unemployment in Germany in period t. Each of these two unemployment variables is multiplied by a matrix of dummy variables D_k that takes on the value of 1 when the observation relates to the drug type k. This allows us to estimate the drug specific effects of unemployment on treatment β_{Ck}, β_{Nk}, γ_{Ck}, γ_{Nk}, δ_{Ck}, δ_{Nk}. Finally, S_t measures the supply of treatment centers in Germany in period t. Because of the potential of reverse causality (number of drug clients causing the number of treatment centers to increase) we used instrumental variables (IVs). We selected two such IVs, total health expenditure as a percent of GDP and the log of population. The results are shown in table 6

The results are very much in line with our previous results. First, changes in unemployment affect the decisions of unemployed drug users to enter treatment, not of the employed drug users. This is made clear by comparing the second and the third columns in table 6. We observe that the significant negative effects are all to be found in the second column measuring the impact of unemployment on the number on unemployed treatment clients. We find no significant negative effects in the third column measuring the impact of unemployment on employed treatment clients. This confirms our hypothesis that improved labor market prospects gives incentives to the unemployed drug users to seek treatment, not to employed drug users. The result of these opposing effects is that the effect of unemployment on the total number of treatment clients is weak. This can be seen from the first column. Although we find that most coefficients are negative, few are significant.

A second result of table 6 stands out. This is that most of the action comes from the structural component of unemployment. We can see from column 2 that most of the significant effects of unemployment on the number of drug clients are concentrated in the structural component of unemployment, although we also find that the cyclical component of unemployment affects the decision of unemployed drug users to seek treatment

Third, we also find that the opium drug users seem to be insensitive to movements of unemployment in their decision to seek treatment. We noted earlier that heroin users are very dependent or problematic drug users for which the *incentive* effect to look for a job when job prospects improve is very weak.

Finally we wanted to know how economically significant these effects are. Statistical significance is important, but one is also interested in the economic significance of the effects, i.e. in the quantitative importance of these effects. If the latter are small, the statistical significance is of little practical relevance. We compute the quantitative effects of the structural unemployment rate on the treatment numbers in table 7. These quantitative effects are obtained by using the estimated coefficients in table 6 and applying them on the mean numbers treatment data. We observe that a one percent point decline in the German unemployment rate leads to an increase of the number of persons seeking treatment by 2.5 to 5.3%. (Note that this may seem to be large effects given that the coefficients in table 6 are very small. The dependent variable, however, is the share of treatment clients in total population. Thus a small change in that share translates in a relatively large change in the number of treatment clients). Considering that from the bottom of a recession to the peak of a boom the unemployment rate typically declines by approximately 3%, we obtain movements in the treatment numbers from 7.5% to 16%.

Table 6: Estimation results for Germany (equations (8)-(10)): Instrumental variable method

Table 7: Quantitative effect of a one percent point decline in German unemployment rate on the number of drug clients (in percent)

Conclusion

The decision of drug users to enter treatment is influenced by many factors. In general one can say that there must be an intrinsic motivation of the drug user to enter treatment. That is, the addicted person must have a desire to free him/herself from a dependence that is perceived to reduce his/her quality of life. This intrinsic motivation can, however, also be influenced by external factors. One of these factors is the state of the economy, and more specifically, the employment prospects for the dependent person.

In this paper we tested the hypothesis that an improvement in the employment prospects, as measured by a decline in unemployment, strengthens the intrinsic motivation of a dependent unemployed person to seek treatment. Our hypothesis is that the “payoff” for entering treatment increases when the unemployed drug user has a greater probability of finding a job after treatment.

We first surveyed the literature on the subject and we found that there is a large literature substantiating this effect. Paid employment contributes to an individual's ability to create a drug free life in several ways. It makes it possible for the individual to become economically independent, to integrate in a wider social network and to boost his self-esteem. All this makes it more attractive for an unemployed drug user to seek treatment when job prospects improve.

We then tested the hypothesis econometrically using two different data sets, one EU-wide and one German data set. Our main findings are that unemployment has a significant negative effect on the number of drug users entering treatment. In general we find that the structural component of unemployment has a stronger impact on the number of treatment clients, i.e. when the number of structural unemployed declines (increases) the number of drug clients increases (declines). The cyclical component of unemployment generally has a weaker effect on the number of drug clients. The latter makes sense: when unemployment declines temporarily this is likely to have a weaker impact on the decision of drug users to seek treatment than when unemployment declines structurally.

We also found that *unemployed* drug users seeking treatment are most sensitive to variations in the economy-wide unemployment rate. Employed drug users in contrast are not influenced by variations in the economy-wide unemployment rate in their decisions to enter treatment.

While our empirical results are encouraging, there is certainly more research to be done to check the robustness of these results. This is especially the case as the quality of the data is far from perfect. Nevertheless some policy conclusions can be drawn. Our empirical results confirm that the creation of job prospects adds significantly to the willingness of unemployed drug users to see treatment. This lends support to the idea that treatment programs should be embedded in programs aiming at improving the job prospects of drug users.

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