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Research paper

Unemployment and drug treatment[☆]

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ABSTRACT

Background: Since 2007 the economic recession has hit most industrial countries and this raises the question of how economic hardship affects illicit drug users' decisions to enter drug treatment.
Methods: We test the hypothesis that an improvement in the employment prospects, as measured by a decline in unemployment, strengthens the intrinsic motivation of an unemployed drug user 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 reviewed the literature and found considerable evidence to substantiate this effect. We tested the hypothesis econometrically using two different data sets, one EU-wide and one German data set.
Results: Our main findings were 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 treatment clients increases (declines). We also found 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 these variations when deciding 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 drug treatment should be embedded in programmes to improve the job prospects of drug users.

Introduction

Unemployment in the European Union has increased sharply as a result of the financial crisis and as the recession continues, and the unemployed fail to find work, they lose part of their human capital which makes it more difficult to re-enter the labour 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 finds that causation runs in two directions, i.e. a lack of employment is a factor that leads individuals to more serious drug taking, whereas more serious drug involvement works against stable and/or better paid employment. The question of how macroeconomic employment prospects affect drug use – as measured by the aggregate unemployment rate – is less well researched. Even less is known about the effects of the aggregate unemployment rate on the probability of drug users entering treatment and it is this issue that we address here.

Brief survey of the literature

Most of the empirical research has concentrated on how individual employment and drug use are related and "individual employment" is seen as a measure of social inclusion. Typical examples of these studies are: Eisembach-Stangl, Moskalewicz, and Thom (2009), Buchmueller and Zuvekas (1998), Zarkin, Mroz, Bray, and French (1998), MacDonald and Pudney (2000), Pollack, Danziger, Jayakody, and Seefeldt (2002), French, Roebuck, and Alexandre (2001), March, Oviedo-Joekes, and Romero (2006), DeSimone (2002) and 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 reduce employability. A study that stands out as finding little robust relationship between drug use and employability is Van Ours (2006).

To our knowledge the only published study analysing the relationship between the macroeconomic employment conditions and drug use is Arkes (2007). He estimated the impact of the economic cycle on drug use amongst teenagers and concluded that a weaker

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economy leads to greater teenage cannabis and “hard–drug” use. He also showed that teenagers were more likely to sell drugs in weaker economies, which acts as a counter-cyclical mechanism facilitating drug use in economic downturns.

Some studies have concentrated on how treatment affects the probability of getting a job, i.e., Wickizer, Campbell, Krupski, and Stark (2000) confirmed that treatment has a positive effect on “employability”. Meara (2006) and McCoy, Comerford, and Metsch (2007) found that treatment tends to improve the earning status of patients. However, the selection bias, whereby individuals who are more confident of finding a job after treatment are more likely to enter treatment, can lead to overestimating the effect of treatment per se. This problem can be overcome by using randomised sampling methods (see Heckman, 1979).

The reverse causality relation has also been analysed, and a number of studies have noted the importance of paid employment as a key factor in sustaining recovery from drug dependency (DeFulio, Donlin, Wong, & Silverman, 2009; Klee, McLean, & Yavorsky, 2002; McIntosh, Bloor, & Robertson, 2008; Room, 1998; Westermeyer, 1989). 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, Smith, & Sutton, 2004). First, it enables the drug user to fill time constructively and become independent. Second, it helps users to reintegrate into a wider network, facilitating the development of drug-free social relationships. Third, it enhances an individual’s self-esteem. Finally, it works as a symbol of the individual’s capacity to return to a more conventional lifestyle.

Wong and Silverman (2007) discussed extensively which kinds of treatment programmes were more adequate to employment-based drugs users’ interventions. Employment status is frequently used as an outcome in determining treatment efficacy (see Hermalin, Steer, Platt, & Melzerger, 1990). Some treatment includes employment counselling or vocational rehabilitation courses as part of the services provided to clients (Platt, 1995; Reif, Horgan, Ritter, & Topmkins, 2004).

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 to enter treatment is determined by an intrinsic motivation, i.e. 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. According to EMCDDA (2010), most clients enter treatment on their own initiative or as a result of pressure from family and friends (43%); 27% are referred through health or social services; around 20% are referred by the criminal justice system, and the remaining through other referral sources.

Here we 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 test is as follows. An improvement in the employment prospects induced for example by a business cycle upturn, strengthens the intrinsic motivation of a 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 treatment. There is a large literature substantiating this effect (see e.g. Biernacki, 1986; Cebulla et al., 2004; Luchansky, Brown, Longhi, Stark, & Krupski, 2000; McIntosh et al., 2008). Paid employment contributes to an individual’s ability to create a drug free life in that it allows an individual to become economically independent, to integrate in a wider social network and to boost 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 focus on the availability of treatment. The more treatment centres that are available, the more drug users will seek treatment. The supply of treatment 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 centres become available (OECD, 2009). When the economy is in recession, budgetary restrictions may reduce the funding for drug treatment thereby negatively affecting availability.

These demand and supply factors are discussed in the framework of a simple model. 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.

We focused on how the state of the economy and more particularly the employment prospects affect λ_t and N_t in Eq. (1). We used the economy-wide unemployment rate as the indicator of these employment prospects. Thus 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 assumed 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 discuss the signs of the partial derivatives in Eq. (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 made a distinction between the unemployed drug users seeking treatment and those who were employed because we assumed that incentives for the jobless are different from the employed. More specifically, as indicated above, our assumption is that, if employment opportunities improve, unemployed drug users will have more incentive to seek treatment so that this fraction increases. We call this the *incentive* effect. It is not a priori clear how 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 losing their jobs. We let the data decide and assumed that

$$\frac{\partial \lambda_{Ut}}{\partial U_t} \leq 0$$

$$\frac{\partial \lambda_{Et}}{\partial U_t} \leq ?$$

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, namely the *supply* effect. An improvement in the state of the economy also improves the government’s budget, allowing for more spending on drug treatment. Thus when economic activity improves, the supply of treatment centres/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 treatment 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, shows that this depends on a range of factors, including the type of drug, the ingestion method, the dependence level or the quality of the available treatment. An improvement in economic conditions and thus of job opportunities can increase or decrease the number of drug users.

We refer to the articles in this special focus issue, which describe the different effects of the economy on drug use. Thus

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

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 concentrated on measuring the effect of the state of the economy on the number of drug users entering treatment. We distinguished between employed and unemployed drug users. This allowed us to determine which of the four effects in Eq. (4) tended to dominate.

Description of the data

The treatment demand data published by the EMCDDA aims to provide comparable, reliable and anonymous information concerning the number and characteristics of people entering drug treatment in Europe. The drugs considered are opiates, cocaine, stimulants (amphetamines, MDMA and others), hypnotics and sedatives, hallucinogens, volatile inhalants and cannabis. Alcohol is only registered when it is used as a secondary drug.

This data set provides the best available and harmonised information at European level. In order to arrive at the current figures, much time has been devoted to setting up a solid conceptual framework and converging of the definitions used to collect these data.

In this study, treatment data referred to the total number of clients who started treatment during the year (2002–2007). It excluded those who started their treatment before the beginning of the year. According to the EMCDDA protocol, the category "clients" concerns those persons entering treatment during the calendar year regardless of having been treated before (during their lifetime). In case multiple entrances occur, this client is only counted once.

We decided to exclude inpatient/residential services because the data series available are considerably longer and involve a larger number of countries. Additionally, most treatment provision occurs in outpatient centres.

The data have some limitations and comparability across countries is limited. The coverage of the target institutions and the percentage of total clients accounted for can differ from country to country. Furthermore, these data include mostly clients who benefit from specialist treatment. As a result, they do not generally consider those receiving treatment from non-specialists such as 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 (2011) (see reference for URL-address).

Given the limitations noted above, there could be biases in the econometric estimates. These 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 be important.

This study uses the EMCCDA data where clients are split into 6 main categories: "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 employment" was quite broad comprising persons with a regular licit job, part-time, undeclared work, people working in the grey market and also those who benefitted from public employment programmes (EMCDDA, 2000). Even though there is guidance about coding those with irregular employment situations as "Other", this is not always done in practice.

In order to analyse whether the decision to enter treatment varies according to the primary drug used, we used another EMCDDA dataset. This reports the number of clients entering 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 provide information on 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, was obtained from the EMCDDA (2009a,b). The number of units refers to all outpatient and inpatient treatment centres reported annually to the EMCDDA. There is a potential endogeneity problem, i.e. there is a two-way causality between the number of treatment centres and the number of drug users entering treatment. This will tend to introduce a bias in the estimation of the effect of the number of centres on the number of drug users entering treatment. In order to correct for this, 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, 2011).

Data on rates of unemployment (both the structural and the cyclical components) in different member countries were obtained from the AMECO data set of the European Commission.

Whilst there was some inconsistency in definitions of unemployment, employment and inactive population between the EMCDDA and AMECO databases, we consider AMECO was the best available at the time of study.

In a later section we tested 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*, for the period 1988–2007. This provided detailed information on the employment status of persons in treatment, grouped by the type of drug used. The persons in treatment clustered into 3 aggregate groups: employed, unemployed and inactive. We tried to harmonise the definitions of employment status used by the IFT with the ones of the Eurostat and the International Labour Organization (ILO). More information on the German data is available in the Data Description Document (2011).

The empirical model and estimation results

We analysed 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 analysed the total number of drug clients and then we factored out two groups, the unemployed and the employed drug clients, thus obtaining 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 were expressed as a percentage of total population of working age in country i, in period t. We performed this normalisation 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 continue to use the shorthand "number of drug clients".

Eqs. (5)–(7) have a panel data structure, i.e. they combine time series and cross section data. We estimated Eqs. (5)–(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 summarise the idiosyncratic effects originating from individual countries, e.g. cultural, social and political peculiarities that have an affect on individuals in these countries entering 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 were country effects that varied 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 1–3. It should be noted that the results in Table 1 (total number of clients) are based on a larger sample of countries than the results in Tables 2 and 3. This is because there were fewer countries providing information about the occupation of the drug treatment clients.

First, the results with country fixed effects are presented. Table 1 shows that most of the variation in the number of drug treatment 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 can be due to factors such as differences in drug demand reduction and social policies, treatment availability, stages of the epidemics, prevalence rates, culture, per capita income, age of population, etc. Second, we found that the unemployment rate had a significant (at 10% level) negative effect on the total number of drug treatment clients, i.e. when unemployment increases (declines) the number of drug clients seeking treatment declines (increases).

Focusing on Table 2, we found that the unemployment rate had a significant (at 10% level) negative effect on the number of unemployed drug clients seeking treatment (note that we did not show the country fixed effects; these are very similar, as in the previous table). We found no such significant effect of the unemployment rate on the number of employed drug clients seeking treatment. Thus the effect of unemployment on the total number of drug clients seems to come from its effect on the unemployed drug treatment clients, as hypothesised above.

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 centres). The results in Table 2 suggest that the *incentive* effect is probably the more important one. If the *supply* effect was important we would also find that more employed drug users enter treatment when economic conditions improve and we did not find such an effect, leading us to conclude that the negative sign we found in Table 1 most likely reflects the *incentive* effect. It is also consistent with the study of Cebulla et al. (2004) showing that drug treatment providers are viewed as a means to build trust between substance users and employment 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 excluded 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, for example, Kemp and Neale (2005).

The next step consisted of splitting the unemployment rate into a structural and cyclical component. There are different ways to compute these components of unemployment. We used the AMECO data set of the European Commission (EC). The methodology used by the EC involves computing 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. the level of unemployment that is due to rigidities in the labour market or other economic, regulatory or cultural impediments. The cyclical component of unemployment is then obtained

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

Unemployment	−0.000947*		
	(0.000523)		
Country fixed effects			
Austria	0.0274**	Latvia	0.0568***
	(0.0116)		(0.0111)
Bulgaria	0.0501***	Lithuania	0.025**
	(0.0128)		(0.0115)
Cyprus	0.021**	Luxembourg	0.015
	(0.0115)		(0.0111)
Cyprus	0.0464***	Malta	0.0804***
	(0.0111)		(0.0108)
Czech Republic	0.0642***	Netherlands	0.048***
	(0.0107)		(0.0107)
Denmark	0.0455***	Poland	0.0389***
	(0.017)		(0.0126)
Finland	0.0281**	Portugal	0.107
	(0.0109)		(0.0106)
France	0.026**	Romania	0.012
	(0.0121)		(0.012)
Germany	0.0262**	Slovakia	0.0384***
	(0.0108)		(0.012)
Greece	0.0306***	Slovenia	0.036***
	(0.0109)		(0.0107)
Hungary	0.079***	Spain	0.0802***
	(0.0107)		(0.0114)
Ireland	0.0788***	Sweden	0.0256**
	(0.0106)		(0.0109)
Italy	0.0943***	UK	0.125
	(0.0108)		(0.0102)
Observations	215		
R^2	0.829		
R^2 without fixed effects	0.017		

Standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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

	Unemployed (TU_{it})	Employed (TE_{it})
Unemployment	−0.0039*	−0.0015
	(0.0022)	(0.0019)
R^2	0.65	0.90
R^2 (without fixed effects)	0.05	0.01
Number of countries	22	
Number of observations	83	

Note: standard errors in parentheses.
* $p < 0.1$.

Table 3
Estimation of Eqs. (5)–(7) with structural and cyclical unemployment (fixed effects).

Coefficient of	Total (T_{it})	Unemployed (TU_{it})	Employed (TE_{it})
Structural unemployment	−0.0141**	−0.0052**	−0.0030
	(0.0056)	(0.0023)	(0.0020)
Cyclical unemployment	0.0181	0.0036	0.0071
	(0.0117)	(0.0049)	(0.0041)
R^2	0.82	0.77	0.93
R^2 (without fixed effects)	0.15	0.10	0.01
Number of countries	22	22	22
Number of observations	83	83	83

Note: standard errors in parentheses.
** $p < 0.05$.

by taking the difference between the observed unemployment rate and the NAWRU.

The estimation results are shown in Table 3 (we have omitted the estimations of the fixed effects as these were very similar to the ones shown in Table 1). We concluded (see Table 3) 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 of drug treatment clients. Only structural improvements in labour market conditions lead to an improved long-term employment outlook and give sufficient incentives to 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.

The effect of unemployment on the total number of drug treatments is due to the fact that low unemployment (better job opportunities) increases the number of unemployed drug users entering treatment, whilst leaving the number of employed drug users entering treatment unaffected. By comparing columns 2 and 3 in Table 3 we can see that parameter of structural unemployment is significantly associated with the unemployed treatment clients, whilst it is non-significant for the employed clients.

We then distinguished between cocaine, cannabis, heroin and other drugs. Because of lack of data 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 the different reactions of drug treatment clients, depending on type of drug used.

Drug users are not a homogeneous group and it cannot be assumed that all 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 whilst chronic drug use was significantly negatively related to employment, non-chronic drug use was not. In the case of treatment analysed here, there is a very high probability that all clients have some degree of dependency. However, its level varies according to the drug used and the level of dependence. In order to have an even better insight into drug clients' behaviour, it would be interesting to have information on their different stages of dependence, and to take into account what other substances they are using or being treated for.

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

For heroin, we found a positive and significant effect of unemployment on the number of drug treatment clients. This may be related to the fact that heroin users tend to be 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 et al., 2004). UKDPC (2008) stresses the need to stabilise drug use, to treat physical and mental health problems, to build motivation and aspirations, and to provide appropriate stable accommodation as minimal factors required before many problem 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 Eq. (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.

We also focused on the effect of supply factors. In particular when the supply of treatment centres increases, this is likely to have a positive effect on the number of drug users entering treatment.

We tested this hypothesis. 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 centres in country i and period t. We instrumented this variable using the share of government spending on health in country i and period t. Eq. (8) regresses the number of treatment clients on the total unemployment rate (as we

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

	Cocaine	Cannabis	Heroin	New stimulants
Structural unemployment	−1.195***	−1.419***	3.123***	−0.113
	(0.462)	(0.439)	(0.739)	(0.175)
Cyclical unemployment	−1.522**	0.560	1.373	−0.284
	(0.650)	(0.619)	(1.041)	(0.248)
R^2	0.84	0.86	0.90	0.98
R^2 (without fixed effects)	0.23	0.10	0.20	0.02

Note: standard errors in parentheses.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
Estimation results with supply of treatment centres.

	OLS fixed effect		IV fixed effect		
Unemployment	−0.0013** (0.0005)				
Structural unemployment		−0.0006 (0.0008)	−0.0001 (0.0007)	0.0005 (0.0019)	0.0019 (0.0026)
Cyclical unemployment		−0.0026** (0.001)	−0.0021** (0.0010)	−0.0122* (0.0068)	−0.0120 (0.0093)
Supply treatment centres	2.788*** (0.942)	2.905*** (1.95)	2.528 (1.942)	2.207*** (0.705)	2.475** (1.067)
R^2	0.815	0.817			
R^2 (without fixed effects)	0.076	0.085			
Number of countries	22	22	20	17	17
Number of observations	192	192	170	64	64

Note: standard errors in parentheses. R^2 is not reported for the IV model because it has no statistical meaning in the context of the two-stage least squares technique (the model's residuals are computed over a set of regressors different from those used in the model). Number of observations drops for the IV models due to the missing data on health expenditure for (for Eq. (9)) and on labour status of drug clients (Eqs. (10) and (11)).

* $p < 0.1$.
** $p < 0.01$.
*** $p < 0.01$.

did in Eq. (5)); Eq. (9) regresses the number of treatment clients on the cyclical and structural components of the unemployment rate; and Eqs. (10) and (11) 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.

Causality issues

An important econometric problem that arises here is the two-way causality between the number of treatment centres and the number of drug users entering treatment. As a result of this, a regression of the number of drug clients on the number of treatment centres is not an appropriate procedure because the latter variable is not exogenous in such a regression. In order to account for the fact 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 is the log of country-wide population. This is based on the assumption that the number of inhabitants in a country does not influence directly the share of problem drug users who demand treatment, but only through the number of treatment centres in a country (Carlsen & Grytten, 1998; Dranove & Wehner, 1994). There is some evidence that the size of the youth cohort in a jurisdiction is positively related to cannabis 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 healthcare as percentage of GDP (data obtained from the health statistics collected by the World Health Organization). We use this variable as our instrument because it is correlated with the number of treatment centres (the independent variable, corr = −0.293) whilst 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: for example, 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 advertising and outreach activities (e.g., syringe exchange programmes) intended to increase treatment entry. However, the effects of these mechanisms are not always clear, and 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 tested for the statistical validity of instruments in two ways. First, in line with 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.

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 (see Angrist and Krueger, 2001; Staiger and Stock, 1997). This problem, however, does not bias the main estimation results concerning the relevance of the labour market conditions for an individuals' decision to demand drug treatment. This is because 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.

We found that the number of treatment centres had the expected positive effect on the number of drug clients and was highly significant. The unemployment rate had a significant negative effect on the total number of treatment clients. In contrast to our previous results, though, this negative effect came mainly from the cyclical component of unemployment.

We performed two robustness cheques of the estimation results: (a) we modelled labour 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.

Table 6
Estimation results for Germany (Eqs. (12)–(14)): instrumental variable method.

	Eq. (12) total drug clients	Eq. (13) unemployed drug clients	Eq. (14) employed drug clients
Drug type cyclical unemployment effects			
Cannabinoids	0.000726	0.00004	0.000821
Cocaine	−0.00217	−0.00132*	−0.00003
Hallucinogens	−0.00278	−0.00174**	−0.000282
Opiods	0.00264	0.00310	0.000487
Psycotrop sust	0.000322	−0.00169**	−0.000224
Sedative-hypnotics	−0.00265	−0.00167**	−0.000257
Stimulants	0.000314	−0.00151*	0.00003
volatile solvents	−0.00047	−0.00195**	−0.000293
Drug type structural unemployment effects			
Cannabinoids	0.00458	−0.000383	0.000240*
Cocaine	−0.0139*	−0.000628***	0.00001
Hallucinogens	−0.0164*	−0.000742**	−0.000105
Opiods	−0.00095	0.000422	0.000803***
Psycotrop sust	−0.0400	−0.000756***	−0.00009
Sedative-hypnotics	−0.0160*	−0.000717***	−0.00005
Stimulants	−0.0349	−0.000671***	0.00005
Volatile solvents	−0.0368	−0.000799***	−0.000120
Treatment supply β_S	12.32**	5.861***	0.881
Observations	74	74	74
R^2	0.350	0.786	0.852

Note: We use the share of health expenditures in GDP as the instrumental variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$

Empirical analysis using German data

Here we used a German data set to test our main hypothesis. This dataset disaggregated information of treatment by type of drug, which allowed us to find out whether the effect of unemployment on treatment differed by drug used. These data are described in Data Description Document (2011).

We proceeded in the same way as European in the empirical analysis, first presenting 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:

$$T_{kt} = \alpha + \beta_{Ck} UC_i * D_k + \beta_{Nk} UN_t * D_k + \beta_S S_t + \varepsilon_{kt} \quad (12)$$

$$TU_{kt} = \gamma + \gamma_{Ck} UC_i * D_k + \gamma_{Nk} UN_t * D_k + \gamma_S S_t + \eta_{kt} \quad (13)$$

$$TE_{kt} = \delta + \delta_{Ck} UC_i * D_k + \delta_{Nk} UN_t * D_k + \delta_S S_t + \upsilon_{kt} \quad (14)$$

where T_{kt} is 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 allowed us to estimate the drug specific effects of unemployment on treatment β_{Ck}, β_{Nk}, γ_{Ck}, $\gamma_{Nk,}$ δ_{Ck}, δ_{Nk}. Finally, S_t measured the supply of treatment centres in Germany in period t. Because of the potential of reverse causality (number of drug clients causing the number of treatment centres 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.

They were in line with our previous results. First, changes in unemployment affected the decisions of unemployed drug users to enter treatment and not the employed drug users (comparing the second and the third columns in Table 6). We observed that the significant negative effects were all to be found in the second column measuring the impact of unemployment on the number on unemployed treatment clients. We found no significant negative effects in the third column measuring the impact of unemployment on employed treatment clients. This confirmed our hypothesis that improved labour market prospects gives incentives to unemployed – but not to employed – drug users to seek treatment. 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 found that most coefficients were negative, few were significant.

A second result in Table 6 showed 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 found that the cyclical component of unemployment affects the decision of unemployed drug users to seek treatment.

Third, we also found that users using opiates seem to be insensitive to movements of unemployment in their decision to seek treatment. We noted earlier that heroin users are very 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 were. Statistical significance is important, but one is also interested in the economic significance of the effects, i.e. in their quantitative importance. If the latter are small, the statistical significance is of little practical relevance. We computed the quantitative effects of the structural unemployment rate on the treatment numbers in Table 7. These quantitative effects were obtained by using the estimated coefficients in Table 6 and applying them on the mean numbers treatment data. We observed that a one percent point decline in the German unemployment rate leads to an increase in the number of persons seeking treatment by 2.5–5.3%. (Note

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

Cannabinoids	2.57%
Cocaine	4.21%
Hallucinogens	4.98%
Opioids	2.83%
Psycotrop sust	5.07%
Sedative-hypnotics	4.81%
Stimulants	4.50%
Volatile solvents	5.36%

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 into 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 obtained movements in the treatment numbers from 7.5% to 16%.

Conclusion

The decision of drug users to enter treatment is influenced by many factors, including personal motivation and various external factors. One of these external factors is the state of the economy, and more specifically, the employment prospects for the drug user.

Our hypothesis was that the “payoff” for entering treatment increases when the unemployed drug user has a greater probability of finding a job after treatment. The research literature certainly suggests that paid employment contributes to an individual’s ability to create a drug free life, making it possible to become economically independent, to integrate into a wider social network and to boost self-esteem.

We tested this hypothesis econometrically using two different datasets – an EU-wide and German dataset. Our main findings were that unemployment has a significant negative effect on the number of drug users entering treatment. In general we found 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 more sensitive than employed drug users to variations in the economy-wide unemployment rate.

Whilst our empirical results are encouraging, there is certainly more research to be done to check their robustness. 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 *k* treatment. This lends support to the idea that employment programmes need to be integral to drug treatment interventions.

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