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ABSTRACT

Going after the Addiction, Not the Addicted: The Impact of Drug Decriminalization in Portugal*

This paper investigates the impact of drug decriminalization in Portugal using the Synthetic Control Method. The applied econometric methodology compares Portuguese drug-related variables with the ones extracted from a convex combination of similar European countries. The results suggest that a policy change implemented in Portugal contributed to a decrease in the number of heroine and cocaine seizures, a decrease in the number of offenses and drug-related deaths, and a decrease in the number of clients entering treatment. Moreover, the policy change contributed to a reduction in the incidence of drug addicts among HIV individuals.

JEL Classification: C21, D04, K42

Keywords: drug decriminalization policy, illicit drugs, synthetic control method

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"The evidence from Portugal since 2001 is that decriminalisation of drug use and possession has benefits and no harmful side-effects."

The Economist, August, 2009

"In most respects, the law seems to have worked: serious drug use is down significantly, particularly among young people; the burden on the criminal-justice system has eased; the number of people seeking treatment has grown; and the rates of drug-related deaths and cases of infectious diseases have fallen."

The New Yorker, October, 2011

"One moderate alternative to the war on drugs is to follow Portugal's lead and decriminalize all drug use while maintaining the illegality of drug trafficking."

by Gary S. Becker and Kevin M. Murphy, 2013

1 Introduction

On the 22^{nd} of April 1999, the Council of Ministers approved the National Strategy for the Fight against Drugs, which delineated 13 strategic options in accordance with its core values and objectives, one of them being the decriminalization of consumption, possession, and purchase of illicit drugs for personal consumption. The decriminalization law itself was then approved by the Parliament on 29 November 2000 in Law number 30/2000 and was implemented on 1 July 2001. It states that use, purchase, and possession for use of any illicit drugs (hard or soft), in public or in private, not exceeding the average quantity required for 10 days of individual consumption is no longer to be considered a criminal offense, but rather an administrative one. Any amount greater than this is considered drug trafficking and continues to be prosecuted as a criminal offense.

Portugal is the only European Union (EU) member state so far that has dared to explicitly declare the decriminalization of drug use. In the other EU countries a less liberal legal framework prevails: either it is criminalized or, as in most countries, it has been depenalized, particularly for personal cannabis use. Nevertheless, legalization is far beyond the scope of any country's discussion, including in Portugal.

It is essential to distinguish depenalization from decriminalization. In plain words, depenalization comprises a criminal offense but no penal sanctions (imprisonment cannot be imposed), whereas decriminalization means a certain conduct is prohibited but sanctions do not fall within criminal law.

Along with the legal change, the overall attitude toward the Portuguese drug problem has shifted from that of a punitive approach to a comprehensive public health-oriented approach, in which prevention and treatment are core concerns. Offenders are now sent to "Commissions for Dissuasion of Drug Addiction" responsible for adjudicating administrative drug offenses and imposing sanctions (fines and others). Legal proceedings are temporarily suspended if the offender has no previous record of drug offense and is considered non-addict or, alternatively, if the offender is a drug addict but agrees to undergo treatment. Clearly the orientation of the commissions is to encourage dependent drug users to pursue treatment and not to punish their behavior, which previously was very stigmatized and discouraged them from seeking help.

The current paper studies the impact of this policy change in Portugal, using the Synthetic Control Method, proposed by Abadie and Gardeazabal (2003). Even though the effect of such a policy can be observed only in the long-run, it is possible to perform a meaningful analysis after 9 years of the implementation.

We begin with a brief literature review on the subject, which will be followed by a careful explanation of the methodology. Section 4 describes the dataset and Section 5 is devoted to the estimation and inference. In the conclusion the main empirical results are summarized.

2 Literature review

Most studies on illicit drugs address the demand side of the market because the difficulty in collecting reliable data is even greater when it comes to the supply side and the market structure. One of the main contributions of economic analysis of behavior on the demand side is the Becker and Murphy (1988) theory of rational addiction, which states that behavior is the result of intertemporal choices in which the addictiveness of goods contributes to a greater effect of past consumption on current consumption. In fact, the addictiveness and illegality associated with illicit drugs is what makes this area of study so interesting. It forces the economist to depart from conventional economic theories of behavior and standard market dynamics.

International evidence does not suggest a clear-cut impact of drug policy on the prevalence of drug use. It is unknown whether drug criminalization or decriminalization policies contribute to lower drug-use rates. However, according to Mazerolle *et al.* (2006), enforcement of drug laws may have effects in reducing the harm associated with drug markets. Thus, drug policy is far from being irrelevant.

Reinarman *et al.* (2004) sought to determine the relevance of policy concerning cannabis. They compared experienced cannabis users in two cities with opposing policies: Amsterdam (where it is decriminalized) and San Francisco (where it is criminalized). These authors found no evidence that decriminalization increases cannabis use or that criminalization decreases its use.

In Italy, where drug policy has changed its degree of tolerance several times since 1975, the trend of drug use is increasing, and is apparently non-responsive to legislation (Solivetti (2001)).

MacCoun and Reuter (1997, 2001) analyze the evidence on marijuana decriminalization in the United States, Australia, and the Netherlands. They find no evidence that higher marijuana use is associated with decriminalization. Still, regarding the Netherlands, they do conclude that the commercialization of cannabis has contributed to an increase in use.

A study about the United Kingdom drug policy also fails to reach a satisfying conclusion, and refers to the importance of social and cultural factors. Furthermore, it registers higher rates of overall and problematic drug use than in both Sweden and the Netherlands, countries having very different approaches to drug policy (Reuter and Stevens (2007)).

Regarding the Portuguese case, Greenwald (2009) conducted an extensive report, concluding that drug decriminalization has caused no harm and, if anything, has improved the situation. Indeed, empirical data show lower lifetime prevalence rates in the post-decriminalization period for almost every category of drug and for several age groups. Moreover, the author refers to the declining trends for drug-related pathologies, namely the number of deaths due to drug use and the number of drug users among newly infected HIV-positive individuals.

A report by Hughes and Stevens (2010) mentions the decrease of the burden on the criminal justice system as a benefit of drug decriminalization in Portugal. Not punishing drug possession in the penal system has significantly lowered the costs regarding police officers, lawyers and courts dealing with these issues as well as the costs of imprisoning drug offenders. However, while judicial costs have fallen, other costs associated with treatment and prevention have increased. The new health-based approach basically changed the allocation of public expenditure to drug issues, which were directed to the creation of the system of referral to the "Commissions for Dissuasion of Drug Addiction", to the construction of new treatment facilities, and to prevention campaigns, among other target expenditures.

More recently, Gonçalves *et al.* (2015) document a significant reduction in the legal costs associated with criminal proceedings for drug-law offenses and in the number of consumption drug-law offenses in the period between 1999 and 2010, which is line with the health-oriented strategy of the policy change. The authors also estimate that police costs for detection of drug-law offenses increased in the case of the specialized police force responsible for major drug-law offenses and decreased in the case of the non-specialized police forces. On the supply side, Félix and Portugal (2017) show that the prices of opiates and cocaine did not decrease in the sequence of the drug decriminalization in Portugal, which contrasts with the argument that softer drug law enforcement necessarily leads to lower prices and, consequently, higher drug usage rates.

3 Methodology

What the literature on drug policy effects has covered so far is based on careful comparative case studies. Researchers compare the outcome of relevant variables before and after a certain reform is implemented in a country and then extend the comparison to other countries with similar characteristics. The problem with this kind of approach is the lack of accuracy. The data can easily be contaminated by other factors like the natural trends of the outcome variables, the interaction with other policies, the social and economic performance of the country, among other factors.

The aim of this paper is to disentangle the effect of the decriminalization of drugs in Portugal using the Synthetic Control Method (SCM) for comparative case studies.

This method was developed by Abadie and Gardeazabal (2003) to investigate the economic cost of conflict using the Basque country as a case study, and it was further extended by Abadie *et al.* (2010) in order to estimate the effect of Proposition 99, California's tobacco control program. The advantage of this method is to allow for the impact of unobservable country heterogeneity to vary with time, whereas the usual difference-in-differences (fixed effects) estimation does not.

In this study, the SCM will indicate whether decriminalizing drugs in Portugal had an impact in a number of outcome variables. First, we construct what is called a synthetic control region: a weighted combination of European countries that best resembles the Portuguese characteristics before the implementation of drug decriminalization in 2001. Then we compare the verified outcomes of the relevant variables in Portugal in the post-decriminalization period with those that would have been observed in the artificial Portugal where no intervention has occurred. The difference between the two outcome trends reveals the impact of the policy change.

A formal description of the method is presented in the following model.[1] Suppose we have information about $(J+1)$ countries: the J stands for the "donor pool", all the potential control countries, and the 1 refers to the treatment unit. The dataset comprehends T periods and the intervention occurs at period T_0 $(1 \leq T_0 < T)$.

Let Y_{it}^N be the outcome variable of interest for country i in period t in the absence of the policy intervention and Y_{it}^I the corresponding value for the treated country during the implementation period $[T_0+1, T]$. Assuming that the intervention has no effect on the outcome before the implementation period $(Y_{it}^I = Y_{it}^N)$, which implicitly assumes that an intervention implemented in the treated country has no effect on the outcomes of the untreated countries, we can define $\alpha_{it} = Y_{it}^I - Y_{it}^N$ as the effect of the intervention for country i in period t.

Therefore, the observed outcome Y_{it} for country i in period t can be expressed as:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it}, \text{ with } D_{it} = \begin{cases} 1, & \text{if } i = 1 \text{ and } t > T_0 \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

If $i = 1$ is our treatment unit, we wish to estimate: $\alpha_{1t} = Y_{1t}^I - Y_{1t}^N$. Because Y_{1t}^I is observed, we need to estimate only Y_{1t}^N. This is specified by the following factor

[1] We closely follow the description provided by Abadie *et al.* (2010).

model:

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it}, \tag{2}$$

where δ_t is an unknown common factor with constant factor loadings on all countries; θ_t is a $(1 \times r)$ vector of unknown parameters; Z_i is a $(r \times 1)$ vector of observed covariates; λ_t is a $(1 \times F)$ vector of unobserved common factors; μ_i is a $(F \times 1)$ vector of unknown factor loadings; and the error terms are the unobserved transitory shocks at the country level with zero mean.

The proposed estimator of α_{1t} is $\widehat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$, for $t \in \{T_0+1, ..., T\}$ where w_j^* denotes the optimal weight of unit j, and the counterfactual situation for the treated country in the post-treatment period is a linear combination of the outcomes of the potential controls: $\widehat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j^* Y_{jt}$.

The estimator $\widehat{Y}_{1t}^N$ is unbiased if w_j^* is chosen to minimize the distance between X_1 and $X_0 W$:

$$\min_{w} \|X_1 - X_0 W\| \, \nu = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \tag{3}$$

$$\text{s.to}: \begin{cases} w_2 \geq 0, ..., w_{J+1} \geq 0 \\ w_2 + ... + w_{J+1} = 1 \end{cases} \tag{4}$$

where $X_1 = (Z_1', \bar{Y}_1^{K_1}, ..., \bar{Y}_1^{K_M})'$ is a $(k \times 1)$ vector of pre-treatment characteristics of the exposed country; X_0 is a $(k \times J)$ matrix of pre-treatment characteristics of the unexposed countries, where the j^{th} column is $(Z_j', \bar{Y}_j^{K_1}, ..., \bar{Y}_j^{K_M})'$ and $j = 2, ..., J+1$; and $K_1, ..., K_M$ are $(T_0 \times 1)$ vectors corresponding to M linear combinations of pre-treatment outcomes; $W = (w_2, ..., w_{J+1})'$ is a $(J \times 1)$ vector corresponding to the weights attributed to each of the untreated countries and respecting the constraints of the optimization problem (non-negative and summing up to 1); and V is a $(k \times k)$ diagonal and positive semi-definite matrix reflecting the relative importance of each of the K variables. Also:

$$\sum_{j=2}^{J+1} w_j^* \bar{Y}_j^{K_1} = \bar{Y}_1^{K_1}, ..., \sum_{j=2}^{J+1} w_j^* \bar{Y}_j^{K_M} = \bar{Y}_1^{K_M} \tag{5}$$

$$\sum_{j=2}^{J+1} w_j^* Z_j = Z_1. \tag{6}$$

Because the discrepancy between Y_{1t} and Y_{it}^N might merely be a result of chance or of a weakness in the method, a "placebo study" or "falsification test" is performed in the end. It consists of iteratively running the SCM to each and every country in the donor pool where no decriminalization was implemented. After placing Portugal in the donor pool, each country at the time is selected to become a false treatment country and the SCM will determine the impact of the Portuguese drug policy in each of the countries. If on average this impact is greater in Portugal than in the majority of the control countries we can tell with some degree of certainty that the decriminalization of drugs in Portugal did in fact have some impact on the outcome under study. This placebo study is essential to infer the significance of the estimates.

We apply this methodology to our case study in which the treatment unit is Portugal and the treatment period is 2001.

4 Data

Data were collected for 30 European countries: the 28 EU member states plus Turkey and Norway. The time period under analysis goes from 1990 to 2008, covering 11 years of pre-treatment data and 7 years of post-treatment data. Due to the lack of data regarding outcomes on drugs, many constraints were faced when constructing this database. Namely, some countries and years had to be dropped from the panel, since there can be no missing observations for any of the control countries.[2]

We studied the impact of the drug decriminalization policy on several outcome variables: seizures of heroin and cocaine (two of the most common and harmful drugs in the market), drug-law offenses, drug-related deaths, and medical treatment demand.

[2]The following 10 countries were never used in the construction of synthetic Portugal: Cyprus, Czech Republic, Estonia, Latvia, Lithuania, Malta, Romania, Slovakia, Croatia and Turkey.

The choice of these outcomes was largely based on the availability of harmonized data across the countries. We also sought to study the impact of decriminalization on the prevalence of AIDS among injecting drug users, but unfortunately the SCM was not able to deliver a reasonable fit: no convex combination of countries resembled Portugal well enough in the pre-treatment period. Thus, no valid inference could be drawn from the results obtained. However, it is possible to provide linear spline estimates for this outcome variable, which account for a possible trend shift in the number of drug users among HIV infected in the sequence of the policy change. Linear spline estimates for the outcome variables considered in the analysis are provided in Section 5.1.

As for the predictors considered in the SCM estimation, the following were considered: GDP per capita (*GDP*), unemployment rate (*Unemployment*), a civil liberties indicator (*FIW_CR*)[3], the proportion of young (aged 15 to 24) population (*Young*), the retail prices of opiates and cocaine (*Opiates* and *Cocaine price*, respectively), and alcohol (*Alcohol*) and tobacco (*Tobacco*) consumption. The first two predictors characterize the economic situation of the country; the third refers to social freedom; the fourth is to account for the fact that the drug problem occurs in larger scale among the youth; the prices of drugs is a market indicator of the interaction between demand and supply; and finally alcohol and tobacco characterizes the social habits that are more often related to drug environments. Additionally, we included in the list of predictors of each outcome variable the mean of the outcome itself across the potential controls for every two years of the pre-treatment period. This allows for a better fit of the synthetic control country.

A detailed explanation of all the variables as well as their respective sources is in appendix A.

5 Estimation

In this section we present the empirical results of the study, analyzing each outcome separately. We proceed with the estimation in two steps. First, we present linear spline estimates that account for a shift in the linear trend of the outcomes considered in the analysis following the drug decriminalization policy. Second, we apply the SCM

[3]Based on surveys and involving freedom of expression and believe, association, and organization rights, rule of law, and personal autonomy and individual rights.

estimator, which allows for the construction of a "synthetic" Portugal as a convex combination of other countries that best resemble Portugal before the implementation of the drug decriminalization policy in 2001.

5.1 Linear spline estimates

The empirical model considered to estimate the linear spline is given by the following specification:

$$y_{it} = \alpha_i + \lambda t + \gamma(t-2000)\mathbb{1}(t \geq 2001) + \delta \mathrm{Port}_i * (t-2000)\mathbb{1}(t \geq 2001) + \varepsilon_{it}, \quad (7)$$

where i=*1,...,N* designates each country in the sample and the subscript t designates time. The variable t is a linear time trend starting at 1990, the indicator function $(t-2000)\mathbb{1}(t \geq 2001)$ is defined as equal to zero in the pre-treatment period and equal to $(t-2000)$ in the post-treatment period ($Spline_t$), and $Port_i$ is an indicator variable for the treatment group, Portugal. The dependent variable y_{it} represents the possible outcomes (in logarithm, except in the case of the outcome number of drug addicts among HIV infected individuals). The term α_i denotes a full set of country dummy variables and ε_{it} is a zero mean disturbance term capturing all other omitted factors.

We estimate this model applying the ordinary least squares estimator. Estimation results are reported in the appendix Table 1.

Heroin and cocaine seizures

Linear spline estimates for (the logarithm of) heroin and cocaine seizures are depicted in Figures 1 and 2. The estimated trend shift shows a sharper decrease for Portugal than for the other countries in the case of heroin seizures and a moderate decrease for Portugal in the case of cocaine seizures.

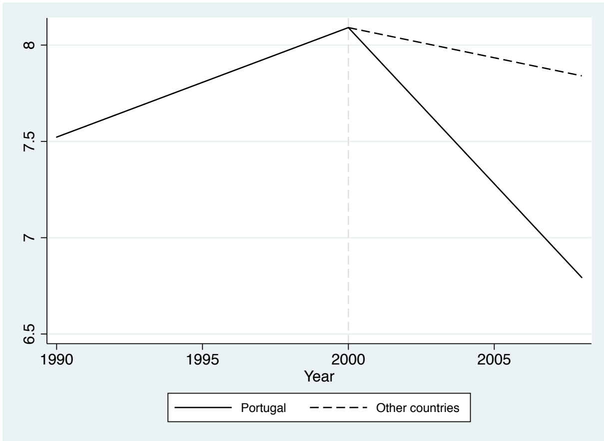

Figure 1 – Linear spline estimates: (logarithm of) heroin seizures.
Notes: For detailed data definitions see Section 4.

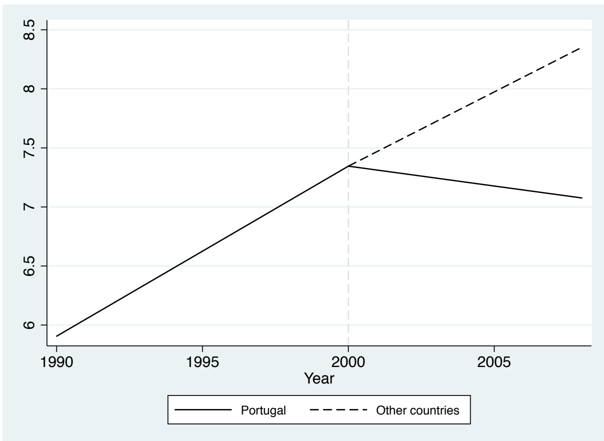

Figure 2 – Linear spline estimates: (logarithm of) cocaine seizures.
Notes: For detailed data definitions see Section 4.

Drug law offenses

Figure 3 shows the trend shift in (the logarithm of) drug-law offenses following the drug decriminalization policy. The estimates suggest a negative impact of the policy change on the number of drug-law offenses, meaning that the number of drug-law offenses was lower than would have been in the absence of the drug decriminalization policy.

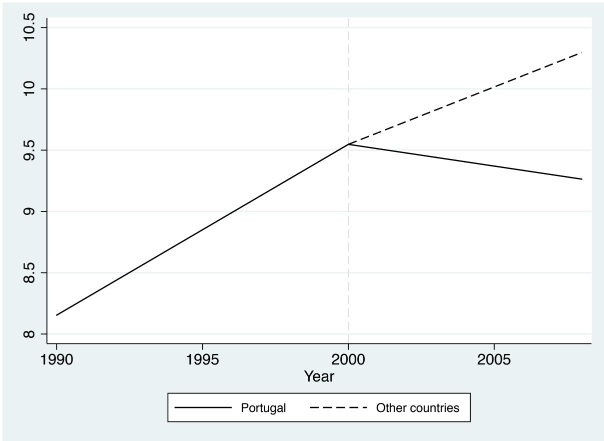

Figure 3 – Linear spline estimates: (logarithm of) drug-law offenses.
Notes: For detailed data definitions see Section 4.

Drug-related deaths

The estimated spline effect in the case of (the logarithm of) drug-related deaths is depicted in Figure 4 and suggests that drug-related deaths would have been higher in the absence of the drug decriminalization policy.

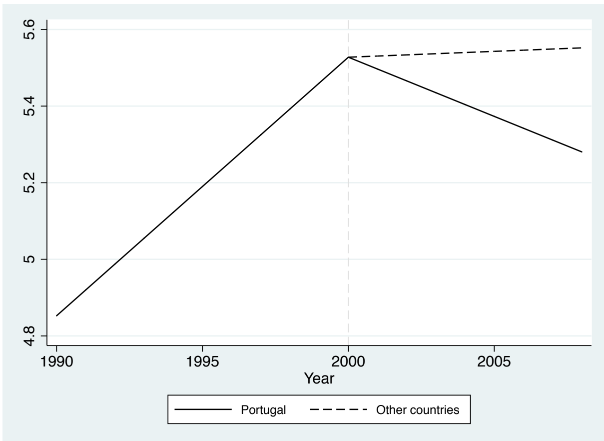

Figure 4 – Linear spline estimates: (logarithm of) drug-related deaths.
Notes: For detailed data definitions see Section 4.

New clients entering treatment

Figure 5 depicts the trends of (the logarithm of) new clients entering treatment for Portugal and the counterfactual Portugal. The estimated trend for Portugal suggests that the number of clients entering treatment has been decreasing in Portugal, which seems unexpected because the new approach towards the drug problem in Portugal was to improve public health by creating more treatment facilities and extending the access to treatment. A more thorough analysis of this outcome is presented in Section 5.2.

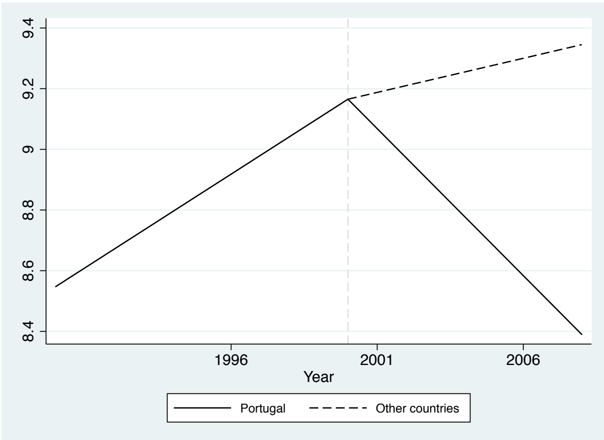

Figure 5 – Linear spline estimates: (logarithm of) new clients entering treatment.
Notes: For detailed data definitions see Section 4.

Drug addicts among HIV infected

The estimated trends in the number of drug addicts among HIV infected for Portugal and the other countries in the sample are shown in Figure 6. The results tentatively suggest that the number of drug addicts among HIV infected was considerably lower than would have been in the case of no policy change. This finding suggests that the health-oriented policy adopted by Portugal was effective in reducing the prevalence of AIDS among injecting drug users.

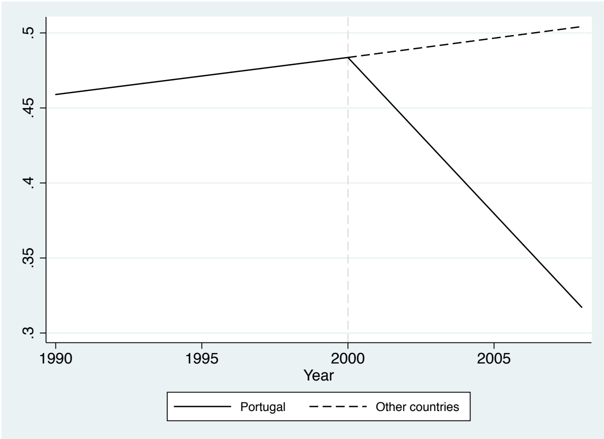

Figure 6 – Linear spline estimates: drug addicts among HIV infected.
Notes: For detailed data definitions see Section 4.

5.2 Synthetic control method estimates

Heroin and cocaine seizures

For both the number of heroin seizures and the number of cocaine seizures, 11 countries were used as potential controls for the period ranging from 1990 to 2007. A number of countries were not considered due to lack of information. The composition of the donor pool and the respective weights attributed to each control country are shown in Table 2.

After having constructed the synthetic Portugal, one can compare the trends of the number of seizures for Portugal and its synthetic counterpart. Figure 7 shows the trends in the number of heroin seizures, while Figure 8 refers to cocaine. We see that in the pre-treatment period, the dotted line representing synthetic Portugal is very close to the one describing the true Portuguese trend. This goodness of fit is also represented in Table 3, where we can see how close the predictor values are to each other. They compare the characteristics of Portugal and synthetic Portugal for the period before 2001, the period for which the difference between the predictor means was to be minimized. The last row of the table indicates the Root Mean Squared Prediction Error (RMSPE): a measure of the goodness of fit, in which a small value indicates a good fit.

The impact of the decriminalization of drugs is given by the estimated difference between the line representing Portugal and its synthetic counterpart in the period following the implementation of the policy. In Figure 7 we see a sharp decline in the number of heroin seizures recorded in Portugal after 2001 and the discrepancy between the lines suggests that this decline would have been much less accentuated in the absence of a policy. In Figure 8 we observe a very modest increase in the number of cocaine seizures in Portugal and the dotted line suggests that this increase would have been more pronounced if no decriminalization had occurred. The results show that the decriminalization had a substantial negative impact on the number of both heroin and cocaine seizures. Note that the actual Portuguese trends for both drugs start declining in the year of 1999 (not 2001), which might be an anticipation effect arising from the adoption of the new National Strategy for the Fight against Drugs in 1999. As the approach to the drug problem shifted from a punitive one to a health-directed one, police enforcement might have directed its focus of action to the supply side. Instead of seizing small quantities from many consumers, police might have preferred to tackle the base of the problem by seizing large quantities from the large dealers.

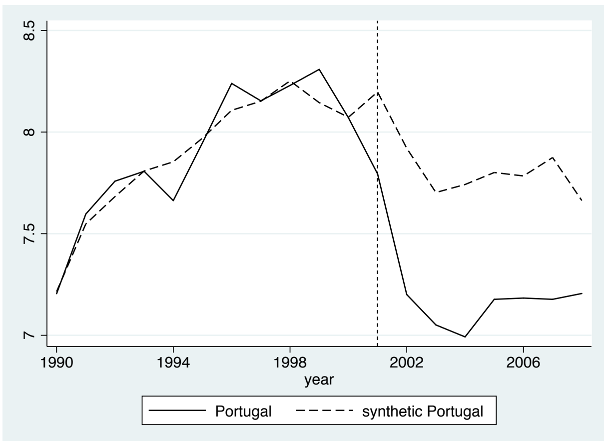

Figure 7 – Trends in (the logarithm of) heroin seizures: Portugal *vs.* synthetic Portugal.
Notes: For detailed data definitions see Section 4.

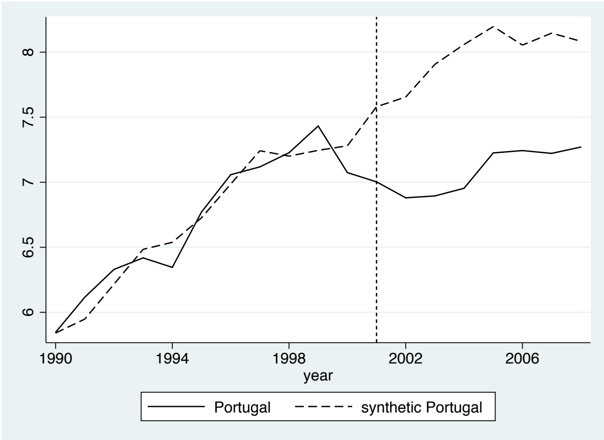

Figure 8 – Trends in (the logarithm of) cocaine seizures: Portugal *vs.* synthetic Portugal.
Notes: For detailed data definitions see Section 4.

In order to access the significance of the results suggesting a negative impact of the decriminalization in the number of seizures, we need to perform the placebo tests. Figures 9 and 10 show the estimated gaps in the number of heroin and cocaine seizures, respectively, between Portugal and all of the other false treatment countries and each respective synthetic counterpart. As we see, the graphs show that our initial results are not very robust in the case of heroin, but are indicative of a significant effect for cocaine.

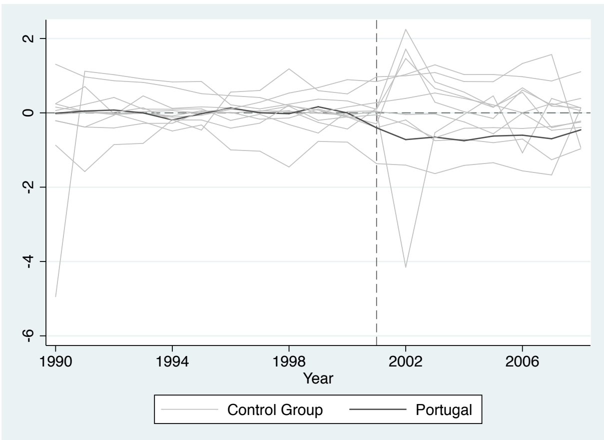

Figure 9 – (Logarithm of) Heroin seizures gaps in Portugal and placebo gaps.
Notes: For detailed data definitions see Section 4.

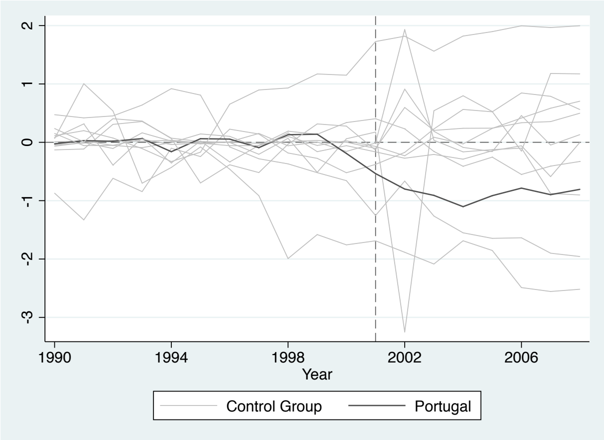

Figure 10 – (Logarithm of) Cocaine seizures gaps in Portugal and placebo gaps.
Notes: For detailed data definitions see Section 4.

Drug law offenses

The study of the impact of drug decriminalization on the number of drug law offenses revealed that the policy was not harmful to the Portuguese drug situation.

Due to data constraints the donor pool of this outcome is composed of 12 countries, with their assigned weights represented in Table 2, covering a time horizon of 17 years: from 1991 to 2007.

Figure 11 shows the trend for the drug-law offenses in Portugal and in the synthetic Portugal. The small gap between the two lines in the pre-intervention period indicates that the convex combination of the 5 countries assigned with a positive weight in the synthetic region is a good approximation of Portugal itself before 2001. Moreover, the mean values of the predictors of this outcome shown in Table 3 reveal this resemblance.

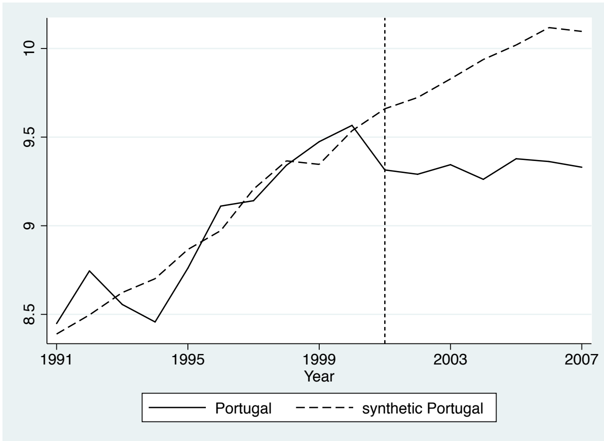

Figure 11 – Trends in (the logarithm of) drug-law offenses: Portugal *vs.* synthetic Portugal.

Notes: For detailed data definitions see Section 4.

The discrepancy between the lines in the period following the decriminalization tells us that the policy had a negative impact on the number of drug-law offenses. Naturally this conclusion is valid only under the assumption that the level of efficiency of the police force is more or less the same across the countries and through time.

The placebo study reported in Figure 12 supports the robustness of the result. Indeed, the estimated effect for Portugal is quite large relative to the effect for a country chosen at random from the pool.

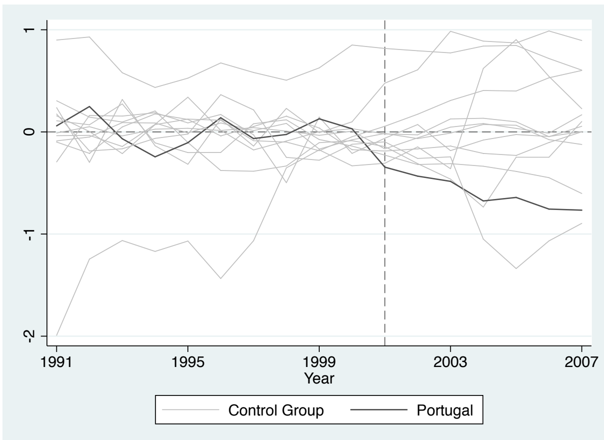

Figure 12 – (Logarithm of) Drug law offenses gaps in Portugal and placebo gaps.

Notes: For detailed data definitions see Section 4.

Drug-related deaths

The estimation suggests that decriminalization contributed to a decrease in the number of drug-related deaths.

The donor pool is a selection of 14 countries for which there are no missing observations of the outcome variable. Norway stands out in the pool with a weight of 61%, as we can see in Table 2.

The SCM was run for a time horizon from 1990 to 2006, and for the period previous to 2001. Table 3 shows the similarity between Portugal and its synthetic counterpart. In the post-treatment period the dotted line (Figure 13) representing synthetic Portugal follows a path above the Portuguese one, but still decreasing. This means that in the absence of the decriminalization there would have been a higher number of drug-related deaths. However, one must be careful when analyzing the Portuguese trend because the Portuguese definition of drug-related deaths is broader than that of most European countries: it contemplates all autopsies testing positive for toxicological examinations, while for most European countries national definitions are stricter, accounting only for overdoses. This weak uniformity represents a major drawback for this comparative case study since it may overestimate the number of deaths in Portugal that are directly connected with drugs.

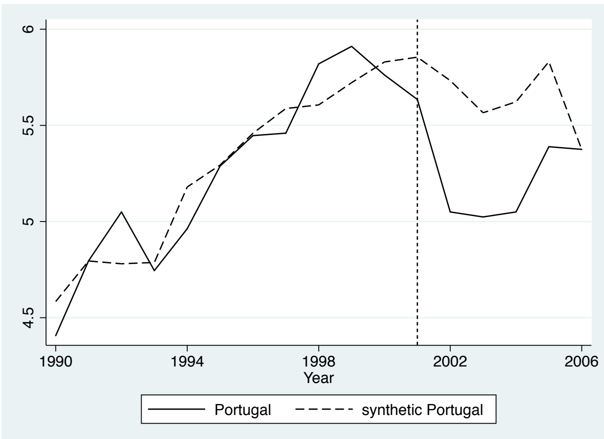

Figure 13 – Trends in (the logarithm of) drug-related deaths: Portugal *vs.* synthetic Portugal.

Notes: For detailed data definitions see Section 4.

The placebo tests that were performed on the control countries seem to validate the estimated impact of the policy (see Figure 14).

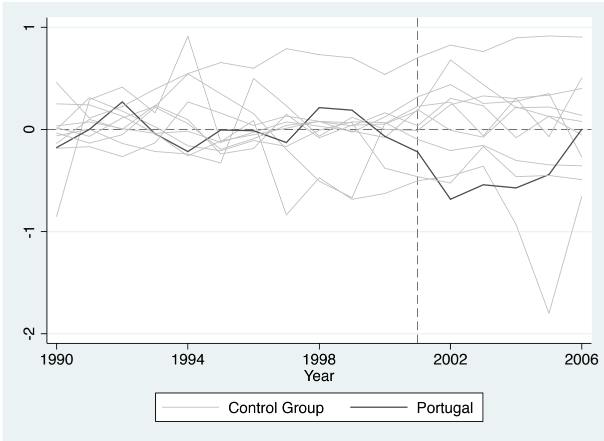

Figure 14 – (Logarithm of) Drug-related deaths gaps in Portugal and placebo gaps.
Notes: For detailed data definitions see Section 4.

New clients entering treatment

Unfortunately, for this outcome variable the dataset is relatively short. Since there are very few data regarding treatment units, the donor pool is composed of only 7 countries and the time horizon goes from 1996 to 2008, being restricted to a pre-intervention period of 5 years.

The weight distribution among the control countries is in Table 2 and the predictor balance is in Table 3. Despite the limited size of the dataset, the goodness of fit provided by the SCM is quite satisfactory.

The Portuguese trend in Figure 15 shows a declining trend in the number of clients entering treatment from 1999 till 2006. Only in the two subsequent years did the country register an increase in this number. The decline is surprising since the course of thinking defined by the new National Strategy for the Fight against Drugs is more health-oriented and focused on treatment improvement. However, one has to understand the strategy involved. In a first stage it sought to enhance the proximity to drug addicts through treatment and prevention campaigns in the streets, and in a subsequent phase encouraged drug addicts to undergo programs in the treatment centers. The ultimate goal is to include drug addicts in treatment programs that include social and psycho-intervention, and not only promote harm-reduction substitution programs (methadone and sanitary intervention). The number of clients entering treatment centers is expected to increase, as possibly suggested by the trend in 2007 and 2008.[4]

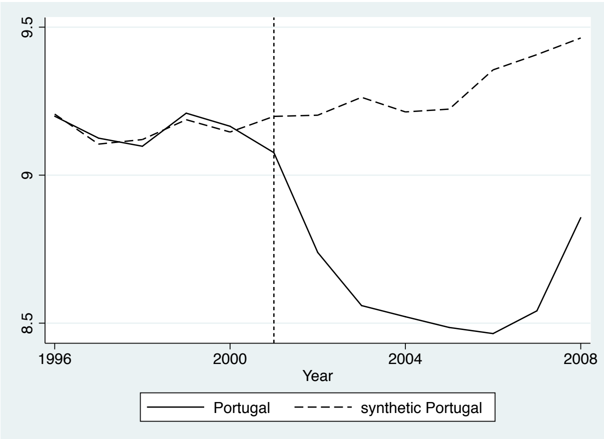

Figure 15 – Trends in (the logarithm of) new clients entering treatment: Portugal *vs.* synthetic Portugal.

Notes: For detailed data definitions see Section 4.

The placebo study in Figure 16 concludes that the result is not by chance but rather that the decriminalization had an impact on the number of clients entering treatment centers.

[4] A possible explanation for the initial decline in the number of clients entering treatment after the decriminalization policy is the presence of governmental budget constraints following the general elections that led to a change in the ruling party.

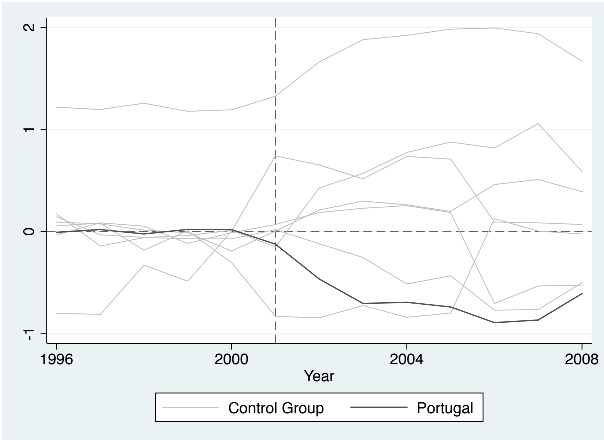

Figure 16 – (Logarithm of) New clients entering treatment gaps in Portugal and placebo gaps.

Notes: For detailed data definitions see Section 4.

6 Conclusion

This paper is a contribution of economic analysis to the area of illicit drugs policy design. It investigates the effect of the decriminalization law in Portugal on some drug-related outcomes using the Synthetic Control Method for comparative case studies of Abadie and Gardeazabal (2003). The results suggest that drug decriminalization in Portugal was not harmful and, if anything, it contributed to the reduction in the number of seizures of heroine and cocaine, the reduction in the number of drug-law offenses and drug-related deaths, and the reduction in the incidence of drug addicts among HIV positive individuals. Moreover, drug decriminalization had a negative impact on the number of clients entering treatment, even though it has been rising since 2007.

These results tally with the available evidence that judicial costs were substantially reduced and support the idea that consumption of drugs did not increase following the drug decriminalization policy, given that the prices of illicit drugs did not change. If anything, the demand for drugs decreased to compensate any rightward displacement of the supply curve of drugs.

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Appendix A: Data sources and description

Variable	Source	Description
Heroin seizures	EMCDDA	Number of heroin seizures by law enforcement agencies, mainly police, customs officials and national guard. The numbers of seizures are usually considered as a better indicator of trends than the quantities seized because the latter may fluctuate from one year to another due to a small number of large seizures. Note that the variable is affected by differences in police practices.
Cocaine seizures	EMCDDA	Same as above, but concerning cocaine.
Drug law offenses	EMCDDA	Number of reports of drug law offenses, including drug use and possession for use, production, trafficking and dealing. It reflects differences in legislation and law enforcement.
Drug-related deaths	EMCDDA	Number of acute drug-related deaths recorded in EU Member States according to national definitions.
New clients entering treatment	EMCDDA	Number of clients entering a treatment center for the first time in their life.
Gross Domestic Product per capita	OECD (National accounts data files)	Constant 2005 US dollars.
Civil Liberties Indicator	Freedomhouse.org	Rating of civil liberties from 1 (most free) to 7 (least free). It reflects an overall judgment based on survey results involving questions grouped into four subcategories: freedom of expression and belief; associational and organizational rights; Rule of Law; and personal autonomy and individual rights.
Unemployment Rate	International Labor Organization (ILO)	Total unemployment as a percentage of total labor force.
Proportion of youth	EUROSTAT	Proportion of population aged between 15 and 24 years old.
Price of Opiates	UN World Drug Report (2009)	Retail price (street price) of opiates, US $ per gram.
Price of Cocaine	UN World Drug Report (2009)	Retail price (street price) of cocaine, US $ per gram.
Alcohol Consumption	OECD Health Data	Liters consumed per capita by individuals aged above 15 years old.
Tobacco Consumption	OECD Health Data	Percentage of population above 15 years old who are daily smokers.

Note: EMCDDA stands for European Monitoring Centre for Drugs and Drugs Addiction. It is responsible for collecting country data on drugs from all European countries. National drug monitoring centers report to this agency, which organizes the information in a harmonized manner to be comparable at the European level. This decentralized EU agency was formally established in 1993 and has been based in Lisbon since 1995.

Appendix B: Results

Table 1 – Linear spline estimates

	(1) Heroin seizures	(2) Cocaine seizures	(3) Drug-law offenses	(4) Drug-related deaths	(5) New clients	(6) Drug addicts among HIV
Trend	0.0569	0.1440***	0.1394***	0.0675***	0.0618	0.0025
	(0.0341)	(0.0345)	(0.0290)	(0.0229)	(0.0372)	(0.0036)
Spline	-0.0882	-0.0183	-0.0458	-0.0644*	-0.0393	0.0001
	(0.0572)	(0.0348)	(0.0363)	(0.0325)	(0.0427)	(0.0062)
Spline×Port	-0.1309***	-0.1593***	-0.1291***	-0.0339	-0.1194***	-0.0234***
	(0.0302)	(0.0358)	(0.0292)	(0.0235)	(0.0164)	(0.0063)
constant	6.3635***	5.0935***	8.4887***	4.4672***	6.1947***	0.2028***
	(0.2191)	(0.2562)	(0.2073)	(0.1545)	(0.3378)	(0.0284)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	375	373	392	419	294	570
Adjusted R^2	0.816	0.936	0.943	0.915	0.961	0.599

Notes: Ordinary least squares estimates with heteroskedasticity-consistent standard errors clustered at the country level. Detailed data definitions are provided in Section 4. ***, **, and * stand for statistical significance at 1%, 5%, and 10%, respectively.

Table 2 – Weight distribution in the donor pool for each outcome

	Heroin seizures	Cocaine seizures	Drug law offenses	Drug-related deaths	New clients entering treatment
Austria	0.070	0.639	0.000	0.000	0.080
Bulgaria	–	–	–	0.000	–
Belgium	0.000	0.000	0.000	–	–
Denmark	0.000	0.000	0.102	0.000	0.000
Finland	–	–	0.000	0.000	–
France	0.000	0.000	0.000	0.000	–
Germany	0.010	0.000	0.097	0.000	0.000
Greece	–	–	–	0.678	0.000
Hungary	–	–	0.044	–	–
Ireland	0.062	0.000	0.000	–	0.159
Italy	–	–	–	–	0.526
Luxembourg	0.000	0.000	–	0.000	–
Netherlands	–	–	–	0.000	0.235
Norway	0.000	0.000	–	0.610	–
Poland	–	–	0.085	0.278	–
Slovenia	–	–	0.173	–	–
Spain	0.487	0.113	–	0.000	–
Sweden	0.371	0.000	0.498	0.000	–
United Kingdom	0.000	0.247	0.000	0.044	–

Table 3 – Predictor's balance for each outcome variable

	Heroin seizures		Cocaine seizures		Drug law offenses		Drug-related deaths		New clients	
Variables	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
log GDP	9.565	10.126	9.565	10.238	9.565	10.088	9.565	9.603	9.556	10.199
log FIW_CR	0.063	0.260	0.063	0.228	0.000	0.284	0.063	0.893	0.000	0.365
Unemployment	5.473	13.083	5.473	6.879	5.550	8.260	5.473	10.296	5.500	8.884
Young	15.845	14.679	15.845	13.390	15.810	13.572	15.845	14.968	15.360	13.356
log Opiates price	4.158	4.928							3.990	4.461
log Cocaine price			4.046	4.775					3.984	4.320
Alcohol	14.236	10.007	14.236	12.748					13.160	10.320
Tobacco	20.050	28.100	20.050	26.184					20.050	28.514
log_x(1990)	7.205	7.215	5.846	5.841			4.407	4.584		
log_x(1992)	7.758	7.683	6.330	6.216	8.745	8.497	5.050	4.780		
log_x(1994)	7.663	7.854	6.346	6.538	8.457	8.701	4.963	5.179		
log_x(1996)	8.239	8.107	7.058	6.986	9.111	8.972	5.447	5.459	9.199	9.206
log_x(1998)	8.230	8.252	7.227	7.201	9.341	9.366	5.820	5.606	9.098	9.120
log_x(2000)	8.071	8.073	7.074	7.280	9.566	9.536	5.762	5.830	9.165	9.146
RMSPE	0.091		0.129		0.134		0.152		0.019	

Notes: The Root Mean Square Prediction Error (RMSPE) is a measure of goodness of fit and measures the fit between the trends of the outcome variable for Portugal and its synthetic counterpart. RMSPE=$\sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1T}-\sum_{j=2}^{J+1}w_j^*Y_{jt}\right)^2}$.