ERASMUS UNIVERSITEIT ROTTERDAM

BACHELOR THESIS

ERASMUS UNIVERSITY ROTTERDAM

DOUBLE BACHELOR ECONOMETRICS AND ECONOMICS

The Impact of Drug Decriminalization on HIV and AIDS Incidence Among Injecting Drug Users in Portugal

Author:
Noemi Savelkoul (473152)

Supervisor:
Prof. Dr. Robin Lumsdaine

Second Assessor:
Jens Klooster

Date: June 30, 2022

Acknowledgements

I would like to, first and foremost, express my utmost gratitude to my supervisor, Prof. Dr. Lumsdaine, who offered me academic guidance and emotional support to succeed in completing my bachelor thesis. Her enthusiasm, sound advice, and personal stories made this process enjoyable and motivated me to take risks. One of those risks was focusing on drug decriminalization, a controversial and challenging topic. I wish her the best in her future endeavors and hope other students will also have the opportunity – and find it as enjoyable – to work with her.

Furthermore, I would like to thank my friends who, throughout this process, provided me with assistance with translating documents, formatting my thesis, programming, and econometrics content. I want to especially thank Nancy, next to whom I sat most days in the library.

Finally, I would like to thank my parents and especially my mother. They provided me with more financial support, opportunities, and guidance than I could have ever requested.

Abstract

This paper uses a modified version of the Synthetic Control Method to evaluate the impact of the Consumption Decriminalization Law — which in 2001 decriminalized illicit substance use, acquisition, and possession in Portugal — on the incidence of HIV and AIDS among injecting drug users. The modified Synthetic Control Method requires individual control series, instead of only the Synthetic Control, to be on the same growth path as the target series to avoid mistaking in-sample overfitting for common trends. This mistake is possible because of the large number of potential controls relative to observations in the pre-intervention period. Altogether, this paper finds supporting evidence of drug decriminalization leading to lower AIDS incidence among injecting drug users in Portugal. Likely, this lower incidence follows from harm reduction programs, such as extensive syringe exchange programs, that the Consumption Decriminalization Law enabled. Importantly, nonetheless, these results are not robust to different interpolation techniques and restrictions and the assumption of when the effects of the policy stabilized.

1 Introduction

In November 2000, Portugal controversially approved decriminalizing illicit drug acquisition, possession for personal use, and consumption. With the approval of *Lei n.º 30/2000* (2000), hereafter referred to as the Consumption Decriminalization Law, the Portuguese government stipulated that most previously-considered criminal violations related to illicit narcotics and psychotropic substances would become administrative offenses starting from the 1st of July 2001, irrespective of the drug. In practice, the enactment of this law implied that the possession, acquisition, and cultivation for personal use would no longer be punishable with imprisonment, with penalties instead consisting of fines and nonpecuniary retributions. Beyond establishing the decriminalization of drugs, the law also described in-depth guidelines for intercepting and prosecuting offenders. These guidelines specified that a devised multidisciplinary team of experts known as 'Commissions for the Dissuasion of Drug Addiction' should sanction offenses to guarantee humane and proportional punishment to offenders.

Portugal's radical move followed widespread drug-related problems in the 1990s. By then, Portugal had one of the highest overdose death rates, the highest rate of drug-related Acquired Immunodeficiency Syndrome (AIDS), and the second highest prevalence of Human Immunodeficiency Virus (HIV) among injecting drug users across Europe (Hughes & Stevens, 2010). As described in Bajekal (2018), thousands of addicts, mainly heroin addicts, roamed around the city as used syringes piled up in gutters. To combat the problem, Portugal proposed a revitalized national drug strategy that prioritized public health over public order (Hughes & Stevens, 2010). The Consumption Decriminalization Law is inextricably linked to this strategy as it allowed prosecution channels to view users as ill and drug traffickers as the only criminals (Ximene, Oliveira, Lameira, et al., 2021) which, in turn, enabled new governmental practices.

Under the new enabling legal system, the Portuguese government was able to divert resources from the criminal system towards prevention, harm reduction, treatment, social reintegration, and supply reduction (Hughes & Stevens, 2010). Harm reduction initiatives aimed mostly at reducing drug-related deaths and the spread of infectious diseases, which were central issues in the 1990s. These initiatives included, for instance, extensive syringe exchange programs (Borges et al., 2020). In addition, drug injection rooms, where users could find clean equipment and knowledgeable professionals, also became commonly available (Van Het Loo, Van Beusekom, & Kahan, 2002). Finally, treatment for infectious diseases, including antiretroviral therapy for HIV, became accessible for free even to illegal immigrants (Dias, Gama, Severo, & Barros, 2011).

While unconventional, the approach from Portugal was not unprecedented. For instance, drug consumption in private and possession for personal use were never considered criminal offenses under Spanish law (Sánchez & Collins, 2018). Furthermore, infamous for its drug culture, the Netherlands officially began tolerating drug consumption and possession as early as 1972 (Booth, 2005). Portugal, regardless, constitutes the most comprehensive and well-documented example of decriminalization (Alliance, n.d.).

This research focuses on the Consumption Decriminalization Law in Portugal and, by ex-

tension, on the national drug strategy this law enabled. Specifically, it quantifies how the law impacted the number of new yearly HIV and AIDS cases – known in epidemiology as HIV and AIDS incidence – among injecting drug users. Quantifying the outcomes of decriminalization is necessary to evaluate its success. Besides, it also provides a foundation for comparing its success to that of other strategies, like widespread criminalization of use and possession. Indeed, unlike Portugal, most countries worldwide have adopted a punitive approach to drug-related offenses, with the most notorious country for its strict drug laws being arguably the United States. As stated in Schoenfeld (2012), in America, possessing, distributing, and using illicit drugs is illegal, with most offenses terminating in imprisonment. Especially in America, this punitive approach has led to massive incarceration, largely affecting ethnic minorities and women (Schoenfeld, 2012). More relevant to the focus of this paper, research proposes that a collateral effect of the American drug strategy is a higher risk of HIV infection among injecting drug users (Bluthenthal, Lorvick, Kral, Erringer, & Kahn, 1999), with black communities being especially vulnerable (J. Kerr & Jackson, 2016).

The reasons for choosing HIV and AIDS as outcomes of interest were two-fold. First, as explained before, the prevalence of infectious diseases among the drug-using population was a leading driver of the policy change. Furthermore, HIV is an incurable, life-threatening virus (Lu et al., 2018), which gravely impacts the lives of those affected. HIV stigma has been widely documented, with HIV possibly leading to poverty (Taraphdar et al., 2011), depression (McDowell & Serovich, 2007), and social exclusion, especially among injecting drug users (Chan, Stoové, & Reidpath, 2008). AIDS, on the other hand, is an eventual but preventable deadly progression of HIV infection and is usually impossible to revert (Lu et al., 2018). Therefore, given the wide implications for those affected, it is important to understand if and how economic policies may aid HIV and AIDS prevention.

The methodology used to quantify the impact of the Consumption Decriminalization Law on HIV and AIDS incidence among injecting drug users is similar to the Synthetic Control approach described in Harvey and Thiele (2021). Briefly, a control group, known as synthetic control, is constructed using a weighted combination of donors from a pool of countries for which data on the outcomes of interest is available. Since this control acts as a counterfactual, the donors used in this combination are selected, and their weights specified, so the growth path before the intervention is similar between the Synthetic Control and Portuguese series. The treatment effect, which is assumed to be dynamic, is the difference between the target and synthetic control series. Furthermore, two models are used to estimate the level and intermediary effects to allow for in-model (Synthetic Control Model) and outside model (Univariate Model) estimation of the weights.

Differently from the original Synthetic Control approach, the method in Harvey and Thiele (2021) further requires individual control series, and not only the synthetic control, do be on the same growth path (cointegrated with) as the target series before the intervention. The authors suggest imposing this additional restriction because, in its absence, it is possible to mistake in-sample overfitting for common trends, which this method relies on for isolating the treatment effect. This mistake is possible because of the large number of potential donors relative to the number of observations in the pre-intervention period.

Altogether this paper finds both conclusive and inconclusive evidence on the effect of the

policy on drug-related disease. Estimating the univariate and synthetic control models for each target series suggests that after the Consumption Decriminalization Law came into force, AIDS incidence among injecting drug users decreased. The univariate model estimated the permanent shift in level as - 430.615 novel cases per year, while the synthetic control model estimated it as - 419.615. Both models also found similar negative estimations of the intermediary effects of the policy for all years preceding the level break. In contrast, it was impossible to construct an appropriate synthetic control for evaluating how the Consumption Decriminalization Law impacted HIV incidence. Results for HIV are, therefore, inconclusive. Nevertheless, because of the evidence this paper was able to find, and because HIV precedes AIDS, the Consumption Decriminalization Law most likely led to lower HIV incidence as well.

2 Literature Review

Literature on drugs encompasses both the supply-side and demand-side of the drug market, being much more extensive for the demand-side because information on the supply-side is scarce. Within the demand-side, research spans various fields, including medicine, public health, public policy, and economics. Because this paper focuses on the impact of decriminalization of drugs on AIDS and HIV among injecting drug users, and these users create demand for drugs, this review will limit itself to analyzing the demand-side literature.

The literature analyzing the impact of different drug policies on drug consumption is generally inconclusive. For example, Reinarman, Cohen, and Kaal (2004) compares representative samples of experienced cannabis users in Amsterdam and San Francisco, two cities with opposing cannabis regulations. Despite cannabis consumption being, at the time the article was published, a criminal offense in San Francisco and practically legal in Amsterdam, both samples did not differ significantly. The authors then conclude that, compared to decriminalization, criminalizing cannabis consumption does not result in people consuming cannabis less. Meanwhile, Greenwald (2009) qualitatively analyses almost ten years of data on drug use in Portugal across multiple drug categories, finding that the lifetime prevalence rates for most drug categories decreased. Literature associating decriminalization with higher drug use was much more difficult to find. MacCoun and Reuter (2001), however, do suggest that the commercialization of cannabis in the Netherlands did lead to more cannabis use.

Given the inconclusiveness surrounding the effect of drug policy on drug use, it appears that containing the spread of infectious diseases by altering drug consumption levels with drug policy is not ideal. However, research does suggest that drug policy can still play a central role in reducing infectious disease spread. N, Kral, Erringer, and Edlin (1999), for instance, conduct a multivariate analysis to evaluate the relationship between injection-related risk behaviors and fear of being arrested while carrying drug paraphernalia. The authors find that users fearing arrest were significantly more likely to engage in syringe-sharing, a dangerous practice that may lead to, for example, them contracting HIV. Accordingly, the authors argue that decriminalizing syringes and needles would most likely result in drug users partaking less in risky behavior that exposes them to blood-borne infectious diseases. Besides, Blankenship, Smoyer, Bray, and Mattocks (2005) outline how incarceration may lead

to increased HIV risk in America. They explain that ex-inmates suffer from reduced individual earning potential, as the lack of transitional programs makes it difficult for them to find a job upon release from prison. Additionally, in the absence of employment, most governmental health and public income maintenance programs become inaccessible, putting ex-inmates even more at risk of financial vulnerability. In turn, this lack of funds decreases their ability to negotiate condom use and retention in drug treatment, both highly associated with HIV risk.

Another way drug policy may assist in reducing infectious disease spread among injecting drug users is by reducing the stigma associated with drug use. Research suggests that substance use stigma results in a lack of adherence to antiretroviral therapy, which, in turn, may lead to those infected having their infection develop into AIDS and even spreading HIV. For example, Stringer et al. (2019) examine the relationship between substance use stigma and optimal antiretroviral therapy adherence in a sample of 172 self-reported HIV-infected drug users. Using a Multivariable logistic regression and adjusting for various factors, including HIV-related stigma, they found that users experiencing high levels of stigma were significantly more likely to not participate optimally in treatment. At the same time, research suggests that decriminalization may remove the stigma attached to drug use. For instance, Wogen and Restrepo (2020) explain that decriminalizing drugs may help frame drug addictions as chronic health conditions instead of criminal activities, thereby reducing the stigma associated with drug use. Literature like Vicknasingam, Narayanan, Singh, and Chawarski (2018) and Buchman, Leece, and Orkin (2017) argue similarly for the role of decriminalization in drug use stigma reduction.

Qualitative research on the direct impact of decriminalization on HIV and AIDS among injecting drug users is scarce. Strathdee, Beletsky, and Kerr (2015), for example, propose that criminalization restrains the possibility of the legal environment supporting harm reduction. Because one causes the other, this results in susceptibility to infectious diseases like HIV increasing among people who use drugs. Indeed, upon decriminalization, governments may, for example, instill safe drug-injection facilities, where clean syringes and trained personnel is available to those who inject drugs. As described in T. Kerr, Kimber, DeBeck, and Wood (2007), these facilities even tend to attract and cater for a subset of injecting drug users at higher risk of HIV infection, like daily heroin and cocaine injectors, sex workers, and homeless users.

Beyond safe injection facilities, the Portuguese government made HIV treatment available for free and instilled extensive syringe exchange programs upon decriminalization. Literature on the effectiveness of syringe exchange programs is conclusive and suggests that these programs lead to lower rates of blood-borne infections like HIV (Gibson, Flynn, & Perales, 2001; Heimer, 1998; Laufer, 2001). Meanwhile, the literature on free antiretroviral therapy for those infected with HIV suggests that treatment alone does not prevent the spread of blood-borne infections. For example, Yu et al. (2018) explain that treatment success depends on treatment adherence. However, they found that patients living with HIV that have depression and did not disclose their status to friends and family tended to have poor adherence to treatment, leading free treatment programs to fail. Additionally, Sarna et al. (2008) explain that treatment adherence depends on patient preparation and adherence support.

Quantitative literature, unlike qualitative literature, on the direct impact of decriminalization on HIV and AIDS among injecting drug users is nonexistent. The authors from Tavares (2009) attempted to apply a slightly different version of the Synthetic Control Method used in this paper to study the impact of decriminalization of drugs in Portugal on the prevalence of AIDS in Portugal. However, as they explain, it was impossible to create a synthetic control that resembled Portugal reasonably well in the pre-intervention period. Notwithstanding, they were able to construct appropriate Synthetic Controls for drug-related offenses, drug-related deaths, and heroin and cocaine seizures, finding that decriminalization resulted in fewer occurrences of all of them.

At last, other qualitative and quantitative literature unrelated to AIDS and HIV but specific to the Portuguese decriminalization process also exists. Analyzing the supply-side of the market, Félix and Portugal (2017) conducts an empirical assessment of how drug decriminalization affected the price of opiates and cocaine in Portugal. The authors use the same methodology as in Tavares (2009), similar to the one used in this paper. Altogether, they find no evidence supporting decriminalization leading to lower cocaine and opiate prices, which arguably would have led to higher drug usage and dependence. Furthermore, most literature on drug decriminalization in Portugal references Hughes and Stevens (2007). An intriguing conclusion in Hughes and Stevens (2007), which this review has yet to address, is that decriminalization did not decrease the financial burden on the Portuguese State as previously presumed. The authors describe that not punishing drug possession resulted in fewer judiciary expenses. However, the new health-based approach reallocated the savings towards, for example, the creation of the "Commissions for Dissuasion of Drug Addiction" and personnel for the assisted drug-injection facilities. The authors then conclude that costs remained relatively constant before and after decriminalization because of this cost reallocation.

3 Data

3.1 Selecting potential controls

All the data used in the evaluation is available through the European Monitoring Center for Drugs and Drug Addiction (EMCDDA), the reference point on drug usage for European Union (EU) member states. The EMCDDA database contains time-series information on the outcomes of various drug-related variables for all current EU member states, Norway, Turkey, and the United Kingdom, usually broken down by gender, age, and substance. Besides, the EMCDDA updates datasets yearly, and previous versions of these datasets are available online in their Statistical Bulletin archive.

Specific to infectious diseases, the EMCDDA publishes datasets on the prevalence and incidence of various drug-related illnesses among injecting drug users, including HIV and AIDS. As usual in epidemiology, prevalence is the proportion of a population affected by a medical condition at a given time. Therefore, since EMCDDA datasets contain yearly information, the prevalence of, for example, AIDS is the proportion of injecting drug users that have AIDS in a given year belonging to some country in the database. Meanwhile, the incidence is the number of new cases of a given medical condition reported in a specified period. Ac-

cordingly, that corresponds to the number of new, for instance, AIDS cases a country in the database discloses throughout a given year.

As described in the methodology section, the Synthetic Control Method requires accurate information on the outcome of interest for a few years before and after the intervention year for the target series. Therefore, since much Portuguese data is missing from all prevalence datasets, all prevalence datasets were unusable. For the same reason, the most recent usable incidence datasets are from 2015. While an option to expand the amount of data, imputation could distort the general trend of the Portuguese series. As such, since conserving the general trends of the data is paramount for the Synthetic Control method as it relies on common trends across countries to isolate the treatment effect, imputation could severely impair the accuracy of the results. At the same time, merging datasets is impossible because of unaddressable inconsistencies across datasets published in different years.

Because of missing data, this paper focuses on the incidence of AIDS and HIV among injecting drug users. The EMCDDA codenames all of their datasets according to the outcome of interest. The INF-104-1 dataset contains data on the incidence of HIV cases among injecting drug users, and in the 2015 version specifically, information is available from 1993 to 2013. Moreover, the 2015 version of the INF-104-2 dataset contains information on the number of new AIDS cases among injecting drug users reported from 1995 to 2013. While Data for Portugal is not missing from either dataset, some are for the other countries.

In favor of preventing the loss of potential donors, which, in turn, could compromise the evaluation of the decriminalization policy, missing values were imputed using spline interpolation at the risk of distorting trends of the potential controls. However, since conserving the general trends of the data is so paramount for the Synthetic Control method, countries for which more than two consecutive data points were missing did not participate in the evaluation.

For most countries, the pattern of missingness is due to information only being available from some year onwards. For example, data on the number of HIV cases among injecting drug users in Italy is unavailable until 2004. There are, however, exceptions to this. For instance, data on the number of HIV cases in Latvia is only missing for 1993, 1994, and 1996. Therefore, restricting interpolation to countries where no more than two consecutive years of data were unavailable did not lead to the same result as not interpolating. For the INF-104-1 dataset, interpolation allowed for including Bulgaria, Hungary, Slovenia, Latvia, Finland, and Lithuania in the donor pool. At the same time, for the INF-104-2 dataset, interpolation allowed for retaining Finland and Turkey.

Excluding all countries for which more than two consecutive observations were missing was, in some way, arbitrary. It arose from an attempt to be conservative as two years already correspond to approximately 10% of the evaluation period. Moreover, as explained before, the Synthetic Control method is only valid if the controls did not introduce policies similar to that of Portugal in the post-intervention period. However, as presented in the following section, there is no reason to believe that any remaining country should not participate in the evaluation. Table 1 depicts, for each dataset, the potential donors and their corresponding number and percentage of missing observations:

Table 1: Number and percentage of missing observation for every potential control and each dataset

HIV			AIDS		
Country	**Missing**	**Missing (%)**	**Country**	**Missing**	**Missing (%)**
Bulgaria	4	19	Finland	1	5
Hungary	4	19	Turkey	1	5
Slovenia	4	19	Austria	0	0
Latvia	3	14	Belgium	0	0
Finland	1	5	Denmark	0	0
Lithuania	1	5	France	0	0
Belgium	0	0	Germany	0	0
Croatia	0	0	Greece	0	0
Czech Republic	0	0	Ireland	0	0
Denmark	0	0	Italy	0	0
Germany	0	0	Luxembourg	0	0
Greece	0	0	Norway	0	0
Ireland	0	0	Poland	0	0
Luxembourg	0	0	Portugal	0	0
Netherlands	0	0	Spain	0	0
Norway	0	0	United Kingdom	0	0
Portugal	0	0			
Sweden	0	0			
Turkey	0	0			
United.Kingdom	0	0			

3.2 The national drug strategy of the potential controls

The EMCDDA publishes country-level drug reports, in which historical information on the national drug strategy of different countries is available.[1] Careful analysis of the 2019 versions of those reports suggests that countries that remained after the interpolation restrictions belong to one of three groups. The first group consists of countries that have enacted, what this paper considers, a "similar enough" policy to that of Portugal in the pre-intervention period, introducing strictly small changes to the policy in force throughout the post-intervention period. Meanwhile, countries that have passed "different enough" legislation in the post-intervention period constitute the second group. Finally, countries in the third group have always had a different national drug strategy than Portugal.

Again, the Synthetic Control method requires controls not to have enacted a policy "similar

[1] Country-level reports available in https://www.emcdda.europa.eu/publications/country-drug-reports/catalogue/2019_en.

enough" to that of Portugal only in the post-intervention period. Therefore, since none of the strategies described by each group violate that requirement, this paper argues that all countries that meet the interpolation requirement should participate in the evaluation. Of paramount importance, however, is recognizing that the assumptions underlying this classification are, to some extent, subjective and that if they were to change, results could be strikingly different. Unfortunately, however, subjectivity is often a limitation of empirical research, and a decision is necessary for conducting the evaluation. In this paper, the concept of "similar enough" follows from the two central principles underlining the Consumption Decriminalization Law – leniency towards possession of drugs and a focus on public health instead of public order. Explicitly, countries with a national drug strategy "similar enough" to that of Portugal should not punish minor drug possessions, irrespective of the substance, with incarceration. Besides, robust harm reduction programs should also be available to users.

Given the definition of "similar enough" and groupings, a country belonging to the first group is Italy. In Italy, personal use has been an administrative offense since the 1990s (EMCDDAa, 2019). Besides, comprehensive programs for preventing the transmission of infectious diseases have also been available since the 1990s due to the urgent need to contain HIV among heroin-injecting users (EMCDDAa, 2019). Furthermore, France, where recidivism of minor offenses can lead to imprisonment since 2008, belongs to the second group (EMCDDAb, 2019). Finally, Sweden, where use and possession have been a criminal offense since 1968, belongs to the third group (EMCDDAc, 2019).[2] Table 2 displays which group this paper assumes each country belongs to:

Table 2: Potential controls grouped

Country	Group	Country	Group
Austria	3	Italy	1
Belgium	3	Latvia	3
Bulgaria	2	Lithuania	3
Croatia	2	Luxembourg	3
Czech Republic	2	Netherlands	1
Denmark	3	Norway	3
Finland	3	Poland	2
France	2	Slovenia	2
Germany	3	Spain	1
Greece	2	Sweden	3
Hungary	3	Turkey	3
Ireland	3	United Kingdom	3

[2]Likewise the assumptions underlying country groupings, determining which group a control belongs to is subjective. Even more subjective is deciding whether a national drug strategy violates a "similar enough" requirement.

3.3 Portuguese trends and figures

Table 3 displays, for each dataset, the relevant summary statistics for Portugal, evaluated for the pre-intervention and post-intervention periods and the complete sample. For the HIV incidence among injecting drug users, the pre-intervention period consists of observations from 1993 to 2000 and the post-intervention period from 2001 to 2013. For the AIDS incidence among injecting drug users dataset, the pre-intervention period is from 1995 to 2000 and the post-intervention from 2001 to 2013:

Table 3: Summary statistics for the Portuguese HIV and AIDS among injecting drug users series

	HIV			**AIDS**		
	Pre-Int	**Post-Int**	**Complete**	**Pre-Int**	**Post-Int**	**Complete**
Mean	620.63	436.31	506.52	593.83	281.31	380
Variance	198,527.13	79,528.06	125,613.66	6,141	25,437.06	40,940
Max	1497	1016	1497	680	568	680
Max (year)	2000	2001	2000	1999	2001	1999
Min	169	78	78	455	74	74
Min (year)	1993	2013	2013	1995	2013	2013

The summary statistics show the average yearly HIV incidence among injecting drug users is substantially smaller in the post-intervention period compared to the pre-intervention period. Before the intervention, Portugal reported an average of 620.23 new HIV cases per year. At the same time, after, an average of only 436.31. The same holds for AIDS, as the average yearly reported cases decreased from 593.83 for the pre-intervention period to 281.31 for the post-intervention period. While impossible to formulate conclusions directly, the decrease in averages is indicative of the Consumption Decriminalization Law leading to lower AIDS and HIV incidence among injecting drug users in Portugal.

In 2000, a year before the intervention, Portugal reported 1,497 new HIV cases, the highest number in the pre-intervention and evaluation period. Meanwhile, the lowest number of reports in the pre-intervention period was 169 in 1993, the first year in the sample, and 78 in the post-intervention, the most recent year considered. Together, those values suggest that the HIV problem worsened up until the intervention and improved after the intervention. Likewise, a similar logic holds for AIDS incidence. Figures 1(a) and 1(b), which respectively depict the number of new HIV and AIDS cases reported in Portugal as well as in arbitrary potential control countries throughout the evaluation period, confirm this pattern:

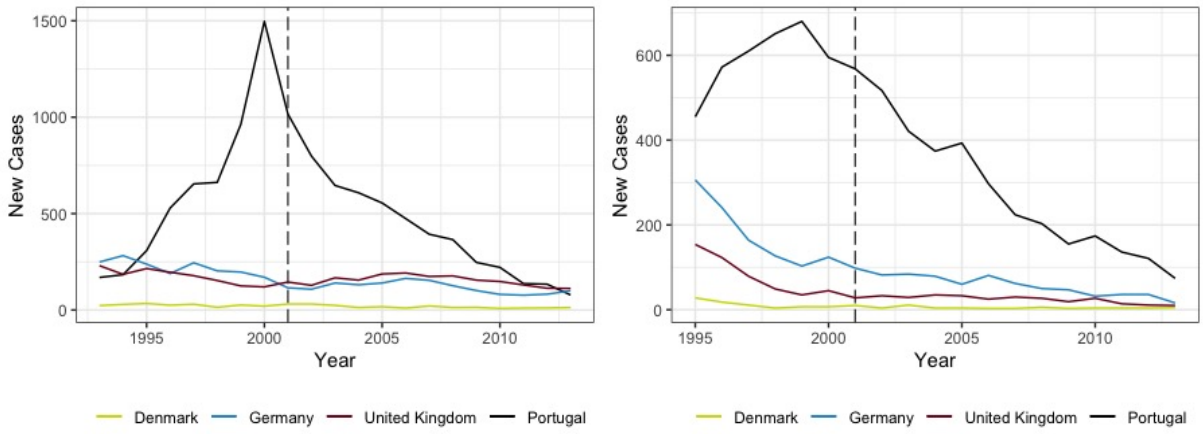

Figure 1: (a) HIV incidence, from 1993 to 2013, and (b) AIDS incidence, from 1995 to 2013, among injecting drug users series in Portugal next to arbitrary potential controls available for both series

The extreme discrepancy between the number of new HIV and AIDS cases among injecting drug users reported in Portugal and the displayed potential controls highlights the severity of the drug problem Portugal experienced in the late 1990s. Besides, the figures also show that, after the intervention, the number of new cases started decreasing, reaching the same level as the controls' around 2010. While this preliminarily suggests that the Consumption Decriminalization Law resulted in lower HIV and AIDS incidence, it is impossible at this stage to attribute the improvements strictly to the intervention. The results in this paper describe whether and to what extent the Consumption Decriminalization Law impacted HIV and AIDS incidence among injecting drug users.

4 Methodology

4.1 The synthetic control approach

An intuitive approach to evaluating the impact of policy changes is to compare outcomes of interest before and after the introduction of the change. However, the target variable could have changed behavior regardless of the intervention, making it impossible to attribute any observed differences strictly to the change in policy. Alternatively, and more appropriately, it is possible to use a control — a group that did not ever undergo a policy change — to assess the impact of the intervention. This approach underlies the method described in Abadie, Diamond, and Hainmueller (2010), which serves as a foundation for the methodology proposed in Harvey and Thiele (2021), from which this paper borrows the notation.

Abadie et al. (2010) propose constructing a control group by taking a weighted combination of N control series, known as donors. Then, for every outcome of interest, the impact of a policy change at time τ is the contrast between the target series and the control, as specified in Equations 1 and 2:

$$y_{ot} - y_t^c, \quad t = \tau, \ldots, T \tag{1}$$

$$y_t^c = \sum_{i=1}^{N} w_i y_{it} = \mathbf{w}'\mathbf{y}_t. \tag{2}$$

In Equation 1, y_{0t} is the target series, and y_{tc} is the control series, known as Synthetic Control. w_i , in Equation 2, is, thus, the weight assigned to donor i when constructing the Synthetic Control and y_{it} the series associated with donor i.

In practice, this weighted combination tries to approximate what would have happened to an outcome of interest if the intervention in question did not come into force. Hence, the controls used in this combination are selected, and their weights specified, so the growth path before the intervention is similar between the Synthetic Control and the target series. Moreover, for the same reason, controls should not have enacted similar interventions in the post-intervention period. Otherwise, it would be impossible to isolate the intervention effect.

Finally, it is possible to consider the effect of the intervention as dynamic, with the target series defined as

$$y_{0t} = \mu_t + \mu_0 + {}_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^* + \epsilon_{0t}, \quad t = 1, \ldots, T,$$

$$d_t = \begin{cases} 0, & \text{for } t < \tau + m \\ 1, & \text{otherwise} \end{cases}, \quad 1 < \tau + m \leq T \tag{3}$$

$$d_{j,t}^* = \begin{cases} 0, & \text{for } t \neq \tau + j - 1 \\ 1, & \text{otherwise} \end{cases}, \quad j = 1, \ldots, m.$$

In equation 3, d_t captures the potential permanent shift in the level of y_{0t} and the m pulse dummies d_t^* capture the intermediate effects. The λ and λ_j are, thus, coefficients. Furthermore, μ_t is a trend common to the target and control series, μ_0 is an intercept, and ϵ_{0t} is the error term.

4.2 Constructing a valid synthetic control

Given a nonstationary target series, a Synthetic Control is valid if, in the absence of an intervention, $y_{ot} - y_{tc}$ is stationary. Since the weighted average of individual control series needs to be on the same growth path as the target series during the pre-intervention period, each control series does not have to be cointegrated with the target series for the synthetic control to be valid. However, because the number of donors N can be greater than that of periods up to the intervention period τ, it is possible to mistake in-sample overfitting for common trends in the absence of further restrictions (Harvey & Thiele, 2021). It is indeed the case that the number of potential controls is far greater than that of observations before the intervention for both the new HIV and AIDS infections among injecting drug users datasets. Referring to Table 1, the number of potential controls for the HIV series is 20, and the intervention period corresponds to the 9th observation. At the same time, for the AIDS

series, the intervention period occurs at the 7th observation, and the number of potential controls is 16.

As a solution, Harvey and Thiele (2021) suggest restricting donor series to those on the same growth path as the target series. Under this additional requirement, the synthetic control and target series will share trends, and it is possible to attribute observed differences to the intervention. After restricting the donor pool accordingly, it is possible to evaluate the weights using restricted least squares, which chooses $\mathbf{w}$ as to minimize:

$$\sum_{t=1}^{\tau-1}(y_{0t} - \boldsymbol{w}'\mu - \boldsymbol{w}'\boldsymbol{y_t})^2 \quad \text{s.t.} \quad \boldsymbol{w}'\boldsymbol{i} = \mathbf{1}. \tag{4}$$

Harvey and Thiele (2021) recommend subtracting one of the controls from the remaining controls and target series to estimate the weights. The weights follow from the regression described in Equation 5, with the remaining weight estimate given as in Equation 6:

$$y_{0t} - y_{it} = \alpha + \sum_j w_j(y_{jt} - y_{it}) + \varepsilon_{it}, \quad \text{for } j \in R - \{i\} \tag{5}$$

$$\hat{w_i} = 1 - \sum_j \hat{w_j}. \tag{6}$$

In equation 5, R is a set of potential controls from the donor pool and y_{it} is an arbitrarily chosen control from the set R. Since Harvey and Thiele (2021) suggest only using three controls in the estimation, R has cardinality three. In addition, α is an intercept and ϵ_{it} is an error term.

4.3 Selecting donors

The pool of potential donors should only include donor series individually cointegrated with the target series throughout the pre-intervention period. Excluding all available controls that do not fulfill this requirement is, thus, necessary. Harvey and Thiele (2021) recommend running various Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests on the differences between donor series in the pool and the target series, known as contrasts, to test whether cointegration holds for every available control when considering observations from before the intervention. Equation 7 describes the contrasts:

$$y_{it} - y_{0t}, \quad i = 1, \ldots, N. \tag{7}$$

The null hypothesis of this test is that of trend-stationarity, while under the alternative, the series has a unit root – not stationary (Kokoszka & Young, 2016). Therefore, a donor series should only be included as a potential donor when failing to reject the null hypothesis. According to Harvey and Thiele (2021), the significance level of the test is arbitrary to some degree, as the goal of performing the test is to rank potential donors according to their validity as controls.

4.4 Estimating the intervention effect

Harvey and Thiele (2021) propose estimating the intervention effect with four different models, each accounting for distinct properties of the series. Straightforwardly, assessing the impact directly from the synthetic control constructed with the weights computed as in Equations 5 and 6 is possible. For each pulse (intermediary effect) and the level shift, the coefficients follow from the regression in Equation 8:

$$y_{0t} - y_t^c = (\mu_0 - \boldsymbol{w}'\mu) + \lambda d_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^* + (\epsilon_{0t} - \boldsymbol{w}'\epsilon_t), \quad t = 1, \dots, T. \tag{8}$$

Notwithstanding, as described by Harvey and Thiele (2021), estimating the weights outside the model can be disadvantageous as evidence suggests efficiency gains from in-model estimation. Accordingly, they recommend three models that assess the controls weights within the model. The first and second are the univariate (first equation in Equation 9) and bivariate (both equations in Equation 9) models:

$$\begin{aligned} y_{0t} - y_{it} &= (\mu_0 - \mu_i) + \sum_{j \neq i}^{N} w_j (y_{jt} - y_{it}) + \lambda d_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^* + \varepsilon_t^{\dagger} \\ y_{it} &= \mu_t + \mu_i^{\dagger} - \sum_{j \neq i}^{N} c_j (y_{jt} - y_{it}) + \varepsilon_{it}^{\dagger}. \end{aligned} \tag{9}$$

In equation 9, the superscript † specifies a linear transformation of the corresponding disturbances and constants in the other series. In addition, the c_j's are coefficients to be estimated.

The second equation of the bivariate model captures stochastic trend dynamics. Therefore, the univariate model is usually less efficient than the bivariate one. The final model Harvey and Thiele suggest is the multivariate one described in Equation 10:

$$y_{0t} - y_{it} = (\mu_0 - \mu_i) + \lambda d_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^* + (\epsilon_{0t} - \epsilon_{it}), \quad t = 1, \dots, T, \tag{10}$$

$$y_{it} = \mu_t + \mu_i + \epsilon_{it} \tag{11}$$

$$\boldsymbol{y_t}^{(-i)} - \boldsymbol{i} y_{it} = (\mu_0 - \mu_i)^{(-i)} + (\epsilon_{0t} - \epsilon_{it})^{.(-i)} \tag{12}$$

In Equation 12, $\mathbf{i}$, $(\mu_0 - \mu_i)^{(-i)}$, and $(\epsilon_{0t} - \epsilon_{it})^{(-i)}$ are $N-1$ vectors, with $\mathbf{i}$ being a vector of ones. Unlike the bivariate model, the multivariate model allows for estimation error in the weights, which usually leads to lower standard errors. Furthermore, after estimating all models, it is possible to compare models by analyzing the standard errors and residual serial correlation.

Unfortunately, it was impossible to estimate the bivariate and multivariate models. Harvey and Thiele (2021) use STAMP, a structural time series analyzer, modeler, and predictor software unavailable through the institution behind this paper. The available software, however, did not allow for structural time series estimation, which is necessary for estimating either model.

5 Results

The evaluation of the effect of the enactment of the Consumption Decriminalization Law on HIV and AIDS incidence among injecting drug users in Portugal now follows, first for HIV and then for AIDS. Table 4 displays the KPPS (2) test statistics values for a deterministic versus a stochastic trend for the individual series, fixed slope in I(1) series versus an I(2) series for each of the series, and the contrast between each of the individual series and Portugal in that order. The variance for each of these contrasts is also displayed. All values are for the pre-intervention period. Importantly, testing for a deterministic versus a stochastic trend is equivalent to testing, under the null hypothesis, for an integration order of zero. Meanwhile, testing for a fixed slope in I(1) versus an I(2) series is the same as testing for an in integration order of one under the null and two under the alternative hypothesis:

Table 4: Multiple KPSS(2) test statistics and the variance of the contrasts between the potential controls and the Portuguese series for the HIV incidence among injecting drug users series

Country	**I(0)**	**I(1)**	**Cointegration (Level)**	**Variance** ($\times 10^{-3}$)
Netherlands	0.137	0.287	0.4072	206.004
Denmark	0.136	0.210	0.4075	200.849
United Kingdom	0.133	0.167	0.4076	231.489
Germany	0.23	0.314	0.4083	226.963
Slovenia	0.155	0.310	0.4083	198.728
Sweden	0.162	0.193	0.4084	199.706
Czech Republic	0.201	0.365	0.4085	198.177
Bulgaria	0.175	0.264	0.4086	198.856
Hungary	0.146	0.187	0.4086	198.677
Turkey	0.166	0.250	0.4086	199.607
Norway	0.133	0.179	0.4087	199.927
Luxembourg	0.140	0.244	0.4088	197.839
Greece	0.161	0.229	0.4089	195.815
Croatia	0.132	0.178	0.4089	198.383
Belgium	0.147	0.293	0.4092	200.548
Lithuania	0.124	0.188	0.4100	182.242
Finland	0.139	0.209	0.4118	177.732
Ireland	0.149	0.373	0.4125	182.578
Latvia	0.157	0.386	0.4158	96.494
Portugal	0.165	0.376		
Critical Value	**0.119**	**0.347**	**0.347**	

The KPSS(2) test rejects the null hypothesis of cointegration between the individual controls and Portugal for all countries. While this is not ideal, Harvey and Thiele (2021) state that the critical value of the test is somewhat arbitrary, with the ranking of potential controls being the added value of the test. Regardless, it is visible from Table 4 the test statistic values are similar for most countries, differing only by 0.001 for the first ten countries. Accordingly, it is unclear from the ranking of the test statistics alone which controls to use.

Since having the same integration order is a cointegration requirement, evaluating the integration order of all individual series may provide clarity on which controls to use. The KPSS(2) test rejects the null hypothesis of I(0) and I(1) for the Portuguese series, implying it is best modeled with an I(2) process. The same holds for the Czech Republic. Meanwhile, the test rejects and fails to reject the null hypothesis of I(0) and I(1) for the Netherlands, Denmark, United Kingdom, Germany, Slovenia, Sweden, Bulgaria, Hungary, and Turkey, indicating they follow an I(1) process. Hence, it is still unclear which countries would be most appropriate for constructing synthetic control.

Because of the uncertainty surrounding the best group of countries, it is best to consider a few combinations of potential controls. The first combination is the Netherlands, Denmark, and the United Kingdom, as their associated cointegration (level) KPSS(2) test statistics are the smallest. Furthermore, notice the variance of the contrast between the United Kingdom and Portugal and between Germany and Portugal is much higher than for the other countries. Excluding both from consideration and choosing the countries with the lowest cointegration (level) statistics results in a group with the Netherlands, Denmark, and Slovenia. Finally, the group with the Netherlands, Denmark, and the Czech Republic is in consideration as the Czech Republic and Portugal have the same integration order, and Slovenia has the highest cointegration (level) test statistic. Table 5 depicts the restricted Least Squares (RLS) weights, which are the ones estimated as in Equation 5 and Equation 6, and the OLS weights, which follow from directly regressing the target series onto the controls. Besides, the KPSS(2) test for the difference between Portugal and the Synthetic Control constructed with each combination of controls using only the pre-intervention period is available:

Table 5: RLS and OLS weights for each combination of controls together with the associated KPSS(2) statistics for the contrast between the Portuguese series and the Synthetic Control

Country	RLS weight	OLS weight
Netherlands	-37.012	-8.085
Denmark	31.940	2.868
United Kingdom	6.072	-8.296
KPSS(2)	*Level = 0.395*	*p-value = 0.079*
Netherlands	-20.507	-31.888
Denmark	53.202	5.995
Slovenia	-31.695	-24.217
KPSS(2)	*Level = 0.365*	*p-value = 0.092*
Netherlands	-19.561	-31.247
Denmark	51.555	5.205
Czech Republic	-30.994	19.145
KPSS(2)	*Level = 0.366*	*p-value = 0.092*

The RLS weights for the group comprising the Netherlands, Denmark, and the Czech Republic are similar to that including Slovenia and substantially different from that containing the United Kingdom. In addition, the KPSS(2) test proposes that Portugal and any synthetic controls are cointegrated. A ranking of the KPSS(2) statistics indicates the Synthetic Control constructed with Slovenia is, nevertheless, the most cointegrated with the target series. Figure 2 displays each Synthetic Control and Portugal:

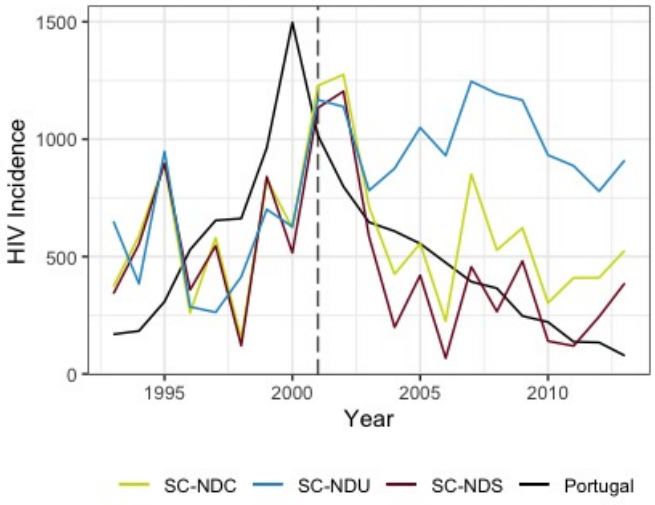

Figure 2: HIV incidence among injecting drug users, Portugal and multiple synthetic controls — SC-NDC (Netherlands, Denmark, and the Czech Republic), SC-NDU (Netherlands, Denmark, and the United Kingdom), SC- NDS (Netherlands, Denmark, and Slovenia), from 1993 to 2013

The figure shows that, in the pre-intervention period, the Synthetic Control constructed with the Netherlands, Denmark, and Slovenia followed a similar growth path to the controls with Slovenia and the United Kingdom. Therefore, it is difficult to say which control group would be best suitable. As such, the intervention effects computed with a Univariate (first equation of Equation 9) and Synthetic Control Model [3] (Equation 8) follow for all three groups in Tables 6, 7, and 8. These tables also display, for each model, the probability value of the Durbin Watson (DW) test, for which the null hypothesis is of no serial correlation, and the alternative is of first-order serial correlation.

Before fitting the models, it is necessary to determine when the intervention effect stabilized. Figure 2 indicates that the Portuguese series is flatter during 2001-2003 than between 2003 and 2013, signifying a level break around 2004. Accordingly, the fitted models include pulse dummies for 2001, 2002, and 2003 as well as level a shift dummy for 2004, for which coefficient estimates are in italic:

Table 6: Univariate and Synthetic Control estimates for the Netherlands, Denmark and the United Kingdom

	Univariate Estimate			**Synthetic Control Estimate**	
Year	*Estimate*	*SE*	*Year*	*Estimate*	*SE*
2001	29.343	445.444	2001	-237.802	385.70
2002	-252.885	453.634	2002	-426.603	385.70
2003	-84.925	351.847	2003	-221.707	385.70
2004	*-479.606*	*252.490*	*2004*	*-762.061*	*172.49*
DW	*p-value = 0.002*		*DW*	*p-value = 0.022*	

Table 7: Univariate and Synthetic Control estimates for the Netherlands, Denmark and Slovenia

	Univariate Estimate			**Synthetic Control Estimate**	
Year	*Estimate*	*SE*	*Year*	*Estimate*	*SE*
2001	23.422	439.565	2001	-295.307	391.74
2002	-231.907	454.965	2002	-560.422	391.74
2003	-124.377	346.115	2003	-149.684	391.74
2004	*-710.657*	*286.408*	*2004*	*-247.429*	*175.19*
DW	*p-value = 0.000*		*DW*	*p-value = 0.178*	

[3] When estimating Synthetic Control models, the standard errors are always the same for the pulse dummies because, for each year, the regressor is a dummy.

Table 8: Univariate and Synthetic Control estimates for the Netherlands, Denmark and the Czech Republic

	Univariate Estimate			**Synthetic Control Estimate**	
Year	*Estimate*	*SE*	*Year*	*Estimate*	*SE*
2001	40.816	433.668	2001	-216.793	398.77
2002	-198.899	452.062	2002	-504.909	398.77
2003	-167.262	343.842	2003	-38.431	398.77
2004	*-817.520*	*329.671*	2004	*-55.897*	*178.34*
DW	*p-value = 0.004*		*DW*	*p-value = 0.144*	

The estimated effect for 2004 – level effect – is negative across all models, varying from -55.897 (Synthetic Control Model – Netherlands, Denmark, Czech Republic) to -817.520 (Univariate Model – Netherlands, Denmark, Czech Republic). Altogether, this suggests that the Consumption Decriminalization Law led to fewer new HIV cases among injecting drug users. Notwithstanding, the standard errors of all models are high, sometimes higher than the estimated coefficients. Besides, the Durbin Watson test only does not reject the null hypothesis of no serial correlation of the residuals for the Synthetic Control model for the Synthetic Control created with the Czech Republic and the one constructed with Slovenia. Thus none of the models fit well, and any conclusion is weak.

The coefficient estimated for all years between the intervention and level break, known as intermediary effects, deviate across Synthetic Controls and models. Interestingly, most models estimate a positive intermediary coefficient for 2001. Nevertheless, the standard error for the 2001 coefficients is usually many times the size of the coefficient itself. Accordingly, it is not possible to conclude from the positive effect.

As Table 4 for HIV, Table 9 shows the KPPS (2) test statistics values for a deterministic versus a stochastic trend for the individual series, fixed slope in I(1) series versus an I(2) series for each of the series, and the contrast between the new AIDS cases series of the controls and Portugal. The variance of each of these contrasts likewise follows. Again, all evaluations only use observations from before the intervention:

Table 9: Multiple KPSS(2) test statistics and the variance of the contrasts between the potential controls and the Portuguese series for the new AIDS cases among injecting drug users series

Country	**I(0)**	**I(1)**	**Cointegration (Level)**	**Variance** ($\times 10^{-3}$)
Belgium	0.147	0.388	0.304	6.550
Poland	0.178	0.351	0.307	5.003
Greece	0.099	0.134	0.308	6.164
Finland	0.138	0.200	0.312	6.145
Norway	0.114	0.170	0.314	6.245
Luxembourg	0.128	0.266	0.315	6.107
Turkey	0.155	0.362	0.315	6.032
Denmark	0.134	0.334	0.317	7.527
Austria	0.113	0.178	0.317	6.736
Ireland	0.115	0.143	0.322	7.202
United Kingdom	0.134	0.319	0.340	15.216
Germany	0.138	0.353	0.344	24.005
France	0.129	0.292	0.364	259.480
Italy	0.123	0.236	0.382	1464.758
Spain	0.116	0.186	0.385	1966.066
Portugal	0.149	0.393		
Critical Value	**0.119**	**0.347**	**0.347**	

The results indicate that the Portuguese series follows an I(2) process since the KPSS(2) rejects the null hypotheses of both I(0) and I(1). Furthermore, the test statistic value for cointegration (level) is similar for the first few countries. The variance, however, differs substantially, with that of Belgium, Norway, and Greece being much higher than that of Poland, Turkey, and Luxembourg. Hence, at first glance, the ranking suggests that the synthetic control should include Belgium, Poland, and Greece. Nevertheless, perhaps Poland, Turkey, and Luxembourg would be more appropriate controls.

Again, having the same integration order is a requirement for cointegration. While Belgium and Poland also seem best modeled with an I(2) process, as does Portugal, there is a failure to reject the null hypothesis that the Turkey and Greece series are I(0). Meanwhile, the Luxembourg series appears to follow an I(1) process. In spite of these results, the cointegration level test indicates that Portugal and all these series are cointegrated. Accordingly, it is inconclusive which group of controls to opt for just by looking at their cointegration with the target and the variance of the contrasts. The RLS and OLS weights and KPSS(2) test for the

difference between Portugal and the Synthetic Control constructed with each combination of controls using only the pre-intervention period are then calculated for both groups and displayed in Table 10:

Table 10: RLS and OLS weights for each combination of controls together with the associated KPSS(2) statistics for the contrast between the Portuguese series and the Synthetic Control

Combination 1			Combination 2		
Country	**RLS weight**	**OLS weight**	**Country**	**RLS weight**	**OLS weight**
Belgium	-6.35	-6.114	Luxembourg	-25.11	-9.728
Poland	5.916	5.997	Poland	7.672	7.637
Greece	1.435	1.561	Turkey	18.438	19.135
KPSS(2)	*Level = 0.455*	*p-value = 0.054*	*KPSS(2)*	*Level=0.134*	*p-value ¿ 0.1*

Interestingly, the RLS and OLS weights are high in absolute value. Likely, this follows because the Portuguese series' level is much higher than the controls', thus making it necessary to have the greater magnitude to fit the RLS model properly. Besides, the test results suggest that the Synthetic Control created with Belgium, Poland, and Greece and the target series are not cointegrated. Meanwhile, the one constructed with Poland, Turkey, and Luxembourg is. Indeed, figure 3, which depicts both synthetic controls and the target series, shows the growth path of the second Synthetic Control more closely resembles Portugal's in the pre-intervention period. Therefore, even though Turkey and Luxembourg do not have the same integration order as Portugal, it is still possible to build a control that meets the validity requirement. Following are Figures 3(a) and 3(b), which display the Synthetic Control constructed with both groups and the individual series of the chosen controls and Portugal:

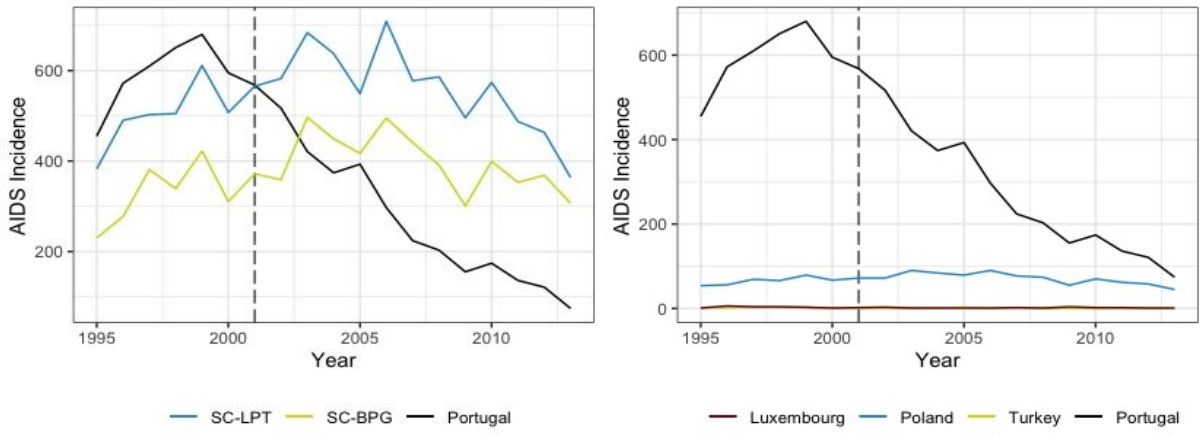

Figure 3: (a) AIDS incidence among injecting drug users, Portugal and multiple synthetic controls — SC-LPT (Luxembourg, Poland, and Turkey), SC-BPG (Belgium, Poland, and Greece) and (b) individual series for chosen controls, from 1993 to 2013

At last, after constructing the control, it is possible to estimate the effect of the decriminalization policy on AIDS incidence among injecting drug users in Portugal. However, it is necessary to determine the number of pulses before fitting the models. Figure 3 suggests the effect stabilized by 2005, as the Portuguese series changed direction in that year. Following in Table 11, then, are the estimated effects with Synthetic Control (equation 8) and Univariate (first equation in Equation 9) models assuming four pulse dummies:

Table 11: Univariate and Synthetic Control estimates for Luxembourg, Poland and Turkey

	Univariate Estimate			**Synthetic Control Estimate**	
Year	*Estimate*	*SE*	*Year*	*Estimate*	*SE*
2001	-72.457	62.934	2001	-91.617	67.86
2002	-121.006	64.498	2002	-159.667	67.88
2003	-329.422	70.722	2003	-356.888	67.88
2004	-340.717	67.187	2004	-357.856	67.88
2005	*-419.737*	*30.841*	*2005*	*-430.615*	*33.12*
DW	*p-value = 0.968*		*DW*	*p-value = 0.660*	

Both models fit well, as the Durbin Watson test suggests no residual autocorrelation, and the standard errors are overall small. The Synthetic Control model estimates more substantial level and intermediary effects than the univariate model. The estimates are, however, very similar. Decriminalizing drugs appears to have positively impacted — negative effect — AIDS incidence among injecting drug users, especially considering Portugal reported a maximum of 680 new AIDS cases, and the level effect hovers around the mid-low 400s.

6 Discussion

The evaluation of the impact of the Consumption Decriminalization Law suggests that decriminalization resulted in lower AIDS incidence among injecting drug users in Portugal. As described previously, decriminalization enabled the Portuguese government to implement various adjacent harm reduction programs, including safe injection facilities, syringe exchange programs, and free antiretroviral therapy for legal and illegal residents. These programs are robust, working on preventing HIV spread and preventing HIV from developing into AIDS. Therefore, decriminalization resulting in fewer new AIDS cases among injecting drug users is unsurprising.

Differently from AIDS, it was impossible to construct an appropriate synthetic control for the HIV incidence among injecting drug users series. However, the analysis using the three suboptimal Synthetic Controls suggests that the Consumption Decriminalization Law resulted in fewer yearly HIV cases, as it did for AIDS. Since HIV precedes AIDS, and it was possible to find evidence in support of new AIDS cases decreasing, most likely it is indeed the case that the law had a beneficial impact on HIV as well.

Importantly, none of the presented results are robust to different interpolation techniques and different interpolation restrictions. It is possible that using other interpolation techniques could have led to alternative distortions of the trends of controls, resulting in different cointegration levels between the target series controls and leading to alternative groups of controls. A similar logic holds for using other interpolation restrictions. Also, the results are not robust to the choice of level break year. Indeed, assuming the level break happened in years other than 2004 (for HIV) and 2005 (for AIDS) could lead to different estimations of the treatment effect.

7 Conclusion

In 2001, after a turbulent decade of drug-related problems, Portugal decreed the Consumption Decriminalization Law that decriminalized acquiring, possessing, and consuming illicit substances. In practice, this meant that drug-related violations would become administrative offenses, punishable with fines and nonpecuniary retributions, instead of criminal offenses, punishable with imprisonment. At the same time, the decriminalization process enabled the government to establish adjacent harm reduction programs, including assisted injection facilities, extensive syringe exchange programs, and free antiretroviral therapy to restrain the spread of dangerous infectious diseases like HIV.

Since a principal driver of the Consumption Decriminalization Law was a high incidence of AIDS and HIV among injecting drug users, this paper quantitatively evaluated the effect of the law on new HIV and AIDS cases among injecting drug users. The methodology used to assess this impact closely follows the Synthetic Control Method described in Harvey and Thiele (2021). Briefly, a Synthetic Control – a weighted combination of the series of other countries for which data on the outcome of interest is available – acts as a counterfactual. The treatment effect the difference between the target series and the Synthetic Control series. Since it serves as a counterfactual, the growth path of the synthetic control must closely resemble the target series before the intervention. Furthermore, because of the small number of observations in the pre-intervention period compared to potential donors, individual series were required to be integrated with the target series to prevent mistaking in-sample overfitting as common trends.

The dataset used in the evaluation was from the European Monitoring Centre for Drugs and Drug Addiction. It contained information on the new HIV and AIDS cases among injecting drug users – known in epidemiology as incidence – reported yearly in all European Union countries, the United Kingdom, Norway, and Turkey. Because of the method used, it was necessary to preserve the trends of the series of all potential controls. Therefore, when data was missing, spline interpolation was applied to the series only if no more than two consecutive observations were missing. In addition, to isolate the treatment effect appropriately, it was necessary to remove all countries that enacted a similar intervention to that of Portugal in the post-intervention period. Accordingly, this paper described a self-made drug policy classification system that proves – subjectively – that all countries that met the interpolation requirement should participate in the evaluation. Importantly, this paper assumed the treatment effect was dynamic, incorporating pulse dummies for the intermediate effects

and a shift dummy for the level shift. The choice of level shift year followed from graphical analysis.

The results of this paper support the notion that the adjacent harm reduction programs the Portuguese government instituted alongside the Consumption Decriminalization Law were beneficial in preventing AIDS among injecting drug users. The models used to estimate the treatment effect suggest a significant level effect of - 419.737 or - 430.615 novel yearly AIDS cases, depending on the model. Given Portugal reported a maximum of 680 new AIDS cases in any given year of the series, the effect of the law is substantial. Estimates of the intermediary effects are also negative for all years. Importantly, these results are not robust to other interpolation techniques, exclusion of interpolation altogether, and different level break years.

Unlike for AIDS, it was impossible to construct an appropriate synthetic control for the new HIV cases among injecting drug users series. Therefore this paper used three suboptimal Synthetic Controls to quantify the treatment effect. Interestingly, for most combinations of controls and models, the coefficient of the first intermediary is estimated as positive, while the expectation is that it would have been negative. Notwithstanding, the standard errors for all estimates are many times the size of the coefficient estimates themselves, suggesting that it is impossible to conclude from this result. All models and control combinations indicate that the level effect is negative, although the magnitudes greatly vary across models and control combinations between -55.897 and -817.520 novel yearly cases. As before for the AIDS series, these results are not robust to other interpolation techniques, exclusion of interpolation altogether, and different level break years. Furthermore, despite the lack of appropriate control, this paper concluded that the Drug Decriminalization Law most likely was beneficial for HIV as it was for AIDS. The conclusion followed because AIDS is a precursor to HIV, and this paper was able to find substantial positive – as in, beneficial – results for AIDS.

Limitations of this paper include subjectivity within the drug policy classification system and a lack of ability to estimate more advanced structural time series models. The classification system in question was subjective, and other interpretations of the drug policy could have resulted in a strikingly different donor pool and, by extension, different conclusions. Standardized classification systems could lead to more systemic interpretations of various policies and, thus, more comparable results across the literature. Likewise, unestimated models could have led to different estimations and conclusions than this paper proposes. Therefore, estimating these models could help corroborate or challenge the outcomes in this paper.

Ultimately, while impossible to extrapolate these results presented in this paper, especially considering the previously mentioned robustness problems, they do indicate that perhaps widespread criminalization of use and possession is not the answer to drug use and problems. In 2016 alone, after decades of the so-called “War on Drugs” (Bagley, 1988), the Center for Disease Control (CDC) in the United States reported that[4] over 200,000 drug users contracted HIV. This incidence is higher (even after adjusting for population size)

[4]CDC statistics available in https://www.cdc.gov/hiv/statistics/overview/ataglance.html

than at the pinnacle of the Portuguese drug crisis.[5] Science, and not prejudice, should guide decision-making, especially for something as afflicting as drug-related problems.

[5]The total population in Portugal in 2000, the peak of the drug crisis, was, according to the World Bank, 10.22 million. The HIV incidence for that year was 1,497. At the same time, in 2016, the population in the United States was 323.1 million, and the HIV incidence was 200,000

References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of American Statistical Association*, *105*(490), 493–505.

Alliance, D. P. (n.d.). *Drug decriminalization in portugal: Learning from a health and human-centered approach (2018)*.

Bagley, B. M. (1988). The new hundred years war? us national security and the war on drugs in latin america. *Journal of Interamerican Studies and World Affairs*, *30*(1), 161–182.

Bajekal, N. (2018, 08). *Want to win the war on drugs? portugal might have the answer.* Time. Retrieved from https://time.com/longform/portugal-drug-use-decriminalization/

Blankenship, K. M., Smoyer, A. B., Bray, S. J., & Mattocks, K. (2005). Black-white disparities in hiv/aids: the role of drug policy and the corrections system. *Journal of health care for the poor and underserved*, *16*(4 Suppl B), 140.

Bluthenthal, R., Lorvick, J., Kral, A., Erringer, E., & Kahn, J. (1999). Collateral damage in the war on drugs: Hiv risk behaviors among injection drug users. *International Journal of Drug Policy*, *10*(1), 25–38.

Booth, M. (2005). *Cannabis: a history*. Macmillan.

Borges, M., Gouveia, M., Fiorentino, F., Jesus, G., Cary, M., Guerreiro, J. P., ... Carneiro, A. V. (2020). Costs and consequences of the portuguese needle-exchange program in community pharmacies. *Canadian Pharmacists Journal/Revue des Pharmaciens du Canada*, *153*(3), 170–178.

Buchman, D. Z., Leece, P., & Orkin, A. (2017). The epidemic as stigma: The bioethics of opioids. *Journal of Law, Medicine & Ethics*, *45*(4), 607–620.

Chan, K. Y., Stoové, M. A., & Reidpath, D. D. (2008). Stigma, social reciprocity and exclusion of hiv/aids patients with illicit drug histories: A study of thai nurses' attitudes. *Harm Reduction Journal*, *5*(1), 1–11.

Dias, S., Gama, A., Severo, M., & Barros, H. (2011). Factors associated with hiv testing among immigrants in portugal. *International journal of public health*, *56*(5), 559–566.

EMCDDAa. (2019). Country Drug Report Italy 2019. (https://www.emcdda.europa.eu/publications/country-drug-reports/2019/italy_en)

EMCDDAb. (2019). Country Drug Report France 2019. (https://www.emcdda.europa.eu/publications/country-drug-reports/2019/france_en)

EMCDDAc. (2019). Country Drug Report Sweden 2019. (https://www.emcdda.europa.eu/publications/country-drug-reports/2019/sweden_en)

Félix, S., & Portugal, P. (2017). Drug decriminalization and the price of illicit drugs. *International Journal of Drug Policy*, *39*, 121–129.

Gibson, D. R., Flynn, N. M., & Perales, D. (2001). Effectiveness of syringe exchange programs in reducing hiv risk behavior and hiv seroconversion among injecting drug users. *Aids*, *15*(11), 1329–1341.

Greenwald, G. (2009). Drug decriminalization in portugal: lessons for creating fair and successful drug policies. *Cato Institute Whitepaper Series*.

Harvey, A., & Thiele, S. (2021). Cointegration and control: Assessing the impact of events using time series data. *Journal of Applied Econometrics*, *36*(1), 71–85.

Heimer, R. (1998). Syringe exchange programs: lowering the transmission of syringe-borne diseases and beyond. *Public Health Reports*, *113*(Suppl 1), 67.

Hughes, C. E., & Stevens, A. (2007). The effects of the decriminalization of drug use in portugal.

Hughes, C. E., & Stevens, A. (2010). What can we learn from the portuguese decriminalization of illicit drugs? *The British Journal of Criminology*, *50*(6), 999–1022.

Kerr, J., & Jackson, T. (2016). Stigma, sexual risks, and the war on drugs: Examining drug policy and hiv/aids inequities among african americans using the drug war hiv/aids inequities model. *International Journal of Drug Policy*, *37*, 31–41.

Kerr, T., Kimber, J., DeBeck, K., & Wood, E. (2007). The role of safer injection facilities in the response to hiv/aids among injection drug users. *Current HIV/AIDS Reports*, *4*(4), 158–164.

Kokoszka, P., & Young, G. (2016). Kpss test for functional time series. *Statistics*, *50*(5), 957–973.

Laufer, F. N. (2001). Cost-effectiveness of syringe exchange as an hiv prevention strategy. *Journal of acquired immune deficiency syndromes (1999)*, *28*(3), 273–278.

Lei n.º 30/2000. (2000). (https://data.dre.pt/eli/lei/30/2000/11/29/p/dre/pt/html)

Lu, D.-Y., Wu, H.-Y., Yarla, N. S., Xu, B., Ding, J., & Lu, T.-R. (2018). Haart in hiv/aids treatments: future trends. *Infectious Disorders-Drug Targets (Formerly Current Drug Targets-Infectious Disorders)*, *18*(1), 15–22.

MacCoun, R., & Reuter, P. (2001). Evaluating alternative cannabis regimes. *The British Journal of Psychiatry*, *178*(2), 123–128.

McDowell, T. L., & Serovich, J. (2007). The effect of perceived and actual social support on the mental health of hiv-positive persons. *AIDS care*, *19*(10), 1223–1229.

N, R., Kral, A. H., Erringer, E. A., & Edlin, B. R. (1999). Drug paraphernalia laws and injection-related infectious disease risk among drug injectors. *Journal of Drug Issues*, *29*(1), 1–16.

Reinarman, C., Cohen, P. D., & Kaal, H. L. (2004). The limited relevance of drug policy: cannabis in amsterdam and in san francisco. *American Journal of Public Health*, *94*(5), 836–842.

Sánchez, C., & Collins, M. (2018). Better to ask forgiveness than permission: Spain's subnational approach to drug policy. *Global Drug Policy Observatory*.

Sarna, A., Pujari, S., Sengar, A., Garg, R., Gupta, I., & Dam, J. v. (2008). Adherence to antiretroviral therapy & its determinants amongst hiv patients in india. *Indian Journal of Medical Research*, *127*(1), 28.

Schoenfeld, H. (2012). The war on drugs, the politics of crime, and mass incarceration in the united states. *J. Gender Race & Just.*, *15*, 315.

Strathdee, S. A., Beletsky, L., & Kerr, T. (2015). Hiv, drugs and the legal environment. *International Journal of Drug Policy*, *26*, S27–S32.

Stringer, K. L., Marotta, P., Baker, E., Turan, B., Kempf, M.-C., Drentea, P., ... Turan, J. M.

(2019). Substance use stigma and antiretroviral therapy adherence among a drug-using population living with hiv. *AIDS patient care and STDs*, *33*(6), 282–293.

Taraphdar, P., Guha, R. T., Haldar, D., Chatterjee, A., Dasgupta, A., Saha, B., & Mallik, S. (2011). Socioeconomic consequences of hiv/aids in the family system. *Nigerian medical journal: journal of the Nigeria Medical Association*, *52*(4), 250.

Tavares, A. (2009). The impact of drug decriminalization in portugal. *The Economist*.

Van Het Loo, M., Van Beusekom, I., & Kahan, J. P. (2002). Decriminalization of drug use in portugal: the development of a policy. *The Annals of the American Academy of Political and Social Science*, *582*(1), 49–63.

Vicknasingam, B., Narayanan, S., Singh, D., & Chawarski, M. (2018). Decriminalization of drug use. *Current Opinion in Psychiatry*, *31*(4), 300–305.

Wogen, J., & Restrepo, M. T. (2020). Human rights, stigma, and substance use. *Health and human rights*, *22*(1), 51.

Ximene, R., Oliveira, M. J., Lameira, C., et al. (2021). 20 years of portuguese drug policy-developments, challenges and the quest for human rights. *Substance Abuse Treatment, Prevention, and Policy*, *16*(1), 1–11.

Yu, Y., Luo, D., Chen, X., Huang, Z., Wang, M., & Xiao, S. (2018). Medication adherence to antiretroviral therapy among newly treated people living with hiv. *BMC public health*, *18*(1), 1–8.

8 Appendix

8.1 Smoking in California

The replication results for the "Smoking in California" application in Harvey and Thiele (2021) follow. In January 1989, Proposition 99, which contained a range of measures to reduce smoking, came into effect. The authors of Harvey and Thiele (2021) look at how this proposition affected cigarette consumption in California using the Synthetic Control method they propose. All replication results match the original publication, corroborating the negative level and intermediate effects the authors find. Table 12 shows for all American states that did not enact a similar policy to that of Proposition 99 during the post-intervention period (after 1989), the KPSS(2) test statistics for the contrasts between each state and the California series (pre-intervention). Besides, the variance of each of these contrasts is also available. Note that, in the original publication, results are displayed only for a selection of all states:[6]

[6]Idaho, North Carolina, Colorado, Montana, Wyoming Nevada, Kentucky, North Dakota, Delaware, Indiana, Connecticut, and Utah

Table 12: KPSS(2) statistics and variance for the contrasts between potential control states and California

State	KPSS(2)	Variance	State	KPSS(2)	Variance
Idaho	0.218	24.9	*Ohio*	0.679	152.9
North Carolina	0.249	364.5	*West Virginia*	0.684	60.0
Colorado	0.286	20.3	*Louisiana*	0.685	109.5
Montana	0.309	19.4	*Nebraska*	0.688	62.8
Wyoming	0.334	129.9	*New Mexico*	0.696	36.3
Nevada	0.422	183.7	*South Dakota*	0.696	93.0
Kentucky	0.506	375.2	*Illinois*	0.697	40.6
North Dakota	0.522	123.4	*Virginia*	0.708	100.5
Delaware	0.531	55.1	*Rhode Island*	0.721	126.0
Indiana	0.547	67.4	*Wisconsin*	0.722	83.2
Connecticut	0.593	95.3	*Pennsylvania*	0.725	144.5
Vermont	0.606	191.0	*Georgia*	0.730	211.0
Oklahoma	0.614	154.0	*Arkansas*	0.734	313.1
New Hampshire	0.624	589.7	*Tennessee*	0.741	325.2
Utah	0.625	56.7	*Alabama*	0.742	252.5
Texas	0.652	137.5	*Maine*	0.748	50.2
Kansas	0.658	116.7	*South Carolina*	0.748	184.5
Iowa	0.669	76.9	*Missouri*	0.749	104.6
Minnesota	0.677	116.6	*Mississippi*	0.752	162.5

Table 13 displays the Restricted Least Squares (RLS) and Ordinary Least Squares (OLS) weights for all combinations of controls in Harvey and Thiele (2021). As in the original publication, OLS weights are not available for the Colorado, Wyoming, and Idaho as well as Colorado, North Carolina, and Idaho control combinations:

Table 13: RLS and OLS weight estimates for different combinations of controls

State	RLS weight	OLS weight
Colorado	0.385	0.356
Montana	0.327	0.308
Idaho	0.288	0.275
Colorado	0.609	
Wyoming	−0.019	
Idaho	0.410	
Colorado	0.645	
North Carolina	0.037	
Idaho	0.318	

Finally, Table 14 presents the estimated intermediary and permanent effects for the Univariate Model (first equation in Equation 9) and Synthetic Control Model (Equation 8). As explained before, unlike in (Harvey & Thiele, 2021), it was impossible to produce estimates for the Multivariate and Bivariate models because the available software did not allow for structural time series estimations. Furthermore, like in the original publication, here the assumption is that the level break occurred in 1995, for which estimates are in bold:

Table 14: Univariate and Synthetic Control estimation of the treatment effect assuming level break in 1995

	Univariate Estimate			**Synthetic Control Estimate**	
Year	*Estimate*	*SE*	*Year*	*Estimate*	*SE*
1989	-1.16	4.28	1989	-0.81	3.68
1990	-7.27	4.71	1990	-7.75	3.68
1991	-15.67	4.08	1991	-15.99	3.68
1992	-17.54	4.40	1992	-17.58	3.68
1993	-21.88	4.39	1993	-22.06	3.68
1994	-29.15	4.89	1994	-29.59	3.68
1995	**-28.41**	**4.14**	**1995**	**-27.82**	**1.68**

8.2 German reunification

The replication of results in the German Reunification application in Harvey and Thiele (2021) follow. On October 3rd, 1990, West and East Germany reunified. The authors of

Harvey and Thiele (2021) look at how this reunification affected real GDP per capita in West Germany. Unlike the previous application, the results for this replication do not match the original publication. It is believed the original authors mistook the United Kingdom for Austria when computing the KPSS(2) test statistics for the contrast between the potential controls and the target series in the pre-intervention period. In turn, this led them to use Austria, which, in reality, is not co-integrated with West Germany, instead of the United Kingdom as a control. This section displays the results for the control groups constructed with Austria and the United Kingdom. Table 15 displays the KPSS(2) statistics for a deterministic versus a stochastic trend for the individual series, fixed slope in I(1) series versus an I(2) series for each of the series, and the contrast between each of the individual series and West Germany in that order. In the original publication, these results are only available for a selection of controls.[7] Besides, like in the original publication, the variance of the contrasts, OLS weights, and RLS weights are also displayed.

After Table 15, Table 16 shows the estimated intermediate and level effects for the Synthetic Control Model for synthetic controls constructed with either Austria or the United Kingdom as a control. As in the original publication, the assumption is that the effect stabilized by 1999, for which estimates are in bold:

[7] West Germany, United States, Austria, Netherlands, Switzerland, Japan, France, and Italy

Table 15: Multiple KPSS(2) test statistics and the variance of the contrasts between the potential controls and the West German series for the log(GDP) series as well as OLS and RLS weights

	Null Hypothesis			Weights (Austria)		Weights (United Kingdom)	
Country	**Cointegration (level)**	**I(0)**	**I(1)**	**OLS**	**RLS**	**OLS**	**RLS**
Belgium	0.074	0.193	0.460				
France	0.078	0.192	0.461	0.212	0.474	0.646	0.647
USA	0.145	0.197	0.536	0.396	0.373	0.574	0.552
UK	0.203	0.205				-0.222	-0.199
Portugal	0.223	0.126	0.137				
Spain	0.288	0.177	0.397				
Austria	0.479	0.196	0.516	0.382	0.153		
Denmark	0.593	0.191	0.551				
New Zealand	0.608	0.150	0.363				
Switzerland	0.610	0.135	0.146				
Australia	0.639	0.192	0.468				
Greece	0.642	0.200	0.578				
Italy	0.659	0.193	0.446				
Norway	0.664	0.195	0.508				
Netherlands	0.688	0.194	0.417				
Japan	0.723	0.177	0.319				
West Germany		**0.192**	**0.432**				

Table 16: Synthetic Control estimates for the original combination of controls – Unites States (US), France (FR), Austria (AU) and Unites States (US), France (FR), Austria (UK))– level break in 1999:

	Synthetic Control (US FR AUS)			**Synthetic Control (US FR UK)**	
Year	*Estimate*	*SE*	*Year*	*Estimate*	*SE*
1991	0.0276	0.0093	1991	0.033188	0.0081
1992	0.0137	0.0093	1992	0.015746	0.0081
1993	-0.0183	0.0093	1993	-0.013516	0.0081
1994	-0.0387	0.0093	1994	-0.030438	0.0081
1995	-0.0466	0.0093	1995	-0.036558	0.0081
1996	-0.0556	0.0093	1996	-0.042163	0.0081
1997	-0.0820	0.0093	1997	-0.070101	0.0081
1998	-0.0915	0.0093	1998	-0.081107	0.0081
1999	**-0.1147**	**0.0045**	**1999**	**-0.095693**	**0.003959**

It is visible from Table 16 that the estimated coefficients are similar for both control combinations and suggest that the main conclusion in the original publication holds irrespective

of choosing Austria as a control – reunification negatively impacted real GDP per capita in West Germany.

8.3 Description datasets and code

The zip file contains seven files:

1. A `XLSX` file, entitled `INF-104-1.xlsx` containing the original "INF-104-1" dataset available through the EMCDDA database (https://tinyurl.com/2rjdf99k) on the first sheet. Blacked-out countries in this original dataset do not meet the interpolation requirement. The file also includes, in the second sheet, the restricted "INF-104-1" dataset, which contains all countries that met the interpolation restrictions for the HIV series. Finally, the summary statistics for this restricted dataset are available in the third sheet.
2. A `XLSX` file, entitled `INF-104-2.xlsx` containing the original "INF-104-2" dataset available through the EMCDDA database (https://tinyurl.com/4bxhvhb8) on the first sheet. Blacked-out countries in this original dataset do not meet the interpolation requirement. The file also includes, in the second sheet, the restricted "INF-104-2" dataset, which contains all countries that met the interpolation restrictions for the AIDS series. Finally, the summary statistics for this restricted dataset are available in the third sheet.
3. A ready to use in `RStudio` `CSV` file, entitled `California_Smoking_Data.csv` containing data used in the replication of the California Smoking Ban application in Harvey and Thiele (2021). It is available through the original publication.
4. A ready to use in `RStudio` `CSV` file, entitled `German_Reunification_Data.csv` containing data used in the replication of the German Reunification application in Harvey and Thiele (2021). It is available through the original publication
5. A ready to use in `RStudio` `CSV` file, entitled `INF-104-1.csv` containing data on the incidence of HIV among injecting drug users across all countries that met the interpolation requirements.
6. A ready to use in `RStudio` `CSV` file, entitled `INF-104-2.csv` containing data on the incidence of AIDS among injecting drug users across all countries that met the interpolation requirements.
7. An `R` file. It contains the script used to produce the results in this thesis. This code is self-sufficient. It is possible to run the script chronologically, most likely without problems. Setting the directory using the "Session" drop-down menu in `RStudio` is necessary since no path code is available in the script.