DSSR

Discussion Paper No. 102

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An assessment of the 2012 revised drug policy

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October, 2019

Data Science and Service Research
Discussion Paper

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Abstract

The Netherlands has since the 1970s focused on decriminalizing to address the issue of drugs within society. As a result of implementing this decriminalization policy, commercial establishments called coffee shops quickly appeared afterwards to meet market demand for marijuana within the Netherlands. The growth of this newly established marijuana industry was tolerated by the Dutch government leading to an eventual regulatory framework of the AHOJ-G criterion. However, even with the framework in place, the number of tourists seeking to experience marijuana continued to exponentially increase leading to issues of drug tourism and other associated nuisances. In 2012, the Dutch government selected three provinces in the South of the Netherlands where marijuana would no longer be sold to non-residents in order to stymie drug tourism. Qualitative studies on this issue found that there was a significant reduction in drug tourism as a result of implementing the policy in 2012 but was coincided with a rise in illicit drug activity due to the legal purchase channel being shut-down for non-residents.

The aim of this study is to analyze the impact of the 2012 sales restriction on coffee shop municipalities within these three provinces and the subsequent economic impact on local firms. Propensity score matching was used to create a control group of coffee shop municipalities that were similar to the treated coffee shop municipalities on the basis of observed characteristics with socio-economic data from the public Statline database maintained by the Dutch Statistics Bureau. Several robustness checks were conducted to ensure the validity of the matching procedure. The difference-in-difference model used municipal drug crime data from the Statline database for the years 2009 to 2014 to analyze the impact on committed drug crimes. Findings revealed that the policy did not have a significant impact on drug crimes within treated areas even after controlling for municipal characteristics. Placebo test of the policy presented that the policy had a lagged treatment effect which can be attributed to the sharp increase in illicit drug market activity in 2012 due to policy disrupting the legal purchase channel of marijuana. Therefore, this study shows that even though prior literature cites that drug tourism was significantly reduced, limiting sales to residents did not lead to an increase in either soft- or hard drug crimes indicating that the policy had an overall beneficial impact on reducing illicit drug market activity

Keywords: Drug tourism, difference-in-difference, propensity score matching

JEL classification: R11, K23

Introduction

The continuing trend of changing perceptions and acceptance of drugs within society, especially marijuana, has led to a string of sweeping legislative changes ranging from decriminalization to the existence of fully legalized recreational marijuana with the creation of an multimillion dollar industry to meet popular demand as can be seen in earlier cases such as Amendment 64 in Colorado and Initiative 502 in Washington. The increase in acceptance of marijuana for medicinal and recreational usage around the world gives government institutions an additional lucrative revenue stream as documented by Henchman (2014) and Henchman and Scarboro (2016). However, the benefits of allowing drug tourists are often accompanied with its numerous documented negatives such as nuisance and crime as has been documented in The Netherlands (Snippe, Naayer, and Bieleman, 2006; Van Ooyen-Houben, Bieleman, and Korf, 2014; Nabben et al, 2015). Therefore, policy makers within urban areas with the prime potential of experiencing drug tourism will look for literature and statistical evidence on what policies can effectively reduce drug tourism and its associated pollution.

The motivation of this study is to analyze the impact of restricting the commercial sales and usage of marijuana within the Southern Netherlands on drug crimes. There is currently a limited amount of literature on the effectiveness of drug policies. Prior literature on Dutch drug policies, qualitative in nature and limited in scope, found that there was an increase in illicit drug activity within specific municipalities and noted a significant decrease in drug tourism after introduction. Therefore, this study seeks to answer the question on whether the revision and implementation of the 2012 drug policy within the three Southern provinces of Limburg, Noord-Brabant, and Zeeland had a significant impact on the drug crimes within those municipalities.

The data used for this paper comes from the Dutch Statistics Bureau in the form its public Statline database which provides the crime data on municipal level with various socio-economic characteristics of municipalities located within the Netherlands. Using balanced panel data with data from 2009 to 2014, propensity score matching was used to create a counterfactual group and using difference-in-differences to assess the impact while controlling for municipality- and time fixed effects. Findings reveal that the implementation of the policy led to reduction in the magnitude of the reported coefficient for soft- and hard drugs, these results were not reported as significant. However, implementing a placebo test by delaying the period of implementation by one year reported that the policy did significantly affect the soft- and hard drug crime rate which may be due to the fact that during the initial implementation of the policy led to a sharp increase in committed drug crimes as a response due to the legal channel of purchasing marijuana being disrupted, leading to an expansion of the illicit drug market activity within the border regions of The Netherlands.

The contribution of this paper is that the empirical evidence indicates that the restricting the commercial sales to municipal residents in an effort to combat drug tourism does not lead a significant increase in illicit crime even though there was a short increase in illicit drug crime during its implementation. In addition, findings reveal that this type of policy, while reducing drug tourism does not statistically affect local firm revenue. Thus, the policy has had an overall beneficial effect without significantly increasing illicit drug activity nor affecting the local economy within Southern coffee shop municipalities. Additionally, this is the first study on this topic that uses propensity score matching with difference-in-differences, to assess the impact of addressing drug tourism within the Southern Netherlands thereby controlling for the possibility of observed and unobserved heterogeneity.

The paper is structured as follows. The next section contains a short review on the on-going debate and literature between drug prohibition and liberalization followed by an overview of prior and existing situation within the Netherlands regarding drugs, drug policies and the economic role of marijuana. The third section presents the methodology used for estimating the possible impact on drug crimes and the performance on the local economy as a result of implementing the revised drug policy within coffee shop municipalities. The fourth section provides an overview of the data sources used for the results and how the data set was constructed. The fourth section presents the main results including robustness checks, and the fifth section contains the conclusion.

Background

One of the early pioneers of adopting decriminalization policies on drug usage was the Netherlands in the early 1970s. However, like many neighboring countries at the time, it maintained a policy focused on prohibition on the basis of sources that alluded that marijuana usage would result in physical and psychological issues for users and thus presented a significant danger for society at large. The continued difficulty of governmental institutions in dealing with drug usage within society eventually led to the Dutch government in appointed the Hulsman commission in 1968 and the Baan commission in 1972 to analyze the issue of drugs within society and how to best deal with the increasing problem.

Based on the works of Cohen (1975), the Commissions' recommendation was to create and enforce a policy based on decriminalization of drugs and toleration of usage within a set of limitations referred to in modern literature as the "Dutch model". The main emphasis of this model was on harm reduction and ensuring continuation of public order, health, and safety of the general public but also drug users. By adopting a harm reduction model in combination with decriminalizing the purchasing, possession, and cultivation of marijuana for personal usage, law enforcement would alter its target to combatting large-scale illicit drug dealing and growing operations within the Netherlands.

With increases in international tourism and the normalization of attitudes towards drugs and drug usage within society, especially within the Western hemisphere in the early 2000s, the coffee shop industry provided a lucrative revenue stream for the government. Earlier estimates by the research institute Intraval in 2013 on the coffee shop industry found that coffee shops had a revenue approximately between 875 million and 1.25 billion euros based on a sample of 30 coffee shop establishments. An assessment by OWP Research (2008) on the benefit of the coffee shop industry within the Southern municipality of Maastricht in Limburg found that the expenditure of coffee shop visitors resulted in a benefit of 78 million euros for the retail industry and 37 million euros for the hospitality industry and an employment benefit of 1,617 FTEs of which 958 retail industry and 608 in the hospitality industry. Recent studies such as on the marijuana industry in the United States show similar benefits for municipalities that legalized the purchase of recreational marijuana such as Henchmann (2014) and Henchmann and Scarboro (2016). The rise of drug tourism, though economically beneficial overall, it came with various negative externalities within coffee shop municipalities, especially considering the legal, medical, and safety risks for drug tourists. Earlier studies have linked that drug tourists have significantly linked with nuisance (Bieleman, Mennes, and Sijtsma, 2017)

In a report by the Dutch government in 1995, it detailed three aspects that required action which was the problem of nuisance associated with not only hard drug users but also increasingly soft drug users and the coffee shops, the increase of large-scale illicit drug activity by organized crime within the Netherlands, and the role of drug tourism within and outside the Netherlands. Therefore, while the main focus of the policy would remain unchanged, the limitations set by policy makers for drug users and coffee shops would be expanded through the addition of the AHOJ-G criteria on the national level which prohibited drug advertisements (A), the sales of hard drugs as defined by the Opium Act (H), to cause public disorder or nuisance associated with drugs (O), that minors could not enter coffee shops nor be sold soft drugs (J), that no more than 5 grams of marijuana per transaction would be sold to customers, and that coffee shops would have a limit of a maximum inventory of 500 grams of marijuana (G). Though the AHOJ-G criteria was a start in further defining the Dutch model in addressing the three key issues raised by the Baan commission, the lack of a regulatory framework on the back-end operations of coffee shops facilitated the continued operations of illicit marijuana cultivation by organized crime to meet market demand.

Though the impact on public order and local residents is well understood at this point, few studies have been conducted on the negative impact of drug tourism on local economies, prior studies such as Snippe, Naayer, and Bieleman (2006) and van der Torre, Cachet, and Dijk, (2008) provide an indication as both studies focus this exact relationship by examining firms located within coffee shop municipalities within border regions attributed with high degrees of drug tourism. Snippe, Naayer, and Bieleman (2006) focused on the border town of Venlo in the province of Limburg adjacent to Germany and experiences a large degree of drug tourists. In their research, they compared the financial performance in qualitative survey between 1999 and 2003 and found that firms located within a high degree of drug tourism reported lower revenue (57 percentage points to 33 percentage points) in comparison to those in no or low degree areas (34 percentage points to 25 percentage points). Van der Torre et al. (2008) focused on the municipalities of Roosendaal and Bergen op Zoom in the province of Noord-Brabant adjacent to Belgium and found similar evidence of reduced retail revenue of firms located with a high concentration of drug tourism when compared to firms in no or low concentration districts.

In 2009, the government appointed Van de Donk commission presented its findings on what measures should be taken on addressing the issue of the illicit domestic and international drug production and trade, the lack of a regulatory framework on the back-end of coffee shops, and the ever-increasing presence of drug tourism and its associated negative aspects.

The recommendation of the Van de Donk commission on reducing drug tourism was to create a closed membership system for coffee shops to limit drug tourists from purchasing marijuana within the Netherlands (van de Donk et al., 2009). However, the report noted that such a system would result in a sharp increase in illegal street dealing of drugs and local nuisance respectively. Regardless of the stated issues of implementing the closed membership system, the then Justice minister, Ivo Opstelten, announced that the government was seeking to implement two additional criteria in 2012 to the existing AHOG-J criterion, namely the closed membership system (B) and local municipal sales restriction (I) for coffee shops located within the Southern provinces of Limburg, North-Brabant, and Zeeland as a trial to assess the effectiveness of the policy and, if successful, expand the policy nationwide (TK, 2011)

The initial response from various stakeholders was anything but positive as the proposal was rejected by parliament and led to the creation of an alternative proposal which sought to implement the policy of restricting sales to non-residents as a trial but limited in scope by seeking a trial area to assess the feasibility and impact of the policy and dropping the requirement for a closed-membership system for coffee shop municipalities.. The trial would start 2012, the AHOJ-G criterion would be expanded in the three Southern provinces by adding the restriction that coffee shops could not sell marijuana to non-municipal residents or risk fines, a temporary suspension of their commercial license, or a permanent closure of the coffee shop. Since then, several studies were conducted on the initial effect of the policy in treated areas.

Van Ooyen-Houben, Bieleman, and Korf (2014) conducted a qualitative survey within five coffee shop municipalities of which three were located within the three Southern provinces. The findings revealed that the policy implementation was quickly followed by an increase in nuisance, drug activity, and reduction in feeling safe in their neighborhood. Nabben, Wouters, Benschop, and Korf (2015) followed up on this research by expanding the sample size to 31 coffee shop municipalities across 11 provinces and in addition examining the impact on the municipal crime rate. As a result of restricting sales to non-residents, Nabben et al. (2015) found that there was an overall increase in illicit drug activity, especially in coffee shop municipalities located within border regions in comparison.

Review of existing studies on the topic of drug tourism and the illicit black markets portrays the following knowledge gap. Prior studies are qualitative in nature and do not encompass all coffee shop municipalities that implemented the I criterion in 2012. While the research results from these studies capture the effect of the policy in specific municipalities that experience a high degree of drug tourism, these studies do not account for heterogeneity, do not control for differences between coffee shop municipalities, and have more limited sample set. This study seeks to add to the existing body of literature by analyzing the policy impact on all coffee shop municipalities at the time of implementation but also two years after implementation.

Methodology

The aim of this paper is to estimate the impact of the implementing the 2012 revised drug policy on the registered municipal drug crime rate and the revenue performance of firms located within Southern coffee shop located in the Netherlands.

I used propensity score matching (abbrev. PSM) in constructing a control group that is not statistically different from the treatment group on the basis of their observed characteristics, in combination with a linear difference-in-differences model (abbrev. DD) with a binary dummy variable for drug policies with firm-, municipal and year fixed effects to assess the change in the national drug policy on the municipal crime rate and firm performance using the following standard DD specification:

$$y_{it} = \alpha + \delta D_i \times d_t + \mu_i + \lambda_t + \omega_i + \epsilon_{it}, \quad (1)$$

where y_{it} is the output of interest of coffee shop municipality or firm *i* in year *t*, α is the constant, *D* denotes the treatment variable which is equal to 1 when a coffee shop municipality is covered by the 2012 revised drug policy and 0 if the municipality was not mandated to implement it in 2012, *d* is the interaction term for the time period which is equal to 1 for year 2012 and afterwards and 0 for years prior to 2012, μ_i and λ_t capture the municipality- and time fixed effect which controls for municipality- and time-variant and invariant characteristics for coffee shop municipalities, ω_i introduces linear time trend to control for macro-economic effects, and ϵ_i is the error term. The parameter of interest for the DD model in equation 1 is δ which captures the average impact of the intervention on the outcome of interest of the treatment group.

For the DD model, an important component that validates the results of the DD model is the parallel trend assumption which states the trend of the dependable variable of the control- and treatment group is statistically significant different as this would lead to a biased estimator. In order to verify the parallel trend assumption, I follow the recommendation of Autor (2003)and estimate the parallel trend assumption through the following specification:

$$y_{it} = \sum_{k=1}^{2} B_k \, D_i \times d_{t+k} + \sum_{k=0}^{2} B_{-k} D_i \times d_{t-k} + \mu_i + \lambda_t + \omega_i + \epsilon_{it}, \qquad (2)$$

where $D_i \times d_{t+k}$ represents the interaction terms capturing the variable of interest of coffee shop municipalities in the pre-treatment period (2009-2011), $D_i \times d_{t-k}$ represents the interaction dummies of the outcome of interest in the post-treatment period (2012-2014), and μ_i plus λ_t capture the municipality and time-fixed effects, and ω_i introduces a linear time trend as explained in equation 1. The importance of equation 2 is two-fold. First, it provides a year by year change of the coefficient of the dependent variable and to assess whether the initial impact of the intervention, which in this case is the revision to the drug policy, and the increase or decrease in the magnitude of the coefficient over time. Second, in order to verify that the DD model satisfies the necessary assumptions of a parallel trend between the control- and treatment group, the trend of the dependable variable of both groups in the pre-treatment period can be compared. If the outcome variable in the pre-treatment period, represented by the lead dummies, is reported as statistically significant, then this would indicate that the pre-treatment trend is different between the treatment- and control group and thus the reported outcome in the post-treatment period would be considered biased. As a robustness check for the DD model, the main analysis was repeated with a lead and lagged treatment indicator where the revision to the drug policy was implemented two years earlier (2010) and one year later (2013) as a placebo test. In the case of the lead treatment indicator being reported as statistically significant, this would provide an indication that the reaction to the drug policy was predated and if the lagged treatment indicator is reported as significant, it is possible that the policy had a delayed effect on the outcome of interest.

In order to control for the possibility of statistical difference between the observed differences between the treatment- and control group in the DD model, I use propensity score matching in the pre-treatment period to create a control group that consists out of coffee shop municipalities that is similar to coffee shop municipalities in the treatment group on the basis of their observable characteristics. Rosenbaum and Rubin (1983) propose a statistical matching technique referred to as propensity score matching (henceforth abbreviated as PSM) to overcome the issue associated with a high dimensional vector. The PSM technique uses a single index named the propensity score which 47 captures the probability of an observation to be selected for treatment based on their observed characteristics. Let the $P(X_i)$ be the propensity score which is defined as $P(X_i) \ = \ P(D_i \ |X_i)$. The validity of the PSM technique relies on two assumptions.

The first assumption is the conditional independence assumption which is expressed as $y_i^0, y_i^1 \ \coprod D_i \ |X_i$ where $\coprod$ indicates that the treatment assignment is independent of the outcome variable of interest and solely based on the set of observed characteristics. Fulfilling the conditional independence assumption eliminates the bias attributed due to differences in the observable characteristics between treated- and control coffee shop municipalities. The second assumption is the common overlap which states that coffee shop municipalities with a similar X values have an equal probability of being both treated and control coffee shop municipalities which is necessary to form valid counterfactuals for treated observations. The propensity score is estimated with either a probit- or logit model using a set of observed characteristics before the start of the treatment and then matches treated- and control coffee shop municipalities on the proximity of their propensity score.

The main matching method used for creating the control group is the nearest-neighbor matching (NNM) algorithm. The NNM method compares treatment observations with control firms with the nearest propensity score. The NNM method always varying degree of options of altering the matching procedure. In the case of this study, the number of neighbors were set to the nearest two, four, and six and included a caliper that consisted of 25% of the standard deviation of the logit model as advised by Austin (2011). The caliper will limit the range of the propensity score and thus prevent matches that beyond a specified range and improve the matching quality. Lastly, the NMM matching model can also be used with the option of common support between treatment- and control observations. Should common support not be used within a matching specification, it will lead to matches whose propensity score are distant from one another and may not prove to be a viable match. To improve matching quality, this study used common support with nearest-neighbor and kernel matching.

There are several methods to determine the quality of the matching model afterwards. First is to check the bias of the chosen variables between the treatment- and control group in the pre- and post-policy period. Literature on this topic such as Rosenbaum and Rubin (1983), Sianesi (2004) and Caliendo and Kopeinig (2008) argue that the bias should be reduced to or below 5% under a strong ignorability assumption and 10% for weak ignorability.

The second method is to verify whether a variable is significantly different when compared between the treatment- and control group as the matching procedure should in theory have balanced both groups and eliminate significant differences between the two. Secondary check would be to verify if a similar matching result can be replicated using an alternative matching algorithm.

The third method follows the recommendation of Sianesi (2004) by checking the joint significance and Pseudo-R^2 before and after the matching procedure. The joint significant test should be reported as insignificant and the Psuedo-R^2 should report a lower value after matching due to significant differences. Fourth is to compare the common overlap between the treatment- and control group by checking the mean difference in the outcome variable and the density of the propensity scores given to observations within each propensity block.

The last method is to apply the Rosenbaum Bounds by Rosenbaum et al. (2002) which assesses the sensitivity of a matching specification. According to Rosenbaum et al. (2002), Gangl, (2004) and Caliendo and Kopeinig (2008), it is important to check whether the probability of the treatment assignment is vulnerable and can be altered by unobservable factors. Let π_i be the treatment assignment, X_i be the set of observed characteristics, Γ is the effect of unobserved characteristics on the treatment assignment probability, and let u_i be the unobserved component in the following specification:

$$\pi_i = \Pr\,(D_i = 1|X_i = F(\beta X + i + \Gamma u_i) \tag{3}$$

which states that the probability of treatment assignment is determined by observed and unobserved characteristics. Parameter Γ captures the effect of the unobserved characteristics on the probability that coffee shop municipalities are selected as either treated- or control observations. If there is no unobservable bias influencing the probability, then Γ would be zero and $\pi_i = P\,r(D_i = 1|X_i)$ is solely determined by the observed characteristics. Existing literature often cited on the issues is Duvendack and Palmer-Jones (2012) who state that in the case of the social sciences, a Γ value of 2.0 would indicate strong insensitivity to unobserved characteristics influencing the probability of treatment assignment.

Data

The empirical analysis is based on the combination of two separate data sources containing a wealth of information collected and maintained by the Dutch Statistics Bureau. The first data source, Statline, is a publicly accessible database and gathers information on the Netherlands through government institutions and other stakeholders and thus the databank contains a range of national, provincial, and municipal statistics. The dependable variables of interest chosen for this study are the number of registered soft and hard drugs within municipalities and a range of variables such as population density, employment- and unemployment rate, number of registered students, mean household income, mean real-estate value, industry- and coffee shop density within a municipality. These set of characteristics are used during propensity matching to construct a counterfactual group of coffee shop municipalities that closely resemble the coffee shop municipalities required to implement the policy in 2012. Two unique filters were used to limit the control- and treatment group observations. First, a dummy variable was created that would identify municipalities that had a coffee shop establishment within their domain by using the coffee shop industry information provided by Bieleman et al. (2017) where a coffee shop municipality would be equal to one and zero otherwise. Municipalities that were categorized as “Non-coffee shop municipalities” were dropped from the sample set. Second, the creation of another dummy variable with the purpose of identifying which of these coffee shop municipalities had a coffee shop before the implementation of the policy of 2012 and had remained coffee shop municipalities after 2012 again based on information provided in the annual coffee shop report by Bieleman et al. (2017). Coffee shop municipalities that had closed coffee shops within their domain before 2012 and remained closed were dropped from the sample set. Finally, coffee shop municipalities with missing crime or socio-economic data were dropped from the sample resulting in balanced data set with 20 coffee shop municipalities in the treatment group and 83 number in the control group with a total of 618 municipal observations over six-year period from 2009 to 2014.

Table 1 presents the descriptive statistics of treated- and control coffee shop municipalities in the pre-treatment period. Column 1 and 2 present the mean values of a set of dependent and independable variables divided in crime and municipal socio-economic characteristics. Column 3 reports the mean difference of coffee shop municipalities in the treatment- and control group. Examining the reported values in Column 3, an important note is that the number of committed soft drug crimes is more numerous in the treatment group and the difference between the two is reported as statistically significant. This provides evidence on the rationality on why governmental institutes implemented the trial policy within the three border regions as the descriptive statistics show that there is a larger presence of drug tourism when compared to other regions.

One possible explanation is the geographical proximity of the coffee shop municipalities in the three border regions to neighboring countries such as Belgium and Germany as can be seen in Figure 1. The addition of high-quality road and train infrastructure between neighboring countries allows drug tourists to easily visit these border regions in comparison to those further North. However, the same is not reported when examining the hard drug crime rate.

Comparing the municipal socio-economic characteristics, the difference in the mean value of coffee shop municipalities in the treatment- and control group is negligible and not reported as statistically significant which indicates that municipalities that allow for the commercial sales of marijuana are quite similar. However, it is important to indicate that even though there are more committed drug crimes in treated coffee shop municipalities, the density of coffee shops is higher in the control group even though the difference is not reported as being statistically different.

Results

Based on the descriptive statistics presented in the previous section, there is a significant mean difference between the treated- and control coffee shop municipalities when looking at the outcome of interest, namely the soft drug crime rate. To verify whether PSM is required for this study is to check the results of the DD model without prior matching between the treatment- and control group which are presented in Table 2 and Table 3 for the yearly change in the DD coefficient. Table 2 shows the DD model as specified in equation 1 and shows that the policy had a statistically significant impact on the soft drug crimes but not on hard drugs when controlling for municipality- and time fixed effects.

To verify whether the DD model without prior matching can be considered robust, equation 2 to show the yearly change in the coefficient is examined in Table 3. The interaction terms for the pre-treatment years of 2009 and 2010 are both reported as being statistically significant indicating that results of the DD model are biased as there is no parallel trend between the treatment- and control group. One method in controlling for this issue to create a control group that more specifically matched the treatment group on a select set of covariates.

The control for the main analysis was created using the nearest-neighbor matching algorithm with up to four neighbors and a caliper of 25% of the standard deviation.[1] The set of covariates chosen for the propensity score specification is the degree of poverty, median household income, average real-estate value, density of café and other establishments within a 5 kilometer radius, number of employed residents, the number of university graduates, the coffee shop density and the percentage change in the number of arrests made on municipal level.

Table 4, Table 5, and Table 6 provide information on the success of the matching procedure of balancing the covariates between the treatment- and control group. Table 4 reports an overview of the treatment- and control group before and after matching. Columns 1 and 2 list the mean values of the treatment and control group respectively. The difference between both groups differs on the chosen covariate. Column 3 shows the percentage difference between both groups where the percentage difference for most covariates is above 10% such as poverty, household income, café density, university graduates, coffee shop density, and the change in arrested suspects. However, when examining the percentage difference after matching in column 6, there is a large reduction in the mean values of the treatment- and control with the majority of covariates being under 10% and a few under 5% indicating that the matching procedure resulted in better fit at the expense of losing two treatment observations due to being "off support" due to the caliper being included.

The remainder of the statistics are presented in Table 5. Following the recommendation of Sianesi (2004) as detailed prior, the Pseudo R^2 in column 1 has decreased significantly after matching (0.198 to 0.011) indicating that the matching procedure resulted in observations in both

[1] Propensity score matching procedure was completed using the Stata module -psmatch2- by M. Leuven and Sianesi (2003)

groups to have similar characteristics. Column 2 the test of joint significance and is reported as insignificant when compared before matching (0.013) and after matching (1.000) further validating the quality of the control group. Columns 3 presents the absolute bias which according to literature should be lower than 25 and this match resulted in an absolute bias of 24.4 which can be seen as relatively high. Table 6 presents the results of using kernel matching and nearest-neighbor matching with a different degree of neighbors. Comparing the before (U) and after (M) matched statistics, it is evident that the matching specification can be considered robust as all statistics are within specified parameters.

Another test of robustness is to check the sensitivity of the matching specification through the Rosenbaum Bounds. Table 7 presents the Rosenbaum bounds for NNM up to four neighbors matching specification.[2] Column 1 shows the unit increase of Γ starting at 1 up to 2. The sensitivity of the matching specification can be assessed by checking at which unit of Γ the significance level, shown in column 2, becomes insignificant using the Wilcoxon signed-rank test. The unit increase did not lead to a significance of 0.05 prior to 2 indicating that the unobserved variable of Γ would have to increase with more than 200% before the matching specification would become sensitive to a form of hidden bias. On the basis of this, it can be argued that the matching specification is insensitive to the possibility of hidden bias.

The last test is to verify whether there is evidence of common support between the treatment- and control group using visual representation. Figure 1 shows the propensity score density on the y-axis and propensity score on the x-axis before matching (left) and after matching (right). On the basis of Figure 1, there is a significant increase in the overlap between

[2] Stata module -rbounds- by Gangl (2004)was used for assessing the Rosenbaum bounds for the propensity score matching specification.

the treatment- and control after matching. While the control group lacks a certain amount of overlap at specific propensity score blocks (.04 - .06), the visual representation indicates that there is significant overlap which further validates the matching procedure. Having completed the matching specification, the main analysis will first present the policy's impact on drug crimes followed by examining the impact on firms. The robustness checks have established that the construction of the control group passes various requirements as seen in existing literature.

Table 8 presents the impact on hard- and soft drugs using the DD model on municipal level while controlling for municipality-, time-, and adding a linear time trend. Columns 1 and 2 present the impact on soft drugs and the interaction term of the DD model reports no statistical significance indicating that the implementation of the policy in 2012 and continued enforcement up to 2014. Similar result is reported in Columns 3 and 4 when examining the impact on hard drugs. These two results would indicate that the coffee shop municipalities in the treatment group did not see a statistical effect in comparison to control coffee shop municipalities. Though prior literature mentions that illicit drug activity did increase in the beginning but states that this phenomenon was not wide-spread or large enough to cause statistical difference.

Table 9 presents the yearly change in the DD estimator to assess not only the validity of the DD model as done previously but also to check whether any specific year during or after the implementation of the policy is reported as significant. Columns 1 and 2 present the soft drug crime and report no significance for the years 2009 up to 2014. However, when comparing the DD coefficient for 2011 and 2013 in column 1, there is a strong decrease in the reported magnitude from -.17.08 to -5.43 verifying the mention of rising illicit drug activity referenced in existing literature but returning back to pre-policy levels in 2014 most likely due to a set of factors such as increased police presence and / or enforcement or the lack of market demand due to the reduction in drug tourism. Column 2 presents the soft drug crimes with the addition of introducing a linear time trend. The coefficient in column 2 present a similar pattern as seen in column 1 in the pre-policy period for 2010 and 2011, the magnitude turns positive in the year of implementation (-9.22 to 6.35) indicating that there may have been an initial increase in illicit drug activity. However, the coefficient in 2012 is reported as statistically significant with negative magnitude (-7.35) possibly indicating that the policy has a lagged treatment effect.

The results of the PSM-DD model present the fact that the policy did not lead to a increase reported as statistically significant when examining either hard- or soft drug crimes after controlling for municipal- and time fixed effects. However, when examining the reduction in magnitude by checking the lead and lag indicators as seen in Table X, there is the possibility that the policy has a delayed effect after implementation in treated coffee shop municipalities.

As presented in the methodology of this paper, two alternative placebo tests are used to determine whether or not there is a form of precipitation before the policy is implemented or a delay of the policy having an effect. Table 10 shows the lead- and lag placebo and reveals that there is statistical significance when delaying treatment by one year indicating that the policy had a lagged effect after implementation when comparing it to estimations presented in Table 8 which were reported as statistically insignificant.

An alternative explanation for the discrepancy in significance between Table 8 and Table 10 can be that the short-term increase in the number of committed drug crimes, as seen in Figure 3 which portrays the yearly committed soft drug crimes, shows a sharp increase between 2011 and 2012 for coffee shop municipalities in the three Southern provinces of Limburg, Noord-Brabant, and Zeeland.

The main results of this study thus show that on an overall level, the I criterion, which was introduced into the drug policy for Dutch coffee shop municipalities in three border regions resulted in a decrease in committed drug crimes when compared to a control group constructed using propensity score matching on the basis of a set of chosen covariates similar to the treatment group.

Conclusion

The purpose of this study was to analyze the impact of the changes in 2012 to the Dutch drug policy on crime within Dutch coffee shop municipalities and whether firms located within these coffee shop municipalities were significantly affected after a significant reduction in drug tourism based on prior qualitative studies. Using data from the Statline and Microdata databanks for the period between 2009 to 2014 while employing propensity score matching with difference-in-differences to estimate the impact on variables of interest, namely drug crimes and firm revenue. The matching procedure balanced the coffee shop municipalities in the treatment- and control group on a various set of municipal characteristics and, in the case of the firm data, on a set of financial ratios. Nearest-neighbor and Kernel matching were used to create the control group and matching quality was considered to be sufficient based on recommendations from existing literature.

The findings of the difference-in-difference model revealed that the policy did not cause a statistically significant impact on hard- and soft drug crimes of treated coffee shop municipalities after controlling for municipal- and time fixed effects with and without a linear time trend. However, considering the negative magnitude of the DD coefficient, the occurrence of drug crimes is still higher within matched coffee shop municipalities. Examining the yearly change by using year dummies proved that the DD model was robust as the DD coefficients in the pre-treatment were not reported as significant and using alternative starting years for treatment as a placebo further revealed that there is the possibility of a lagged treatment effect.

Therefore, the evidence presented in this paper seems to conclude that the introduction of the *I* criteria in the *AHOJ-G* criterion for coffee shop municipalities in the border provinces of Limburg, Noord-Brabant, and Zeeland did not cause a discernable increase in the number of registered drug crimes and led to a reduction in drug tourists visiting coffee shops located in municipalities that implemented the new criterion in 2012.

There are some limitations of this study that should be addressed. The first limitation is the limited range of years analyzed in this study from 2009 to 2014. While data before 2009 is available, several municipalities prior to 2009 held corroborative police projects that were designed in reducing the negative issues of drug tourism through increased police presence, and temporary closure of coffee shops within their municipal domain. Second, while the national law mandated that municipalities within the chosen three provinces had to implement and enforce this policy in 2012, municipalities were given autonomy in enforcing the policy. Several of these municipalities chose not to continue enforcement activities and others re-aligned enforcement to a lower priority. However, no exact data is available to control for this issue which led to the study merely focusing from 2009 to 2014. The second limitation of note is the narrow scope of this research project as it focuses primarily on committed drug crimes within coffee shop municipalities.

Future research on this topic is promising with the recent change in the perspective of using marijuana for medicinal purposes or for recreational usage in society, especially within the United States of America that has since the early 1950s been the driving force behind drug prohibition policies around the world. The most important gap within existing literature with regard to this policy is the lack of a more comprehensive research study that examines the impact of the policy on the local economy, especially on firms that benefit greatly from tourism such as the retail-, hospitality-, and accommodation industries. Prior studies have primarily qualitative in nature and focused on crime and the change in attitude of residents that live in close proximity or in an area with a high degree of tourism. With the rapid legalization of full recreational marijuana in Washington, Colorado, and Illinois, these areas will undoubtably experience the positives and negatives of drug tourism. Policy makers within these local governmental institutions would be able to reference this and future studies on what policy to implement with the purpose of addressing drug tourism.

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Appendix

Definition of variables

Statline Databank

Variables	Definition
GEMCODE	Municipality code given by the Dutch Statistics Bureau
POLICY	Dummy variable to indicate whether the municipality implemented the 2012 *I* criteria
TIME	Dummy variable to indicate the pre- and post-treatment period
EMPLOYMENT	The number of residents within a municipality that at a minimum has a part-time or full-time employment
UNEMPLOYMENT	The number of residents within a municipality that receive unemployment benefits from the Dutch UWV
POVERTY	The number of residents within a municipality whose income is below or near poverty level and receive a welfare subsidy from the UWV
REALESTATE	The average value of housing real-estate located within a municipality
SOFTDRUGS	The number of registered crimes that fall under the soft drug category as framed by the Opium Act of 1970
HARDDRUGS	The number of registered crimes that fall under the hard drug category as framed by the Opium Act of 1970
NUISANCE	The number of crimes that are classified as nuisance under criminal code 50 of the Dutch justice system
SUSPECTS	The number of criminal suspects arrested within a municipality
HHINCOME	The median income of households within a municipality
COFFEESHOP	The number of coffee shops located within a municipality based on the industry reports published by the Intraval institute
HOSPITALITY DENSITY	The density of cafes, restaurants, and hotels within a five-kilometer radius from residents that are located within a municipality
STUDENTS	The number of students that are registered as in either belonging to a vocational or university based on their residential address
GRADUATES	The number of students that graduated from vocational or university according to their residential address

Table 1

Descriptive statistics of treated- and control coffee shop municipalities pre-treatment period

	(1)	(2)	(3)	(4)
	Coffee shop municipalities		Mean difference	Standard error
Variable	Treated	Control		
		Crime characteristics		
Soft drugs	96.13	50.54	-45.58*	20.15
Hard drugs	56.88	62.71	5.84	39.63
Suspects	2775.50	2981.20	205.70	1264.72
		Municipality characteristics		
Poverty	2560.25	2981.20	550.49	1264.72
Household income	27.09	27.96	0.87	0.76
Real-estate value	8773.75	9182.64	408.89	3117.42
Café density (5km)	26.49	35.30	8.82	14.85
Employment	52.77	51.05	-1.72	18.51
University graduates	218.43	292.85	74.43	183.27
Coffee shop density	4.40	6.99	2.59	5.68
Observations	20	83		

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Household income and real-estate value are reported in €1,000

Table 2

The impact of the policy on soft- and hard drug crimes of coffee shop municipalities before propensity score matching

Policy ≥ 2012	(1)	(2)	(3)	(4)
	Soft drug crimes		Hard drug crimes	
Coffee shop municipalities × $\text{Policy}_{2009\_2014}$	-26.14* (8.40)	-6.17 (6.81)	-6.01 (5.68)	-0.74 (6.99)
Municipal fixed effects	Yes	Yes	Ye	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Linear fixed effects	No	Yes	No	Yes
Observations	618	618	618	618
R^2	0.077	0.501	0.028	0.385

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

DD coefficient is captured by $(D_i \times d_t)$ *in equation 1*

Clustered standard errors are grouped on municipal level and reported in parenthesis.

Source: Statline databank

Table 3

The impact of the policy on soft- and hard drug crimes of coffee shop municipalities before propensity score matching

Policy ≥ 2012	(1)	(2)	(3)	(4)
	Soft drug crimes		Hard drug crimes	
Policy Implementation	-12.63*	-5.27	0.96	2.46
– 2 Years	(-4.97)	(4.85)	(7.42)	(7.34)
Policy Implementation	-30.37**	-15.66*	-5.76	-2.77
– 1 Years	(9.73)	(7.78)	(9.37)	(8.55)
Policy Implementation	-17.23	4.83	0.80	5.30
	(10.07)	(6.79)	(7.52)	(6.41)
Policy Implementation	-38.34**	-9.43*	-7.36	-1.38
+ 1 Year	(10.84)	(3.78)	(10.68)	(6.18)
Policy Implementation	-43.37**	-6.61	-9.80	-2.31
+ 2 Years	(12.82)	(3.95)	(9.49)	(2.83)
Municipality fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Linear time trend	No	Yes	No	Yes
Observations	618	618	618	618
R^2	0.107	0.524	0.030	0.388

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

DD coefficient is captured by $(D_i \times d_t)$ *in equation 2*

Clustered standard errors are grouped on municipal level and reported in parenthesis.

Source: Statline databank

Table 4

Covariate balancing of treated- and control coffee shop municipalities before and after matching in the pre-policy period

Before matching				After matching			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	Treated coffee shops municipalities (mean)	Control coffee shop municipalities (mean)	Bias	Treated coffee shop municipalities	Control coffee shop municipalities	Bias	Bias reduction (%)
Poverty	2560.3	3110.7	-11.0	2527.8	2217.1	6.2	43.6
Household income	27.088	27.959	-30.5	27.061	27.178	-4.1	86.5
Real-estate value	8773.8	9182.6	-3.9	9166.1	8376	7.5	-93.2
Café density 5km	27.108	35.301	-16.2	27.85	28.818	-1.9	88.2
Employment	52.768	51.048	2.7	54.317	50.137	6.6	-143.1
University graduates	218.43	292.85	-11.9	237.47	203.8	5.4	54.8
Coffee shop density	4.4	6.988	-14.3	4.6667	4.125	3.0	79.1
Registered suspect change	-.08207	-.0077	-83.3	-.07213	-.07374	1.8	97.8
Observations	20	83		17	81		

Note: Covariate balancing was achieved using nearest-neighbor matching with up to 4 neighbors with a caliper 25 % of the standard deviation

Table 5

Propensity score statistics before and after matching in the pre-policy period

	Pseudo R^2	$LR\chi^2$	$p > \chi^2$	Rubin's B
Unmatched	0.198	19.29	0.013	62.3*
Matched	0.011	0.56	1.000	24.4

Table 6

Propensity score statistics of alternative matching algorithms and specifications before and after matching in the pre-policy period

	Unmatched versus Matched statistics							
	(1)		(2)		(3)		(4)	
	Kernel matching		Nearest-neighbor (2NN)		Nearest-neighbor (4NN)		Nearest-neighbor (6NN)	
	U	M	U	M	U	M	U	M
Pseudo R^2	0.198	0.003	0.198	0.068	0.198	0.011	0.198	0.007
LRχ^2	19.95	0.14	19.29	3.41	19.29	0.56	19.29	0.34
$p > \chi^2$	1.000	0.011	0.013	0.906	0.013	1.000	0.013	1.000
Mean bias	21.9	2.5	21.7	8.2	21.7	4.6	21.7	2.3
Median bias	13.1	2.1	13.1	8.9	13.1	4.7	13.1	1.6
Rubin's B	62.7*	12.2	62.3*	59.0*	62.3*	24.4	62.3*	18.9*

Note: *Nearest-neighbor and kernel matching is based on a logit model*

Caliper used in the PSM specification is 25% of the standard deviation

Source: Statline databank

Table 7

Rosenbaum bounds to check for sensitivity in the propensity score matching specification in the pre-policy period

	(1)		(2)		(3)	
Gamma (Γ)	Significance levels		Hodges-Lehmann		95% Confidence intervals	
	Sig-	Sig+	T-hat-	T-hat+	CI-	CI+
1	.001146	.001146	54.375	54.375	22.5	129.375
1.1	.002017	.000618	45	57.5	21.25	132.5
1.2	.003242	.000334	42.5	63.75	19.375	135
1.3	.004857	.000181	42.5	72.5	16.875	140
1.4	.006884	.000099	41.25	75	11.25	150
1.5	.009332	.000054	40	77.5	8.75	158.75
1.6	.012200	.000029	38.75	88.125	5	171.875
1.7	.015477	.000016	38.125	91.25	3.75	177.5
1.8	.019146	8.8e-06	37.5	93.75	2.5	190
1.9	.023187	4.8e-06	37.5	101.25	1.875	190
2.0	.027577	2.7e-06	36.25	106.25	-1.25	192.5

Table 8

The impact of the policy on soft- and hard drug crimes after propensity score matching

	(1)	(2)	(3)	(4)
	Soft drug crimes		Hard drug crimes	
Coffee shop municipalities × $\text{Policy}_{2009\_2014}$	-13.80 (9.18)	0.39 (5.99)	-8.85 (4.50)	2.67 (5.48)
Municipal fixed effects	Yes	Yes	Ye	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Linear time trend	No	Yes	No	Yes
Observations	312	312	312	312
R^2	0.164	0.620	0.084	0.402

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

DD coefficient is captured by $(D_i \times d_t)$ *in equation 1*

Clustered standard errors are grouped on municipal level and reported in parenthesis.

Source: Statline databank

Table 9

The yearly change in the DD estimator after propensity score matching

Policy ≥ 2012	(1)	(2)	(3)	(4)
	Soft drug crimes		Hard drug crimes	
Policy Implementation – 2 Years	-8.10	-4.17	-0.39	2.41
	(4.74)	(4.68)	(3.86)	(4.29)
Policy Implementation – 1 Years	-17.08	-9.22	-5.19	0.41
	(11.09)	(5.67)	(5.09)	(5.05)
Policy Implementation	-5.43	6.35	-2.12	6.29
	(11.09)	(7.34)	(5.09)	(4.96)
Policy Implementation + 1 Year	-23.06	-7.35*	-13.56*	-2.36
	(11.81)	(3.07)	(5.64)	(3.10)
Policy Implementation + 2 Years	-25.85	-6.21	-15.33*	-1.32
	(13.90)	(4.18)	(7.42)	(2.47)
Municipality fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Linear time trend	No	Yes	No	Yes
Observations	312	312	312	312
R^2	0.194	0.644	0.118	0.420

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

DD coefficient is captured by $(D_i \times d_t)$ *in equation 2*

Clustered standard errors are grouped on municipal level and reported in parenthesis.

Source: Statline databank

Table 10

The impact of the drug policy firm revenues when using a placebo policy in 2010 and 2013

Policy ≥ 2010	(1)	(2)	(3)	(4)
	Soft drug crimes		Hard drug crimes	
Coffee shop municipalities	-15.90	-3.46	-7.32	2.67
× $Policy_{2009\_2014}$	(8.86)	(4.74)	(4.44)	4.77
Municipal fixed effects	Yes	Yes	Ye	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Linear time trend	No	Yes	No	Yes
Observations	312	312	312	312
R^2	0.160	0.623	0.068	0.403

Policy ≥ 2013	(5)	(6)	(7)	(8)
Coffee shop municipalities	-16.80*	-9.15	-12.52*	-9.00
× $Policy_{2009\text{-}2014}$	(8.10)	(6.79)	(4.60)	(5.52)
Municipal fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Linear time trend	No	Yes	No	Yes
Observations	312	312	312	312
R^2	0.177	0.623	0.113	0.408

Note: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

DD coefficient is captured by $(D_i \times d_t)$ *in equation 1*

Clustered standard errors are grouped on municipal level and reported in parenthesis.

Source: Statline databank

Figure 1: Coffee shop municipalities in the Netherlands

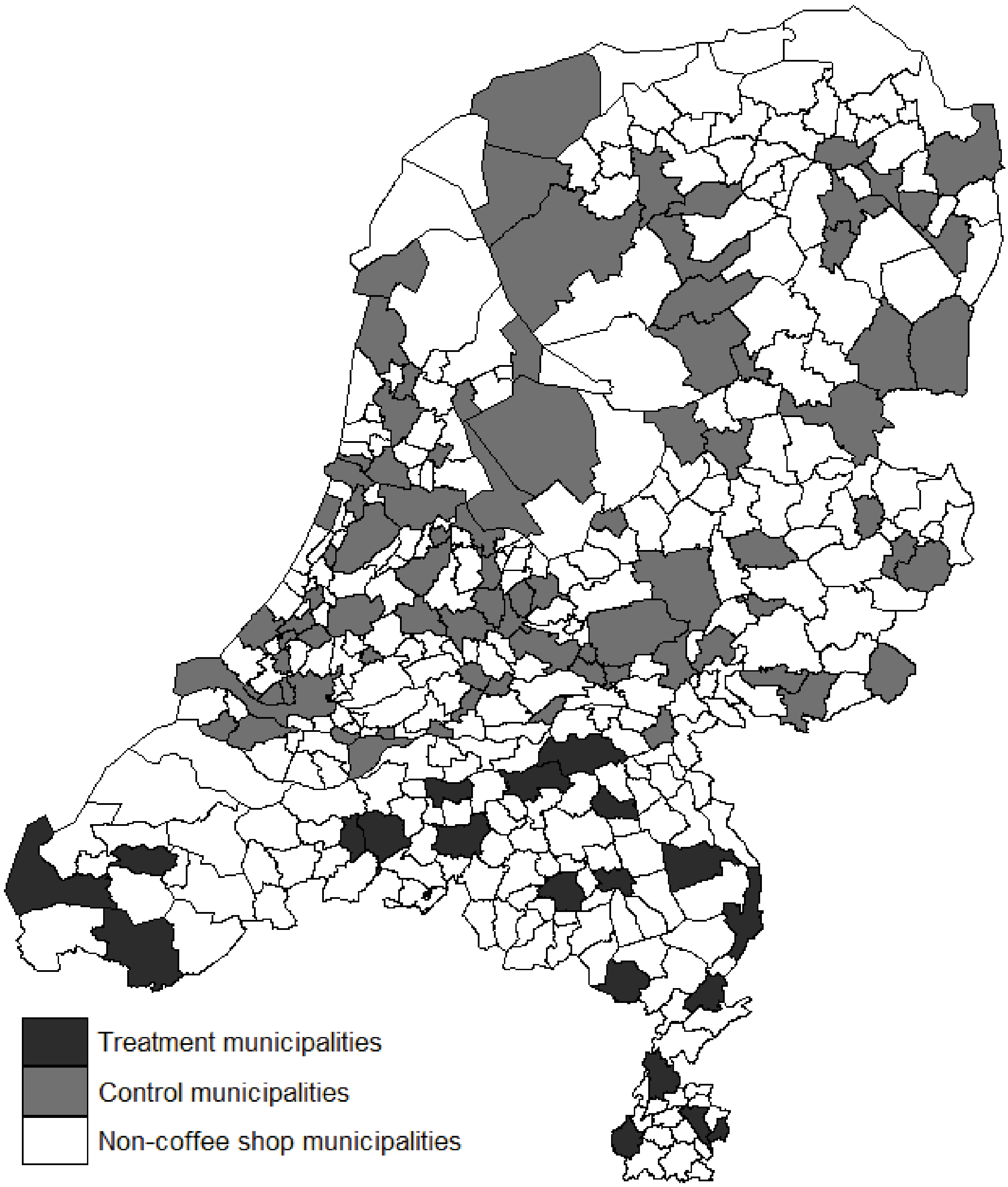
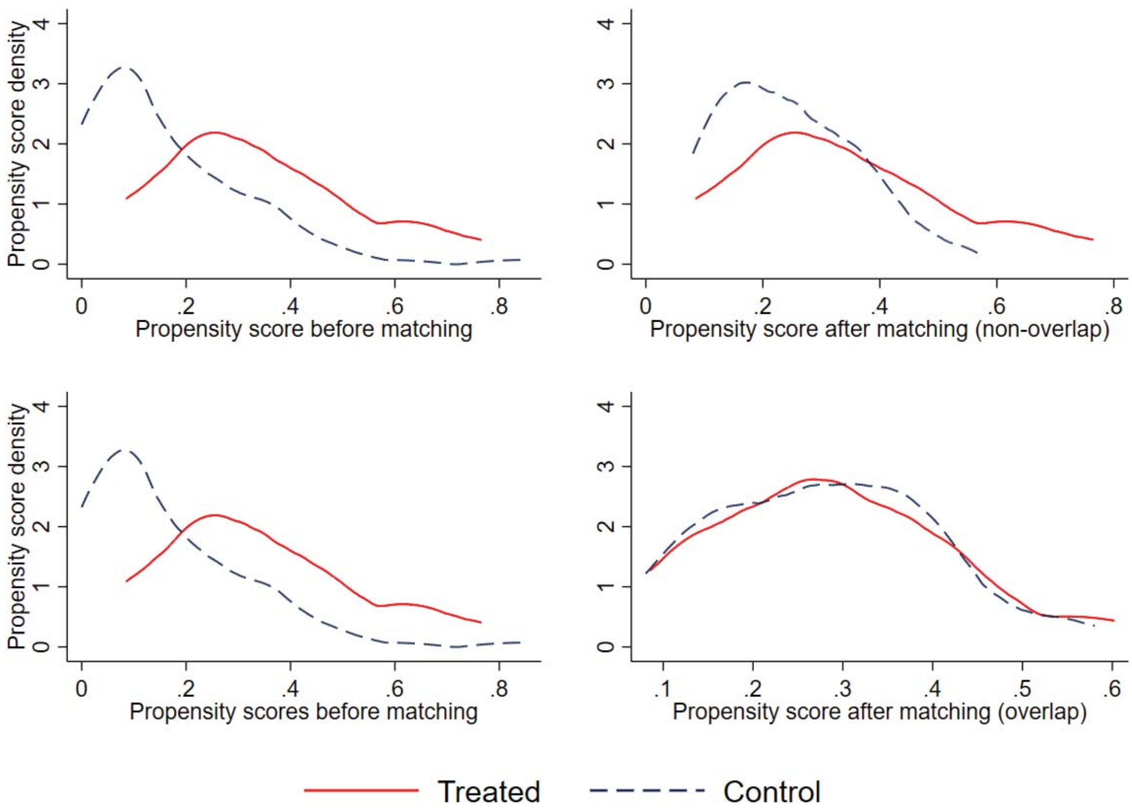


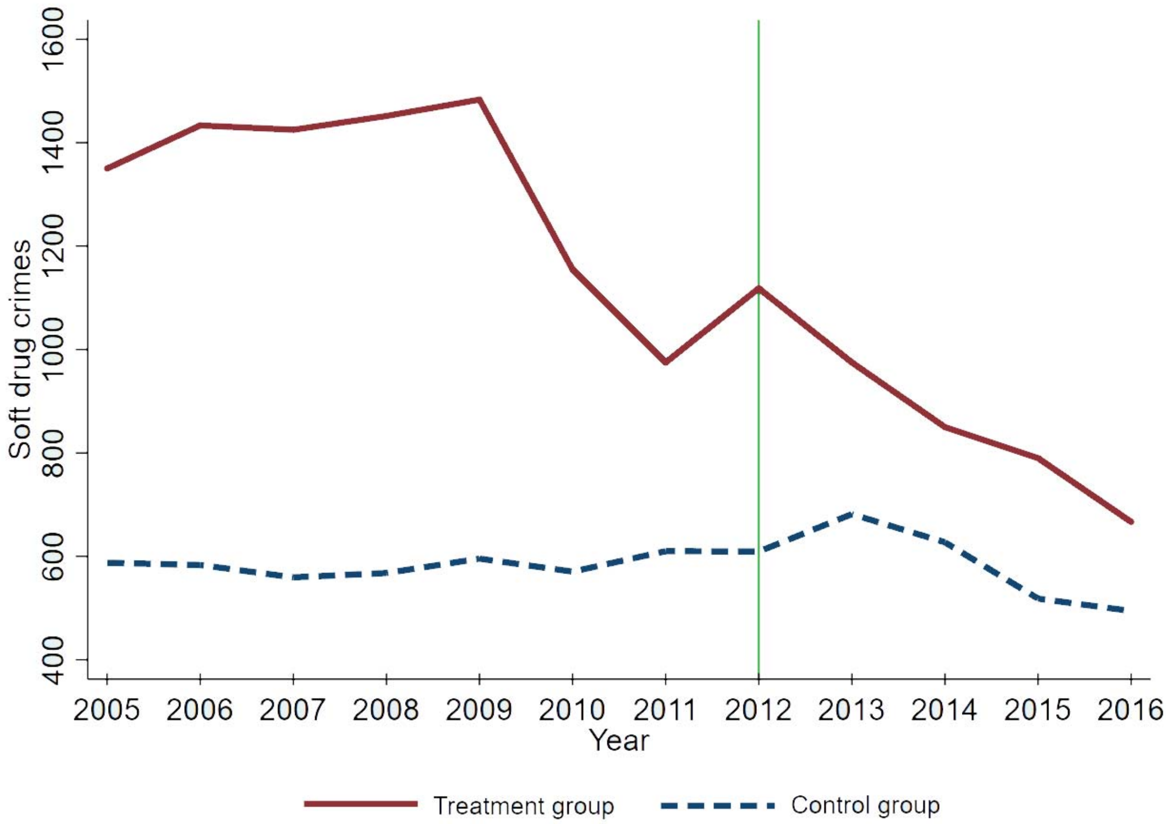
Figure 2: Common overlap between treatment- and control observations before and after matching



Note: Matching result based on the 1st propensity score specification using nearest-neighbor logit model with up to four neighbors with a caliper of 25% of the standard deviation (0.045)

Matching leads to three treated coffee shop municipalities being labeled as "off-support" indicating that no viable control coffee shop municipality was available within the caliper radius

Figure 3: Soft drug crime trend from 2005 to 2016



Note: Green line signifies the start of policy implementation and enforcement in the Southern provinces of Limburg, Noord-Brabant, and Zeeland.

The large decrease in 2009 is due to two coffee shop municipalities, Bergen op Zoom in Noord-Brabant, and Roosendaal in Zeeland closing their coffee shops due to the issues associated with drug tourism