# Master Thesis

# The effect of Coffeeshops on School Dropouts

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**Abstract**

This thesis investigates the relationship between the prevalence of coffeeshops and dropout rates of teenage and adolescent students in the Netherlands. As the distribution of coffeeshops is not random, the distance of the coffeeshop to the Dutch border is used as an instrument in a 2SLS approach. Two datasets are used; one with data of intermediate education students (MBO), and one with high school students. The data on MBO students suggest that no significant relationship between coffeeshops and dropout rates exists, while the data on high school students suggests that it in fact does. This may be due to the fact that not only soft drug usage, but also the additional effects of coffeeshop prevalence seem to have a negative effect on school performance.

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# 1 Introduction

The Netherlands has a rather liberal policy when it comes to soft drugs, when compared to other western countries (Spapens et al., 2015). Contrary to the view taken in most European countries, the Dutch government does not regard soft drugs use as a criminal issue, but rather as a health issue. Middelburg (2001) has assessed however, that the supply of soft drugs has been increasingly organised by Amsterdam criminal organisations. Furthermore, since the implementation of the Schengen Agreement in 1995, drugs tourism from neighbouring countries has increased dramatically (Spapens, 2008); for example: Maastricht, located close to the border, received 2.7 million foreign coffeeshop visitors in 2011 (van der Torre et al., 2013). Private use of soft drugs is in principle prohibited, but not punished, and therefore *de facto* legal. Contrary to soft drugs purchase, the large scale purchases of soft drugs for resale by coffeeshops *is* enforced, and this leads to an increase in criminal activity surrounding coffeeshops.

Coffeeshops act as a regulatory instrument to guide consumers when consuming soft drugs, and aim at making high quality drugs available to consumers, reeling soft drugs usage out of criminal activity (Government, 2015). This does mean, however, that soft drugs are easily accessible, both for adults as well as for teenagers, who can gain access to soft drugs through their older, 18+ friends (Harrison et al., 2007). The effect of soft drug use by teenagers and adolescents on their school performance and social indicators has been researched widely: literature reviews by Lynskey and Hall (2000), Fergusson and Horwood (1997) and Townsend et al. (2007) all point to a negative relationship between drug use and educational attainment. However, the effect of prevalence of coffeeshops on education has not been researched. Theoretically, the prevalence of coffeeshops in a city can have multiple effect on teenagers and adolescents. First, because the wholesale of soft drugs is criminal activity, teenagers and adolescents are more likely to come in contact with criminal activity, and are therefore more likely to become involved in criminal activity (Trapman and Verheul, 2014). Second, because soft drugs are more easily available, soft drugs usage of teenagers and adolescents is more likely to occur (Lynskey and Hall, 2000). Therefore, it may be that the prevalence of coffeeshops has a negative effect on the school performance of teenagers and adolescents. Policy makers currently have no information regarding the effect of allowing coffeeshops to exist within a city on school performance of children within their municipality.

This thesis will try to map the effects of the prevalence of coffeeshops in a city on the dropout rate of schools in that city. Because coffeeshops are not randomly distributed across the country (and neither are schools), but are often located in larger cities and close to the border (to attract foreign customers), an ordinary regression analysis is not able to identify the causal effect due to this selection bias. Instead, the random variation of the distance between a city and the distance to the border can be exploited in an instrumental variable approach. There appears to be a quadratic relationship between the distance of a city to the border and the number of coffeeshops in a city. Using this variation, 2SLS estimation is used to predict the effect of coffeeshops prevalence on dropout rates. Using data on intermediate education students, no significant effect can be identified. When comparing the results with high school students, a significant effect is observed, though: if the coffeeshops per 10.000 citizens ratio increases with one, the proportion of students that drops out is predicted to increase with 1 percentage point.
In the next section, the literature relating coffeeshops, soft drug use and high school performance will be surveyed. Also in section 2, the theoretical framework will be discussed, while section 3 will describe the data and the empirical strategy. Section 4 describes the obtained results, after which a conclusion will be drawn in section 5.

# 2 Theory and related literature

This section will explain the soft drugs policy of the Netherlands and survey the literature on coffeeshops, soft drugs usage and education. It will show that there are two channels through which coffeeshops may influence educational attainment. The first is through increased availability of soft drugs, which increases usage of it, and in turn worsens school performance. The second channel is through criminal activity; the literature suggests that coffeeshops attract criminal activity, which increases exposure of students to criminal activity, causing them to engage in criminal activity themselves, and inducing them to drop out of school.

## 2.1 Soft drugs policies in the Netherlands

In the Netherlands, soft drug sale is prohibited, but not prosecuted. The Opium Law prohibits the sale, ownership and usage of several psychoactive substances. These substances are mentioned on two separate lists, list I and list II. List II is colloquially referred to as 'soft drugs', and it is these substances that can be resold by coffeeshops. However, only the possession of no more than 5 grams of cannabis or the possession of no more than 5 cannabis plants is not prosecuted. Therefore, in practice, coffeeshops only resell cannabis. Furthermore, coffeeshops must adhere to the 'AHOJ-G'-criteria:

- Coffeeshops cannot advertise
- Coffeeshops cannot resell hard drugs
- Coffeeshops cannot cause nuisance
- Coffeeshops cannot sell to minors
- Coffeeshops cannot stock more than 500 grams of soft drugs

Municipalities can decide themselves how many coffeeshops they allow within their borders (Government, 2015), and they can set further rules next to the AHOJ-G criteria. Although reselling soft drugs is not prosecuted, producing soft drugs is in fact prosecuted.

## 2.2 The effect of soft drugs on school performance

A recent study by the Dutch police, using survey data and crime statistics, found that in the Netherlands, cannabis use is not higher than in other European countries (Jansen, 2012); 26% of the respondents had ever used cannabis. However, when specifically looking at the age group 15 to 24 years, about 5% of this group uses cannabis on a regular basis.

Lynskey and Hall (2000) survey the literature on cannabis use and school performance. They formulate several hypotheses that have been researched in the literature which could explain a relationship between cannabis use and school dropout:

- Cannabis use produces an 'amotivational' syndrome;
- Cannabis use may produce cognitive deficits;
- Early cannabis use leads to precocious adoption of adult roles.

The literature finds little support for the first hypothesis. Hall et al. (1998) use standardised performance measures and fail to identify a decline in performance due to cannabis use. They then conclude, after reviewing the literature on this hypothesis, that

> "[t]he evidence for an amotivational syndrome among adults is, at best equivocal. The positive evidence largely consists of case histories, and observational reports. The small number of controlled field and laboratory studies have not found compelling evidence for such a syndrome... It nonetheless is reasonable to conclude that if there is such a syndrome, it is a relatively rare occurrence, even among heavy, chronic cannabis users."

As far as the second hypothesis goes, Solowij (1998) has observed adults using cannabis, and concluded that cognitive deficits do not regularly occur in cannabis users. He did conclude that long-term cannabis users (those using cannabis on a daily basis for over 10 years) suffer from an impairment of selective attention.

The third hypothesis is tested for example by Fergusson and Horwood (1997), and they find that cannabis use often occurs in individuals with a difficult socio-economic background, which can in turn explain a higher dropout rate in these individuals. However, the context in which cannabis is used and obtained may also reinforce this effect. Fergusson and Horwood (1997) conclude that

> "[m]ost of the elevated risk seen among early onset cannabis users is likely to arise from factors that were antecedent to the decision to use cannabis, rather than as a consequence of cannabis use. Nonetheless, early onset usage is not without risks and those engaging in these behaviours may be more vulnerable to later psychosocial problems as a result of the social context within which cannabis is used and obtained."

Fergusson and Horwood (1997) conclude that cannabis use often occurs in friend groups that reject conventional values, and that socioeconomic factors alone cannot explain the relationship between cannabis use and dropping out of school. Bray et al. (2000) find that the use of cannabis makes high school students 1.4 to 3.9 times more likely to drop out. Mackleod et al. (2004) do a literature review of 48 studies, and find that most studies find a consistent relationship between cannabis use and lower educational attainment. They do note that most studies either suffer from selection biases, small samples, a lack of controlling for confounders, or a combination of these factors.

Townsend et al. (2007) do a literature review as well. They survey 46 empirical studies, and signal the same design issues as Mackleod et al. (2004), pointing out that most studies fail to identify confounding factors. Nevertheless, they point out that most studies find a negative relationship between cannabis use and educational attainment.

Harrison et al. (2007) investigate how minors (students aged 14-17 years) get access to alcohol and cannabis. They conduct a case study where they analyse survey databases. In these surveys, students were questioned about drug use and purchase on 39 sites located in Philadelphia, Toronto, Montreal and Amsterdam. In all cities but Amsterdam, minors often buy drugs or alcohol from adults on the street. In Amsterdam however, cannabis is often obtained through other students at school.

Given what is known in the literature, it seems as if there is sufficient evidence to conclude that cannabis usage by teenagers and adolescents has a negative effect on their educational attainment. Criminal activity also seems to be tied to coffeeshops. The relationship between coffeeshops and educational attainment is unclear, however. In the subsequent sections, this thesis will try to identify this effect.

## 2.3 Coffeeshops and crime

Trapman and Verheul (2014) emphasise the abrasive nature of the Dutch coffeeshop policy: on the one hand coffeeshops can 'legally' resell soft drugs, which creates a demand for this product and pulls it out of criminal circuits. However, when coffeeshops try to restock their inventory, they have to rely on illegal suppliers, as the legal limit of 5 plants is not enough to supply all customers. Trapman and Verheul argue that this creates an even larger criminal sector, as demand has increased through legalised reselling, and supply can

only be increased through illegal activities. A study by Bieleman and Snippe (1999) found that in Amsterdam, about 25% of the coffeeshops were violating the rules set by the government; often regulations about stock were violated, but coffeeshops were also found to have XTC, stolen goods, weapons and counterfeit products present. Huisman et al. (2003) further found that criminals often meet in coffeeshops. Bieleman and Goeree (2005) further analysed all Amsterdam coffeeshop owners, and found that 79% of them had a history of organised crime convictions. In other Dutch cities, Venlo and Enschede, this percentage was 60% and 76% respectively. A case study of the Dutch city Enschede found that an extra coffeeshop in a neighbourhood increased the number of crime reports per 100 households with 0.63 (Galiën, 2014). Galiën uses data from the Residential Burglary Database Enschede and regional police department covering the 2004-2008 period. These datasets contain data on the number of reported criminal incidents in Enschede, a Dutch city. While this research fails to control for relevant crime indicators, nor addressing possible endogeneity in this design, it is one of the few studies which directly tries to identify the effect of coffeeshops on crime prevalence.
The question rises why the government has not legalised soft drugs usage and reselling. The Dutch parliament has proposed to do so, however the minister of Safety and Justice has explained that this is not possible without breaking international treaty obligations (Peeperkorn, 2003). It seems that these conflicting rules maintain the criminal activity surrounding coffeeshops.

## 2.4 The two channels

Based on the literature, reviewed above, the effect of coffeeshops on educational attainment is twofold. On the one hand, an increase in the amount of coffeeshops makes softdrugs easier to buy. This means that adolescents can get their hands on soft drugs, which increases usage of soft drugs in this age group. Soft drugs usage decreases school performance (as suggested by Bray et al. (2000), Mackleod et al. (2004) and Townsend et al. (2007)), which should be observed in the dropout rates. Not only should we expect to see this effect for 18+ students; the literature seems to suggest that coffeeshop prevalence also induces a secondary (black) market, where adults buy soft drugs and then resell these to minors, either on the street or at school (Harrison et al., 2007). The second channel is through crime rates; the literature suggests that coffeeshop owners and those supplying to coffeeshops are often involved in criminal activities (Bieleman and Goeree, 2005). Furthermore, criminals also tend to meet in coffeeshops (Huisman et al., 2003). This means that those visiting coffeeshops, but also those living near coffeeshops are more easily drawn into criminal activity themselves. This should then also have an effect on the dropout rate.

It is difficult to disentangle these effects when the effect of coffeeshops on dropout rates is investigated in the following sections; there is no data that indicates which students use soft drugs. It is therefore difficult to distinguish between soft drugs-related dropouts and criminal behaviour-related dropouts.

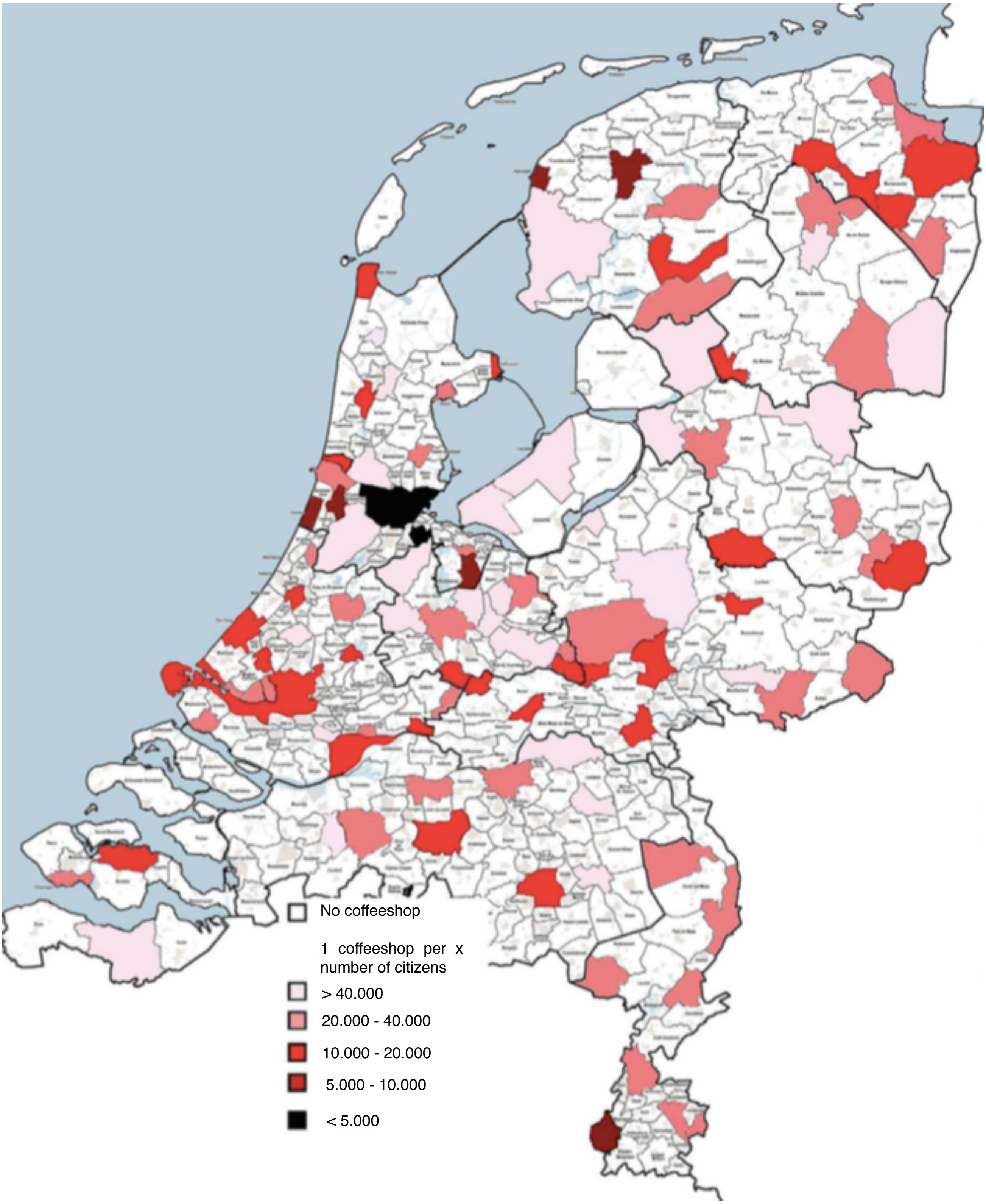
# 3 Data and Methodology

## 3.1 Data

To investigate the effect of the presence of coffeeshops on dropout rates, data on the location of coffeeshops, the number of dropouts per school and the distance from the coffeeshops to the Dutch border have been collected. In this section, this data will be discussed and explored. The location of coffeeshops has been collected by the research bureau 'Intraval', commissioned by the Dutch ministry of safety and justice (Bieleman et al., 2013). This data comprehends the number of coffeeshops per municipality, ranging from 1999 to 2012, and has been gathered by approaching each municipality and registering the number of coffeeshop permit they had given for that year. No data on 2008 is collected, and data on 2009 have only been collected if municipality had indicated that they had changed their policy on coffeeshops between 2007 and 2009. Therefore a gap in the data may exist. However, out of all the 415 municipalities, only 4 of them experienced a change in the number of coffeeshops between 2007 and 2009[1]. It seems unlikely that a full dataset, containing data on all municipalities in 2008 and 2009, would yield very different results. The distance between a municipality and the closest Dutch border has been calculated by the Netherlands Bureau for Economic Policy Analysis (CPB). This dataset also contains data on the type of road connecting the city to the border, as well as indicators of urbanisation, such as acreage, number of inhabitants, and population density. Note that the data has been graphically described in figure 1 (Bieleman et al., 2013). From this data the instruments *distance* and $distance^2$ are obtained, as well as the explanatory variable of interest: the number of coffeeshops.

[1]These are Amsterdam, Bergen op Zoom, Beverwijk and Breda. All but Amsterdam experienced a change of 1 shop.

Figure 1: Density of coffeeshops per x citizens (Bieleman et al., 2013)



Data on the number of dropouts is published by the Dutch ministry of education, culture and science. Schools register the number of children in a certain year, and also keep track of the number that drop out. There are two datasets available; one dataset contains data of one of the three forms of intermediate and higher education, MBO schools, while the other one contains data on dropouts in all forms of secondary education. The data on secondary education is less informative, as children in secondary education are aged 12 to 18, and are therefore not allowed into coffeeshops. Three types of secondary education exist: vmbo, havo and vwo. Obtaining a vmbo diploma is the only diploma that does not lift the obligation to pursue education. Children usually finish this education at age 16, and then have to continue pursuing education. Therefore, MBO schools are the only higher education institution that report dropout rates. Students are usually aged 18 to 22, so that part of the student *can* enter a coffeeshop, and the other part cannot. Therefore, for the main estimation, the dataset on MBO dropouts is used. The Dutch education system is depicted schematically in figure 2. The dotted box indicates the education types which, upon completion, lift the mandatory education attainment. The institutions providing education within or leading up to the red box, have to keep track of their students' attendance, to make sure that they comply with their compulsory attainment. It is for this reason that either high school data must be used, or MBO data, as the other forms of education do not keep track of dropouts.

The dataset contains data on the number of dropouts per school, per type of education, per gender and per age group. This dataset comprehends data of 2005 to 2012. This dataset contains data on all 71 MBO schools, which are located in 43 different cities. This means that one observation is for example the number of dropouts in mbo sector economics, year 3, girls aged 13 to 17, education type part-time, of school $x$. In table 1, an overview of the number of MBO participants and dropouts per year is reported. The dataset contains the number of dropouts, and the total number of participants, such that the

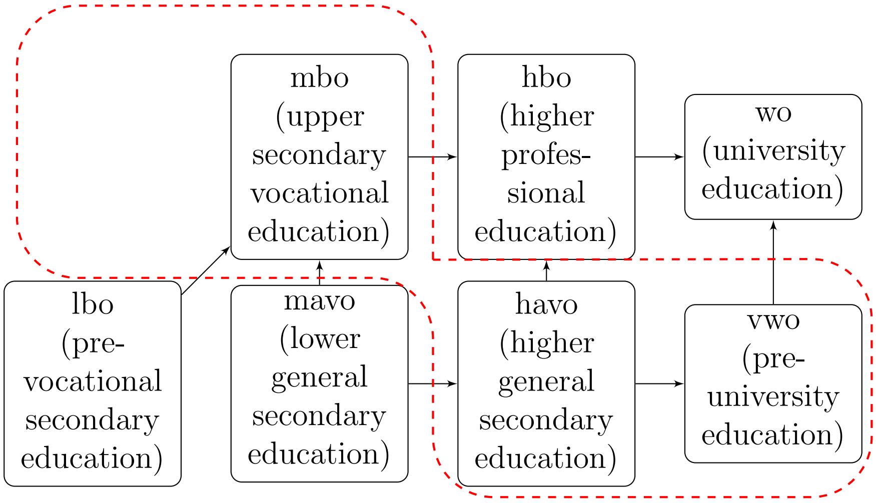



Figure 2: Schematic chart of the Dutch education system

Table 1: Summary statistics of total MBO participants and dropouts per year

| Year | Participants | Dropouts | |
|---|---|---|---|
| 2005 | 381,965 | 39,093 | 10,23% |
| 2006 | 388,664 | 38,794 | 9,98% |
| 2007 | 388,527 | 37,194 | 9,57% |
| 2008 | 386,997 | 33,522 | 8,66% |
| 2009 | 388,733 | 33,286 | 8,56% |
| 2010 | 386,904 | 32,614 | 8,31% |
| 2011 | 385,058 | 30,238 | 7,85% |

outcome variable can be constructed: the proportion of dropouts.

Using the datasets described above, we can thus examine the 2005 to 2012 period. In table 2, the percentage of dropouts is set out against the number of coffeeshops. In figure 3, a scatterplot of the number of coffeeshops per city and the number of dropouts is given. Both indicate that there is a positive correlation between coffeeshops and dropouts.

### 3.2 Empirical Strategy

We would like to investigate the effect of coffeeshops on the number of dropouts, using the proportion of dropouts as the outcome variable, and the number of

Figure 3: Scatterplot of average number of dropouts per city against number of coffeeshops

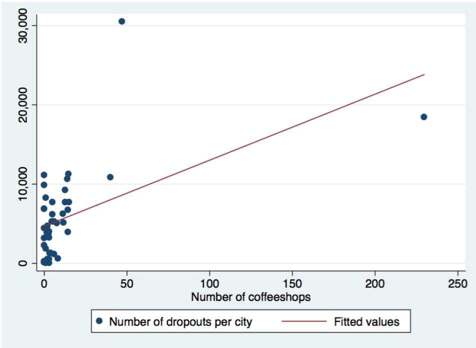



Figure 4: Scatterplot of figure 3 without Amsterdam, Rotterdam and Utrecht

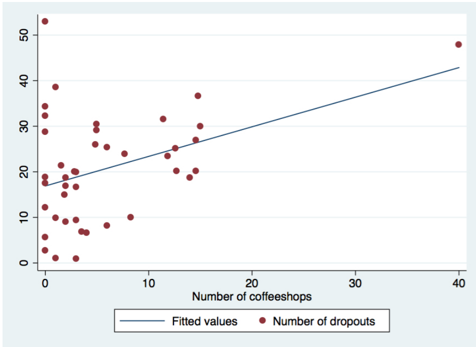



Table 2: Percentage of average number of dropouts

| Number of dropouts | Percentage of dropouts | Standard deviation |
|---|---|---|
| No coffeeshops | 8.2% | 2.3% |
| 1 to 5 | 11.7% | 8.7% |
| 6 to 10 | 8.9% | 2.2% |

coffeeshops as the explanatory variable of interest. The most straightforward, OLS estimation would look like equation 1

$$d_{ikj} = \beta_1 + \beta_2 c_i + \beta_3 sector + \beta_4 type + \beta_5 year + \beta_6 age + \beta_7 province + \varepsilon_i \quad (1)$$

Here, $d$ would be the proportion of dropouts of school $k$ in municipality $j$, while $c$ would be the number of coffeeshops. The control variables include age, year of the observation, province, type of education[2] and sector of education[3]. This OLS estimation would only hold under the very strong assumption that coffeeshops locate randomly across the country and between cities. However, coffeeshops do not exist in Belgium or Germany, countries bordering the Netherlands, nor do these countries allow the sale of soft drugs. Therefore, coffeeshops have an incentive to locate themselves in cities closer to the border,

[2]There are two types of MBO education: BBL and BOL, where BBL involves working while studying, while BOL does not

[3]Sectors include for example health, economics and craftmanship

as they can attract foreign customers. This would break the OLS assumption and bias the results.

Therefore, it is better to use an instrumental variable approach, in which exogenous variation is used to describe the effect of coffeeshops on dropouts. As mentioned earlier, coffeeshops may want to locate closer to the border to attract foreign customers. As the location of the border is exogenous, this provides variation which can be exploited in an instrumental variable analysis. By using the distance to the border as an instrument, there is exogenous variation in the location of coffeeshops. The assumption is of course that the distance to the border is randomly distributed. Furthermore, it is assumed that MBO schools do not locate themselves based on the distance to the border. Later on, an extra instrument will be added; Amsterdam has a very large number of coffeeshops (over 250) compared to other cities. It is likely that this large amount of coffeeshops is also due to tourism, but this cannot be explained by its distance to the border. Therefore, a dummy variable indicating whether an international airport is located near that city is added as an extra instrument. The assumption is that there is no endogeneity here: coffeeshops locate near aiport because tourists will visit and buy soft drugs, but it is assumed that airport do not locate themselves in a specific city because it has a lot of coffeeshops. When we look at table 3, we see that in cities with an airport, there are almost three times more coffeeshops per 10.000 inhabitants than in those without an airport.

Table 3: Average number of coffeeshops per 10.000 citizens

| | |
|---|---|
| No airport | 0.507 |
| Airport | 1.150 |
| Eindhoven | 0.750 |
| Rotterdam | 0.798 |
| Groningen | 0.818 |
| Maastricht | 1.199 |
| Amsterdam | 3.157 |

It should be noted that it is unclear which explanatory variable should be used: on the one hand, one could argue that the relative number of coffeeshops is the most important variable: if a city inhabits *relatively* more coffeeshops per citizen, then it is more likely that students will enter such a shop, that they will encounter the negative effects of soft drugs, and thus drop out. On the other hand, one could argue that the *absolute* number of coffeeshops should be used as independent variable, as having a coffeeshop in a city creates the possibility of encountering negative effects of soft drugs, and therefore the size of the city is irrelevant to the number of coffeeshops. In this thesis, both variables will be used separately; in section 4.1, the relative number of coffeeshops will be used, while section 4.2 will use the absolute number of variables.

The regression that will be estimated is:

First Stage:

$$c_i = \gamma_1 k_i + \gamma_2 k_i^2 + \gamma_3 sector + \gamma_4 type + \gamma_5 year + \gamma_6 age + \varepsilon_i \tag{2}$$

First Stage including airport as instrument:

$$c_i = \gamma_1 k_i + \gamma_2 k_i^2 + \gamma_3 airport + \gamma_4 sector + \gamma_5 type + \gamma_6 year + \gamma_7 age + \varepsilon_i \tag{3}$$

Second stage:

$$d_{ikj} = \beta_1 \widehat{c_i} + \beta_2 sector + \beta_3 type + \beta_4 year + \beta_5 age + \eta_i \tag{4}$$

Here, $c_i$ denotes the number of coffeeshops per 10.000 citizens, $k_i$ denotes te distance to the border in kilometers and $d_{ikj}$ denotes the proportion of dropouts of school $k$ at school $j$ in municipality $i$.

When the absolute number of coffeeshops is used, the estimated equations are quite alike:

First stage:

$$C_i = \gamma_1 k_i + \gamma_2 k_i^2 + \gamma_3 sector + \gamma_4 type + \gamma_5 year + \gamma_6 age + \varepsilon_i \tag{5}$$

First Stage including airport as instrument:

$$C_i = \gamma_1 k_i + \gamma_2 k_i^2 + \gamma_3 airport + \gamma_4 sector + \gamma_5 type + \gamma_6 year + \gamma_7 age + \varepsilon_i \tag{6}$$

Second stage:

$$d_{ikj} = \beta_1 \widehat{C}_i + \beta_2 sector + \beta_3 type + \beta_4 year + \beta_5 age + \eta_i \tag{7}$$

Note that everything is the same as in equation 2, 3 and 4, though the absolute number of coffeeshops is now denoted by $C_i$.

Apart from these estimation, the effect of coffeeshops on dropouts is also estimated separately for boys and girls. This requires us to calculate the interaction effect between the number of coffeeshops and a gender dummy. However, the number of coffeeshops is endogenous, while gender is exogenous. This creates an interaction variable which is partly endogenous. Bun and Harrison (2014) analyse the occurrence of such effects, and find that in general, instrumental variable estimation using 2SLS still gives unbiased estimates when the interaction term is included as an endogenous variable, while also instrumenting for the interaction between the initial instruments and the exogenous part of the interaction term. Therefore, the two endogenous variables are the number of coffeeshops, and the number of coffeeshops interacted with gender. The instruments are distance to the Dutch border and this distance squared (and the airport dummy), as well as both variables interacted with gender, such that we end up with 4 instruments. The regression that is estimated changes too:

First stage regression for the number of shops:

$$c_i = \gamma_1 k_i + \gamma_2 k_i^2 + \gamma_3 gender + \gamma_4 k_i \times gender + \gamma_5 k_i^2 \times gender\big( + \delta_1 airport$$
$$+\delta_2 airport \times gender\big) + \gamma_6 sector + \gamma_7 type + \gamma_8 year + \gamma_9 age + \gamma_{10} province + \varepsilon_i \tag{8}$$

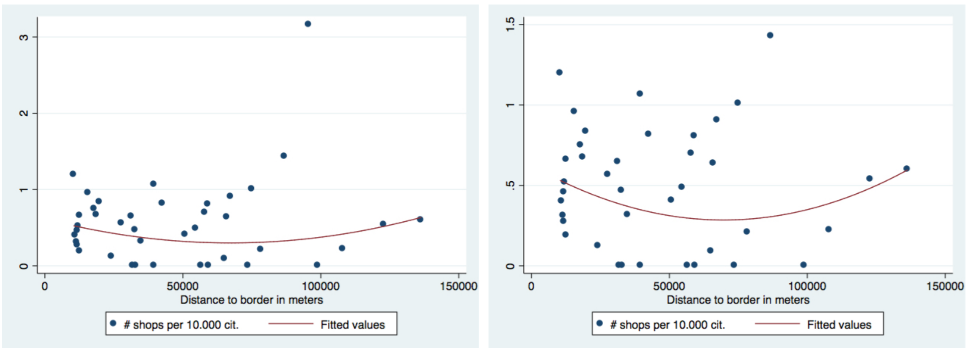
First stage regression for shops $\times$ female:

$$c_i \times female = \gamma_1 k_i + \gamma_2 k_i^2 + \gamma_3 gender + \gamma_4 k_i \times gender + \gamma_5 k_i^2 \times gender\big( + \delta_1 airport$$
$$+\delta_2 airport \times gender) + \gamma_4 sector + \gamma_5 type + \gamma_6 year + \gamma_7 age + \gamma_8 province + \epsilon_i \tag{9}$$

Second stage:

$$d_{ikj} = \beta_1 \widehat{c_i} + \beta_2 \widehat{c_i \times female} + \beta_3 sector + \beta_4 type + \beta_5 year + \beta_6 age + \beta_7 province + \eta_i \tag{10}$$

Figure 5: Scatterplots of # of coffeeshops per 10.000 citizens and distance to border in meters




(a) With Amsterdam (b) Without Amsterdam

Figures 5a and 5b show the scatterplot for the number of coffeeshops per 10.000 citizens and the distance to the border in meters. We will estimate the regression with and without Amsterdam, to test whether it is an outlier. Around 230 coffeeshops are located in Amsterdam, but its distance to the

Dutch border seems irrelevant to that number of coffeeshops. It may be that coffeeshops locate in Amsterdam for (drugs)tourism too, but not because of its distance to the Dutch border, but because it is visited frequently by tourist that come in by plane. When we exclude Amsterdam, there seems to be a negative, quadratic relationship between the distance and the number of coffeeshops. This implies that the marginal benefit of being located closer to the border is increasing; being located very closely to the border means attracting a lot of foreign visitors, but being located further away quickly decreases this benefit, as other coffeeshops will attract the foreign visitors. Apparently there is some gray area, where the distance to the border has increased, such that it is less attractive to locate a coffeeshop there. The larger cities of the Netherlands are located quite far away from the border, so perhaps there is an incentive to locate coffeeshops in these cities for touristic reasons as well. The right-hand side of the parabola could also be explained by the fact that because a lot of shops locate close to the border, there is a 'gap' in the market for customers located in the north and west of the Netherlands, increasing the benefits for a coffeeshop to locate there.

As mentioned earlier, there are a lot of observations in the dataset, but they are far from independent. For example, one observation may be the number of female dropouts aged 13-17 of school $i$ in 2006, following a medical type of education in year 2. The next observation may then be the number of female dropouts aged 13-17 of that same school, also following a medical type of education, but in year 3. To account for this dependency, the standard errors will be clustered at school $\times$ year level in the next section.

# 4 Main estimation results

## 4.1 General results

In this section, the results of the analysis using the data described in the previous section will be reported. Table 4 shows the result of the estimation of equations 2, 3 and 4. For comparison, the OLS estimation has also been reported. Under OLS estimation, the proportion of dropouts would increase with 0.43 percentage points, if the number of coffeeshops per 10.000 citizens increases with 1. Under 2SLS estimation, this effect is somewhat smaller: an increase of 0.33 percentage point. When the extra instrument, the dummy indicating whether airports are near, is added, the effect is somewhat similar: an increase of 0.37 percentage point. When Amsterdam is excluded, the calculated effect is even negative. None of the estimations show a signifiant effect for the relation between coffeeshops and dropout rates.

When the effect is estimated separately for 18+ and 18- students, we can see that for 18+ students, the effect is larger than for 18- students, which is to be expected: those able to enter coffeeshops would experience more negative effects from them than those who cannot. However, neither effect differs significantly from zero.

When we look at the estimations where the effect is estimated separately for males and females (estimations 10 through 18 in table 5), we can see that the effect is somewhat larger for males than for females, as the predicted values are somewhat higher. However, the effect is still not significantly different from zero.

Table 4: OLS and 2SLS estimations of equations 1, 2, 3 and 4

| | (1) OLS | (2) 2SLS | (3†) 2SLS | (4) 2SLS Excluding Amsterdam | (5†) 2SLS Excluding Amsterdam | (6) 2SLS 18-22 yrs | (7†) 2SLS 18-22 yrs | (8) 2SLS 13-17 yrs | (9†) 2SLS 13-17 yrs |
|---|---|---|---|---|---|---|---|---|---|
| First stage, dependent variable: Coffeeshops per 10.000 citizens | | | | | | | | | |
| Distance | | 0.00000902*** | 0.00000354 | 0.00000528** | 0.00000286 | 0.00000895*** | 0.00000360 | 0.00000907*** | 0.00000344 |
| | | (3.85) | (1.70) | (2.72) | (1.51) | (3.86) | (1.73) | (3.78) | (1.62) |
| Distance$^2$ | | -3.52e-11* | 9.77e-12 | -3.18e-11* | -8.66e-12 | -3.48e-11* | 9.37e-12 | -3.55e-11* | 1.05e-11 |
| | | (-2.19) | (0.59) | (-2.50) | (-0.69) | (-2.18) | (0.56) | (-2.16) | (0.62) |
| Airport | | | 0.672*** | | 0.351*** | | 0.658*** | | 0.690*** |
| | | | (6.90) | | (8.21) | | (6.96) | | (6.76) |
| F-value | | 9.81 | 18.15 | 3.76 | 33.30 | 10.14 | 18.61 | 9.41 | 17.47 |
| Dependent variable: Proportion of dropouts | | | | | | | | | |
| Shops per 10.000 citizens | 0.00430 | 0.00326 | 0.00367 | -0.0156 | -0.00463 | 0.00603 | -0.00368 | 0.00125 | 0.0119 |
| | (1.25) | (0.28) | (0.61) | (-0.49) | (-0.37) | (0.41) | (-0.47) | (0.08) | (1.48) |
| Constant | 0.413*** | 0.414*** | 0.413*** | 0.425*** | 0.419*** | 0.512*** | 0.519*** | 0.363*** | 0.355*** |
| | (39.75) | (31.07) | (36.29) | (19.21) | (31.28) | (30.85) | (36.84) | (19.61) | (24.17) |
| $N$ | 7393 | 7393 | 7393 | 7165 | 7165 | 4306 | 4306 | 3087 | 3087 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† These estimations include the extra instrument airport.

Standard errros have been clustered at school × year level.

Table 5: OLS and 2SLS estimations of equations 1, 8 and 10

| | (10) OLS | (11) 2SLS | (12†) 2SLS | (13) 2SLS Excluding Amsterdam | (14†) 2SLS Excluding Amsterdam | (15) 2SLS 18-22 yrs | (16†) 2SLS 18-22 yrs | (17) 2SLS 13-17 yrs | (18†) 2SLS 13-17 yrs |
|---|---|---|---|---|---|---|---|---|---|
| First stage, dependent variable: Coffeeshops per 10.000 citizens | | | | | | | | | |
| Distance | | 0.00000897*** | 0.00000363 | 0.00000524** | 0.00000289 | 0.00000861*** | 0.00000363 | 0.00000943*** | 0.00000362 |
| | | (3.86) | (1.77) | (2.72) | (1.54) | (3.70) | (1.78) | (4.01) | (1.71) |
| Distance$^2$ | | -3.51e-11* | 8.89e-12 | -3.09e-11* | -8.37e-12 | -3.25e-11* | 9.02e-12 | -3.85e-11* | 8.88e-12 |
| | | (-2.23) | (0.55) | (-2.47) | (-0.68) | (-2.04) | (0.56) | (-2.42) | (0.53) |
| Airport | | | 0.672*** | | 0.351*** | | 0.658*** | | 0.690*** |
| | | | (6.89) | | (8.20) | | (6.96) | | (6.75) |
| F-value | | 6.36 | 10.01 | 3.79 | 16.67 | 7.73 | 13.77 | 4.60 | 8.21 |
| Shops per 10.000 cit. | 0.00661 | 0.00390 | 0.00663 | -0.0112 | -0.00191 | 0.00906 | -0.000207 | 0.00428 | 0.0151 |
| | (1.64) | (0.32) | (1.03) | (-0.35) | (-0.15) | (0.60) | (-0.03) | (0.26) | (1.71) |
| Shops × female | -0.00480 | -0.00395 | -0.00552 | -0.00284 | -0.00412 | -0.00476 | -0.00666 | -0.00615 | -0.00664 |
| | (-1.50) | (-0.93) | (-1.38) | (-0.58) | (-0.85) | (-0.90) | (-1.33) | (-0.95) | (-1.06) |
| Constant | 0.412*** | 0.452*** | 0.451*** | 0.461*** | 0.456*** | 0.511*** | 0.518*** | 0.362*** | 0.355*** |
| | (39.73) | (34.53) | (39.89) | (21.17) | (34.15) | (30.81) | (36.82) | (19.61) | (24.17) |
| $N$ | 7393 | 7393 | 7393 | 7165 | 7165 | 4306 | 4306 | 3087 | 3087 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† These estimations include the extra instrument airport.

Standard errros have been clustered at school × year level.

## 4.2 Estimation results using the absolute number of coffeeshops

As mentioned in the previous section, it is not *a priori* clear which variable should be chosen as the outcome variable; either the number of coffeeshops per 10.000 citizens, or the absolute number of coffeeshops. In this section, the latter will be used for the estimations.

Table 6: OLS and 2SLS estimations of equations 1, 5, 6 and 7

| | (1) | (2) | (3†) | (4) | (5†) | (6) | (7†) | (8) | (9†) |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS | 2SLS | 2SLS Excluding Amsterdam | 2SLS Excluding Amsterdam | 2SLS 18-22 yrs | 2SLS 18-22 yrs | 2SLS 13-17 yrs | 2SLS 13-17 yrs |
| First stage, dependent variable: number of coffeeshops. | | | | | | | | | |
| Distance | | 0.000847*** | 0.000450*** | 0.000526*** | 0.000389*** | 0.000814*** | 0.000433*** | 0.000890*** | 0.000475*** |
| | | (5.86) | (3.82) | (6.62) | (6.51) | (5.86) | (3.82) | (5.79) | (3.76) |
| Distance$^2$ | | -4.21e-09*** | -9.50e-10 | -3.91e-09*** | -2.61e-09*** | -4.03e-09*** | -8.80e-10 | -4.44e-09*** | -1.04e-09 |
| | | (-4.43) | (-0.88) | (-6.73) | (-6.33) | (-4.42) | (-0.84) | (-4.35) | (-0.92) |
| Airport | | | 48.57*** | | 19.77*** | | 46.85*** | | 50.92*** |
| | | | (5.86) | | (8.51) | | (5.80) | | (5.89) |
| F-value | | 17.51 | 15.54 | 23.29 | 31.21 | 17.27 | 15.53 | 17.63 | 15.43 |
| Dependent variable: Proportion of dropouts | | | | | | | | | |
| Shops | 0.000147*** | 0.00000868 | 0.0000480 | -0.000193 | -0.0000864 | 0.0000991 | -0.0000475 | -0.0000265 | 0.000155 |
| | (3.40) | (0.05) | (0.57) | (-0.46) | (-0.41) | (0.48) | (-0.44) | (-0.11) | (1.37) |
| Constant | 0.414*** | 0.415*** | 0.415*** | 0.418*** | 0.417*** | 0.514*** | 0.517*** | 0.364*** | 0.361*** |
| | (42.34) | (39.05) | (39.82) | (37.94) | (38.82) | (38.37) | (39.89) | (25.63) | (26.95) |
| $N$ | 7975 | 7393 | 7393 | 7165 | 7165 | 4306 | 4306 | 3087 | 3087 |

$t$ statistics in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

† These estimations include the extra instrument airport.

Standard errros have been clustered at school × year level.

Table 7: OLS and 2SLS estimations of equations 1, 5, 6 and 7 with gender effect

| | (10) | (11) | (12$^{\dagger}$) | (13) | (14$^{\dagger}$) | (15) | (16$^{\dagger}$) | (17) | (18$^{\dagger}$) |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS |
| | | | | Excluding Amsterdam | Excluding Amsterdam | 18-22 yrs | 18-22 yrs | 13-17 yrs | 13-17 yrs |
| Distance | | 0.000841$^{***}$ | 0.000455$^{***}$ | 0.000520$^{***}$ | 0.000388$^{***}$ | 0.000815$^{***}$ | 0.000460$^{***}$ | 0.000874$^{***}$ | 0.000445$^{***}$ |
| | | (5.88) | (3.92) | (6.70) | (6.65) | (5.83) | (4.05) | (5.83) | (3.64) |
| Distance$^2$ | | -4.22e-09$^{***}$ | -1.04e-09 | -3.85e-09$^{***}$ | -2.59e-09$^{***}$ | -4.04e-09$^{***}$ | -1.09e-09 | -4.44e-09$^{***}$ | -9.40e-10 |
| | | (-4.51) | (-0.99) | (-6.82) | (-6.48) | (-4.41) | (-1.06) | (-4.52) | (-0.85) |
| Airport | | | 48.56$^{***}$ | | 19.77$^{***}$ | | 46.86$^{***}$ | | 50.89$^{***}$ |
| | | | (5.86) | | (8.51) | | (5.80) | | (5.88) |
| F-value | | 8.99 | 9.60 | 10.49 | 16.28 | 8.75 | 8.70 | 8.00 | 8.59 |
| Shops | 0.000186$^{***}$ | 0.0000414 | 0.0000886 | -0.000130 | -0.0000364 | 0.000135 | -0.000000863 | 0.0000113 | 0.000197 |
| | (3.78) | (0.24) | (0.99) | (-0.31) | (-0.17) | (0.66) | (-0.01) | (0.05) | (1.60) |
| Shops $\times$ female | -0.00691$^{*}$ | -0.00382 | -0.00538 | -0.00302 | -0.00413 | -0.00466 | -0.00670 | -0.00582 | -0.00630 |
| | (-2.23) | (-0.90) | (-1.34) | (-0.62) | (-0.85) | (-0.89) | (-1.34) | (-0.90) | (-1.00) |
| Constant | 0.414$^{***}$ | 0.454$^{***}$ | 0.454$^{***}$ | 0.456$^{***}$ | 0.455$^{***}$ | 0.515$^{***}$ | 0.518$^{***}$ | 0.365$^{***}$ | 0.362$^{***}$ |
| | (40.39) | (43.29) | (43.96) | (41.91) | (42.71) | (38.64) | (40.28) | (25.58) | (26.86) |
| $N$ | 7975 | 7393 | 7393 | 7165 | 7165 | 4306 | 4306 | 3087 | 3087 |

$t$ statistics in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

$^{\dagger}$ These estimations include the extra instrument airport.

Standard errros have been clustered at school $\times$ year level.

Note that OLS estimation shows a significant effect: if an extra coffeeshop is located in a city, the proportion of dropouts would increase with 0.015 percentage point. This is an incredibly small number; in a class of 30 students, this would lead to 0.00441 students extra dropping out. In a city with 10,000 students, 1.47 students would drop out extra. When we look at the 2SLS estimations, however, the effects are even smaller and insignificant. When using airport as an extra instrument, the predicted increase of the proportion of dropouts is even smaller.
When looking at table 7, OLS estimation would again give a significant result, with the predicted effect for males being larger than that for females. 2SLS estimation again shows an insignificant effect for all estimations.

## 4.3 Comparison: High school students

This thesis has mainly focussed on MBO students, since data on this type of students is available, and roughly half of them is allowed to enter a coffeeshop, and thus use soft drugs legally. We have observed however, that there seems to be a significant relationship between coffeeshops and dropout rates of those younger than 18 as well. Therefore, it might be interesting to look at the data of high school students. Since the Dutch system knows 3 types of education, and normally only the last year of one of these types holds students that might be 18 or older, we can assume that the vast majority of high school students is aged below 18, and can therefore not use soft drugs through legal means. Through a similar estimation as in the previous sections, the effect of coffeeshops on high school dropout rates will be identified. The dataset used is provided by Dutch ministry of education, but is less rich than the dataset on MBO students. It contains data on all Dutch high schools, with the number of dropouts per type and grade. Table 8 shows a summary of the data.

The model that is calculated is as follows:

Table 8: Dataset on High School students, proportion of dropouts

| Education type and grade | Mean proportion | Standard deviation | Number of observations |
|---|---|---|---|
| brug 1-2 | .0099091 | .0330232 | 3788 |
| brug 3 | .011805 | .0568428 | 450 |
| havo 3-5 | .0150753 | .0453159 | 17743 |
| lwoo 1-2 | .0205714 | .0366588 | 2298 |
| lwoo 3-4 | .0445992 | .0428017 | 2286 |
| vmbo 2 | .0308765 | .0481243 | 192 |
| vmbo 3-4 | .0349506 | .0514148 | 3225 |
| vwo 3-6 | .0074849 | .0300562 | 20158 |
| Total | .0145409 | .0402178 | 50140 |

First stage:

$$c_i = \gamma_0 + \gamma_1 k_i + \gamma_2 k_i^2 \big( + \gamma_3 airport\big) + \gamma_4 type + \gamma_5 profile^4 + \varepsilon_i \tag{11}$$

Second stage:

$$d_i = \beta_0 + \beta_1 \widehat{c_i} + \beta_2 type + \beta_3 profile + \eta_i \tag{12}$$

Here, $k_i$ is again the distance to the border in kilometers, $c_i$ is the number of coffeeshops per 10.000 citizens, *airport* is a dummy with value 1 if an airport is located near the city, *type* indicates the type and grade of the students, as displayed in table 8. $d_i$ indicates the proportion of dropouts. As in the previous section, the estimations are repeated with the absolute number of coffeeshops as the outcome variable, such that we estimate:

$$C_i = \gamma_0 + \gamma_1 k_i + \gamma_2 k_i^2 \big( + \gamma_3 airport\big) + \gamma_4 type + \gamma_5 profile + \varepsilon_i \tag{13}$$

Second stage:

$$d_i = \beta_0 + \beta_1 \widehat{C_i} + \beta_2 type + \beta_3 profile + \eta_i \tag{14}$$

[4] Students in grade 4 and 5 of havo and 4, 5 and 6 of vwo choose a profile; a combination of courses geared towards the same subject; there are two profiles geared towards social sciences (CM and EM) and two profiles geared towards natural sciences (NT and NG)

Now, $C_i$ again denotes the absolute number of coffeeshops. We should expect to see results somewhat similar to the result of MBO students aged 13 to 17, as these students are not allowed to enter coffeeshops, as are almost all high school students. Table 9 shows the estimation results for the above four equations. Surprisingly, both the OLS and 2SLS estimations show a significant effect of an increase in the number of coffeeshops on the proportion of dropouts. While OLS predicts an increase of 0.5 percentage points if the number of shops per 10.000 citizens increases with one, 2SLS predicts an increase of 0.1 percentage point. Adding airport as an instrument decreases the estimation somewhat, while excluding Amsterdam does not change the estimation much. When looking at the other explanatory variable, the absolute number of shops, a similar image exists. OLS estimation predicts an increase in the proportion of dropouts of 0.007 percentage point, while 2SLS predicts a 0.002 percentage point increase. Adding Airport as an extra instrument decreases the estimation somewhat, while excluding Amsterdam does not change the predictions much. It is interesting to note that using the high school dataset produces significant predictions for the effect of coffeeshops on dropout rates, while the MBO dataset does not. Both predictions are small, however, so the fact that the second datasets predictions are significant could be due to the fact that this dataset contains more observations.

Table 9: Estimation results for High school data

| | (1) OLS | (2) 2SLS | (3†) 2SLS | (4) 2SLS Excluding Amsterdam | (5†) 2SLS Excluding Amsterdam |
|---|---|---|---|---|---|
| First stage; dependent variable: Coffeeshops per 10.000 citizens | | | | | |
| Distance | | 0.00000702*** | 0.000000427 | 0.00000380*** | 0.00000212* |
| | | (4.46) | (0.31) | (3.65) | (2.18) |
| Distance$^2$ | | 1.24e-11 | 4.55e-11*** | -3.51e-11*** | -1.77e-11* |
| | | (0.85) | (3.82) | (-4.64) | (-2.46) |
| Airport | | | 1.593*** | | 0.518*** |
| | | | (25.45) | | (26.30) |
| F-value | | 84.00 | 250.71 | 16.68 | 321.76 |
| Second stage; dependent variable: Proportion of dropouts | | | | | |
| Shops per 10.000 cit. | 0.00508*** | 0.0104*** | 0.00605*** | 0.00917* | 0.00715*** |
| | (6.27) | (7.60) | (6.59) | (2.34) | (5.81) |
| Constant | 0.00414** | 0.000170 | 0.00341* | 0.00189 | 0.00334* |
| | (2.87) | (0.10) | (2.30) | (0.60) | (2.07) |
| *N* | 20721 | 20721 | 20721 | 19470 | 19470 |

| | (6) OLS | (7) 2SLS | (8†) 2SLS | (9) 2SLS | (10†) 2SLS |
|---|---|---|---|---|---|
| First stage; dependent variable: Number of coffeeshops | | | | | |
| Distance | | 0.000814*** | 0.000312** | 0.000555*** | 0.000454*** |
| | | (7.85) | (3.26) | (13.97) | (13.54) |
| Distance$^2$ | | -4.43e-10 | 2.08e-09* | -4.27e-09*** | -3.22e-09*** |
| | | (-0.42) | (2.42) | (-14.32) | (-13.28) |
| Airport | | | 121.5*** | | 31.34*** |
| | | | (23.13) | | (22.37) |
| F-value | | 155.40 | 265.38 | 104.07 | 251.93 |
| Second stage; dependent variable: Proportion of dropouts | | | | | |
| Shops | 0.0000693*** | 0.000119*** | 0.0000790*** | 0.000212*** | 0.000136*** |
| | (5.59) | (7.87) | (6.70) | (5.61) | (7.18) |
| Constant | -4.531*** | -4.547*** | -4.539*** | -4.582*** | -4.569*** |
| | (-93.74) | (-92.94) | (-93.58) | (-89.05) | (-91.98) |
| *N* | 21177 | 20721 | 20721 | 19470 | 19470 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† These estimations include the extra instrument airport.

Standard erros have been clustered at school × year level.

# 5 Conclusion

This thesis has started out by investigating the existence of coffeeshops in the Netherlands. The literature concerning the effect of soft drugs on school performance was surveyed, as well as the literature on coffeeshops and criminal activity. These two subjects were also identified as the mechanisms through which coffeeshops could have an effect on the number of dropouts; on the one hand, an increase in the number of coffeeshops increases soft drugs usage, which in turn decreases school performance, and as such would lead to an increased number of dropouts. The second effect is that of increased criminal activity in a neighbourhood harbouring coffeeshops. Through an increase of criminal activity, students can engage in criminal activity themselves, and therefore have a higher probability of dropping out.

To formally investigate the hypothesised effect of coffeeshops on dropouts, a dataset containing dropout rates of all MBO schools of the Netherlands was retrieved from the ministry of education. Furthermore, a dataset made by the Netherlands Bureau for Economic Policy Analysis containing data on the distance to the border of each city was retrieved. This dataset also contained other demographic variables per city, such as the number of citizens. These datasets were merged to investigate the relationship between the number of coffeeshops per 10.000 citizens, and the number of dropouts. To properly identify the effect, the distance of the city to the border was used as an instrument, as the variation in distance to the border is thought to be exogenous.

While using the dataset on MBO students, very small increases or decreases in the proportion of dropouts were found; none of them being significant. Using the absolute number of coffeeshops did not change this fact. Using an extra instrument (airport) did not change the predictions either. Based on the analysis of this dataset, one would conclude that there is no significant relationship between the number of coffeeshops and the proportion of dropouts. However, while running the same analysis with a dataset containing data on high school students, significant increases in the number of dropouts were found. In fact, increasing the number of coffeeshops per 10.000 citizens with one led to a predicted increase of the proportion of dropouts with 0.1 percentage point. Increasing the absolute number of coffeeshop should increase the proportion of dropouts with 0.0015 percentage point.

These results should be interpreted with caution, however. As shown in all predictions, OLS estimation led to larger and significant results than 2SLS estimations did. OLS is however not suited to calculate the effect, as argued in section 3. The 2SLS approach used the distance to the border as an instrument to provide exogenous variation in the number of coffeeshops. This instrument is somewhat weak, though. Given the circumstances this was one of the few options to provide exogenous variation, yet it may have biased the results. Furthermore, data on the number of coffeeshops in 2009 was not available. Even though the number of coffeeshops per municipality had changed very little between 2008 and 2010, this may have caused a bias as well.

In conclusion, it appears that coffeeshops may have a negative effect on school performance. The analysis suggest that high school students may experience negative effects from the presence of coffeeshops. It is difficult to assess whether the identified effect is due to high school students indeed experiencing more negative effects, or due to their dataset being larger. Furthermore, this thesis has not been able to identify the exact channel through which adults and minors are affected, because the data that was available did not include any information on the reason of dropping out of school. Further research, with a micro level design, would be needed to be conclusive about the effects of coffeeshops.

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