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Does parental divorce cause more risky behaviour?

The effect of parental divorce on risky behaviour in their offspring

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*Parental divorce does also mean parental separation in this report.

Summary

This report examines the effect of parental divorce on risky behaviour by their children in later life. Risky behaviour will be examined from the perspective of alcohol, cigarettes and hard/soft drug use.

First, the effect of parental divorce on these three risky behaviours will be examined from the literature. The literature shows effects from parental divorce on alcohol, cigarettes and soft drugs. For hard drugs use the literature did not find clear effect. After examining the effects of parental divorce on risky behaviour, a number of mechanisms between parental divorce and risky behaviour will be discussed.

In this study data from the LISS panel will be used. The LISS panel consist of data derived from approximately 7500 individuals that complete online questionnaires every month This study took a close look at the models used to test the hypotheses. The assumptions underlying these models were examined explicitly.

For this study OLS was used. However this method combined with the available data did not fulfil all necessary assumptions. Therefore, Gologit2 and ordered logistic regression methods will be used to look more precise at the effect of parental divorce on alcohol use. Binary logistic regression will be used to look more closely at the effect of parental divorce on smoking and drug use.

The results of this study indicate that parental divorce does have an effect on cigarette, soft drugs and hard drugs use for children in later life. However, no effect was found between parental divorce and alcohol use in children in later life. In the discussion, a number of limitations are discussed and suggestions are made for follow-up studies

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1. Introduction

In 2019, 30041 marriages ended in divorce in the Netherlands. The number of registered partnerships that ended in divorce in 2019 was 2735 in the Netherlands (Centraal Bureau voor de Statistiek, 2019). Richtlijnen Jeugdhulp en Jeugdbescherming (2020) has calculated that in 2016, 86000 minors experienced a divorce from their parents in the Netherlands. Centraal Bureau voor de Statistiek (2018) found that 30 percent of fifteen year olds did not live at one address with both parents in 2017 in the Netherlands.

A divorce can have a great impact on the people involved and especially on children. The turmoil caused by a divorce has emotional but also cognitive impact on children. Children with divorced parents show more difficulty with skills such as reading and math (Amato & Anthony, 2014). Moreover, these children are more likely to have lower self-esteem (Amato & Anthony, 2014) and are often also more likely to exhibit risky behaviour (Zeratsion et al., 2014). It may be that the above issues and other difficulties in children resulting from parental divorce also have long-term effects on these children.

The purpose of this study is to find out whether parental divorce has long-term effects on risky behaviours in adolescents such as drinking, smoking and drug use in the Netherlands. In order to obtain a clear understanding, the following question will be answered:

What are the (long-term) effects of parental divorce during childhood on risky behaviour such as drinking alcohol, smoking and drugs use for their children (in later life/adulthood)?*

In this study the focus will be on the effect of parental separation/divorce before the age of 18 on risky behaviour for people after their 18th birthday. Therefore the focus will be on people who were between the ages of 0-18 when their parents divorced and are now older than 18 years.

This study will also examine whether the effect of a parental divorce on risky behaviour will differ for different age categories. Is there a different effect of the divorce if a child is younger or older?

I will examine whether the effect of parental divorce on alcohol consumption and smoking for offspring can also be found within the Dutch population of the LISS panel. This is of scientific relevance because until today little is known about this relationship in the Netherlands. A novelty in this study is looking at three different age categories. By looking at the effect of parental divorce in different age categories, I may be able to determine at what age children are the most vulnerable to exhibit risky behaviours at older age. If a relationship will be found between parental divorce and risky behaviours in the Netherlands, more attention will have to be paid to preventing children with divorced parents from engaging in risky behaviour. The age of the child could be taken into account if a difference in the effect of parental divorce is found in between different age categories.

When no relationship can be found between parental divorce and risky behaviour, this may mean that parental divorce and the mechanisms involved, such as stress, do not have as much effect on risky behaviour as is thought and expected from hypotheses in the literature.

This study is the first to look at the effect of parents separation on (hard) drugs use. Not much is known about the effect of parental divorce on (hard) drugs use. When an effect will be found here, it is of societal interest to look at new measures to protect children of divorced parents against the temptation of drug use.

The structure of the report is as follow: Firstly, an overview will be given of the links between risky behaviour and parental divorce that have been found in the literature. Secondly, a number of mechanisms that are likely to play a role in the relationship between parental divorce and risky behaviour will be explained. After this, the design of the study will be discussed. Following, the results will be presented, followed by a conclusion as well as a discussion.

2. Theoretical framework

2.1 The effect of parental divorce on alcohol consumption

There is a relatively large body of research on the effect of parental divorce on alcohol consumption. Most research shows an effect for offspring on alcohol consumption when parents are divorced. However, a few studies concluded that divorce and alcohol consumption are also related to other factors. Some studies show that there is an association between the age of the child at the time of parental divorce and alcohol consumption.

Auersperg, Vlasak, Ponocny & Barth (2019) did a meta-analysis of ten studies on the effects of parental divorce. These ten studies mostly used questionnaires, screening questions and diagnostic interviews. A significant association was found between parental divorce and alcohol use.

One study that was included in the meta-analysis of Auersperg et al. (2019) was a study by Huurre, Lintonen & Kaprio (2010) in which they used (postal) questionnaires. There was concluded that one of the main reasons for excessive alcohol use at age 32 for Finnish men was parental divorce at younger age.

Other studies found a significant relationship between alcohol consumption and parental divorce when accounting for various variables (Hope, Power & Rodgers, 1998; Gustavsen, Nayga & Wu, 2015; Thompson, lizardi, Keyes & hasin, 2008; Wolfinger, 1998).

In some studies an effect was found that disappeared when several different variables were taken into account. Jackson, Roger & Sartor (2016) found a significant higher risk of drinking initiation for people with divorced parents at younger age. However, this effect disappeared when accounting for perceived stress, familial alcohol involvement and psychopathology.

Kristjansson, Sigfusdottir, Allegrante & Helgason (2009) reported a significant relationship between parental divorce and adolescent alcohol use. This effect disappeared after controlling for other variables. They found that family conflicts is an important factor for alcohol use in offspring.

According to the study of Jeynes (2001) children with divorced parents are more likely to drink. In contrast with most studies this study also looked at whether the effect was greater when the divorce was at maximum 4 years ago among young people. There was only a significant greater effect found for five or more consecutive drinks at one night (binge drinking according to Jellinek (2020)) and alcohol use during schooltime. There were no significant differences found for the amount of days with alcohol consumption in the last month or last 12 months. Another method that is used to look at the effect of parental divorce on alcohol use is fixed effects. Arkes (2013) used fixed effects and reported that two to four years before divorce and also after parental divorce, youngsters are more likely to engage in alcohol. This effect generally persisted as time passes from the divorce.

These findings on the relationship between parental divorce and alcohol consumption leads to the first hypothesis:

Individuals who were a child (0-18) when their parents divorced are generally more likely to drink alcohol, compared with individuals whose parents did not divorce when they were a child.

2.2 The effect of parental divorce on smoking

Children of divorced parents not only drink more at older age, they would also be more likely to smoke more often.

Parental divorce is significantly associated with an increase in smoking (Amato & Anthony, 2014).

Mostly other variables (partly) influence the effect, some of these variables are socioeconomic characteristics. Wolfinger (1998) found an increase in likelihood for being a smoker after parental divorce, however socioeconomic characteristics also accounted for a portion of this relationship.

Also the relationship with parents can influence the effect or even make the effect of parental divorce on smoking disappear. Kristjansson et al. (2009) reported a relationship between parental divorce in childhood and adolescent cigarette smoking during last 30 days. This relationship was not significant when controlling for relationship with parents.

Auersperg et al. (2019) found a significant association between parental divorce and smoking with a meta-analysis across five studies. Furthermore, a study by Gustavsen et al. (2015) used two surveys to look at an effect and the results suggested that children with divorced parents are more likely to smoke tobacco.

This leads to the second hypothesis:

Individuals who were a child (0-18) when their parents divorced are generally more likely to smoke (cigarettes), compared with individuals whose parents did not divorce when they were a child.

2.3 The effect of parental divorce on drug use

When looking at risky behaviours in children of divorced parents, a direct link between parental divorce and drug use (not including alcohol) is not often made. Nevertheless, there is some correlation found in the literature between parental divorce and drug use.

In a meta-analysis between parental divorce and drugs use there was a significant association found (Auersperg et al., 2019). Windle and Windle (2018) found that parental divorce and maternal alcoholism predicted marijuana use. Skeer, McCormick, Normand, Buka & Gilman (2009) investigated underlying mechanisms in substance use and found that familial conflict is significantly associated with the risk of substance use disorders during adolescence.

Drugs addicts more often come from families were their parents divorces in childhood or adolescence (Zimić & Jukić, 2012). Arkes (2013) found that after parental divorce, youth are more likely to engage in marijuana, and other drug use. The increased risk of using marijuana within two years after the divorce was approximately twelve percent. This effect remained the same as the years passed.

Other studies mainly found an effect for adolescents. Gustavsen et al. (2015) reported that the probability of marijuana use was higher for children aged 18-24 years with divorced parents. This effect was not found for hard drugs.

In contrast with the relationship between marijuana use and parental divorce, from the literature above, no clear results about parental divorce and the use of hard drugs can be found. However, it appears that family circumstances contribute to drug use and addiction (Skeer et al., 2009; Zimić & Jukić, 2012).

Therefore, a relationship is to be expected between parental divorce and (hard) drug use and this leads to the following hypothesis:

Individuals who were a child (0-20) when their parents divorced are generally more likely to use marijuana and/or hard drugs, compared with individuals whose parents are not divorced when they were a child.

As can be seen in the hypotheses above I expect an effect from parental divorce on soft and hard drugs use. However, I expect the effect to be greater for soft drugs, mainly due to the lack of direct evidence from the literature of parental divorce on hard drugs use.

2.4 Mechanisms between parental divorce and risky behaviour: Stress, Emotions processing and (low) self-esteem

Parental divorce sometimes creates problems that affect the risky behaviour of the children later in life, so-called mechanisms. Some of these problems/mechanisms that I expect to have an effect on risky behaviour are stress, emotion processing and low self-esteem. Huurre, Junkkari & Aro (2006) found that parental divorce is an indicator for stress in childhood. The influences of stress in childhood persist in adulthood. This stress could cause children of divorced parents to engage in more risky behaviour.

A link between stress and alcohol use was found (Anthenelli & Grandison, 2012).

Furthermore, people who have more stress also smoke more cigarettes (Jahnel, Ferguson & Shiffman, 2019). People with parental divorce reported themselves to have lower self-esteem, and experience more difficulties in communication with others. Some people even reported difficulties with emotional states such as anger, jealousy and hurt. Children of divorced parents also have trouble with intimate relationships, in later life (Cartwright, 2006). Furthermore, parental divorce can have a profound effect on children's behaviour and emotional status (Stadelmann, Perren, Groeben & Von Klitzing, 2010).

Obeid, Haddad et al. (2020) found that people with high levels of stress and alexithymia (low ability to process emotions) have high(er) risk of alcohol use disorder. Also lower self-esteem is positively associated with smoking and excessive alcohol consumption (Szinay, Tombor, Garnett, Boyt & West, 2019). Logistic models from a study of Veselska, Geckova, Orosova, Gaidosova, van Dijk & Reijneveld (2009) showed associations between negative self-esteem and smoking and cannabis use. A longitudinal study in the USA found that youth from grade 7 through 12 with low self-esteem had higher odds for recent binge drinking (Bartsch, King, Vidourek & Merianos, 2017).

Difficulties in emotion regulation, stressful life events in the last year and perceived stress in the last month are significant predictors of problematic marijuana use (Cavalli & Cservenka, 2021). However, these mechanism cannot be found in the data available for this study and will therefore not be used in this study. This does not have to be a problem since not accounting for mechanisms does not cause biased effects. In this study the treatment is parental divorce. Mechanism are a result of a treatment and so the effect is automatically included by the treatment and including mechanism could take away a part of the effect of the treatment.

2.5 A mechanism or determinant between parental divorce and risky behaviour: Socio-economic status

Another possible mechanism between parental divorce and risky behaviour is (low) Social Economic Status (SES). However, SES has two sides. The first side is that the SES of the separated parents is often lower after a divorce, particularly because of a decrease in income after a divorce. This can have an effect on the risky behaviour of the children at a later age. Divorce has a negative effect on the equalised household incomes for men and woman. However, the decrease in income for women is bigger (De Vaus, Gray, Qu & Stanton, 2017).

Thomas & Högnäs (2015) found evidence that suggests that a decline in family SES experienced after a parental divorce is the most important change in the early environment that perpetuates negative outcomes. Low-SES groups on average face more stress and have less knowledge of risks. This might encourage them to behave more unhealthy (Pampel, Krueger & denney, 2010). Lower parental SES background is associated with increased odds of nicotine, marijuana and prescription drugs use (Bello et al., 2019). Marzban et al. (2017) found an inverse relationship between SES and life-time alcohol consumption.

The other side of the story is that low SES might be a determinant, rather than a mechanism, that increases the chances of a divorce. Lower educated people have a higher divorce risk than the higher educated (De Graaf & Kalmijn, 2006). Female education is positively related to marital stability, thus females with lower education have bigger chance to divorce (Boertien & Härkönen, 2018). For the variable SES only education level with diploma will be used as control variable in this study. This is because most other variables are not available in the data that will be used. If education is primarily a determinant, it is appropriate to include this variable because otherwise the effect of parental divorce on risky behaviour could be biased. However, if education is partly or primarily a mechanism, the effect of parental divorce on risky behaviour will be partly absorbed by the mechanism. Then the effect would be underestimated.

3. Methodology

For this study secondary data from the LISS (Longitudinal Internet studies for the Social Sciences) panel administered by CentERdata (Tilburg University, The Netherlands) will be used. The use of the data has been approved by CentERdata. Quantitative research will be carried out. The LISS panel consist of data derived from approximately 7500 individuals that complete online questionnaires every month. For this research data from the core studies Health, Family and Household and the Background variables will be used. Both Health and Family and Household are longitudinal data. The background variables are a single wave study. Certain variables from waves of the Health and Family and household data and the background variables will be merged. This merged data includes all the necessary data to create the required dependent, independent and control variables.

OLS regression will be carried out for each outcome variable to get an overview of the effects of parental divorce on risky behaviour by children in later life. Hereafter, I will explain why OLS is not the most suitable method. This is because with the available data several assumptions for OLS will not be met. Following other methods will be introduced. The motivation and validation of the assumptions of each method will be explained after the methodology. To validate the first hypothesis, ordered logistic regression analysis will be carried out. For the second hypothesis, binary Logistic regression will be used. For the third hypothesis, binary Logistic regression will be used to look at multiple outcome variables. These methods are the most suitable methods for the dependent and independent variables I will use to look at a long-term effect of parental divorce on risky behaviour. The regression shown below will be used to look at the three hypothesis. There will be one or more different dependent variables for each hypothesis. The rest of the variables will remain the same in the different regressions.

3.1 Outcome variables

To validate the first hypothesis, I will look at the effect of parental divorce on alcohol consumption. Therefore the first variable indicates how much alcohol someone drank per week on average for the last 12 months. This variable has 8 categories (almost every day, five or six days per week, three or four days per week, once or twice a week, once or twice a month, once every month, once or twice a year, not at all over the last 12 months).

The Jellinek guidelines state that no more than one standard glass should be drunk per day. In addition, people should not drink for at least two days a week to prevent habituation (Jellinek, 2020). With this outcome variable there can be checked whether people have at least 2 alcohol free days per week. However, the amount of alcohol consumptions per day/week and binge drinking cannot be examined with this variable. Furthermore, this outcome variable for alcohol use is different from all other studies that are discussed in the literature section. In most studies, alcohol consumption was measured as the amount of drink consumed in a given period of time. For example, one week or one month.

For the second hypothesis, I will look at the effect of parental divorce on cigarette smoking. Therefore, the second outcome variable will be a binary variable that indicates 1 if people smoke or ever smoked cigarettes and 0 if people never smoked cigarettes. In this study, it was decided to look at the effect for people who smoke or have smoked. The effect of parental divorce on smoking could disappear for example because smoking is becoming less normal/socially accepted nowadays compared with the past. It could be argued that a longer period should also be considered for alcohol and drug use. However, smoking was the only for which data was available over a longer period of time.

For the third hypothesis, I will look at the effect of parental divorce on drug use. Drug use is divided in multiple categories in the panel (Sedatives, soft drugs, XTC, hallucinogens, hard drugs, laughing gas). Two outcome variables will be made to look at the effect of parental divorce on soft and hard drugs separately. The third outcome variable will be a binary variable that will indicate whether someone used soft drugs (such as hashish, marijuana) last month. The fourth outcome variable will be a binary variable. For this variable the amount of sedatives, XTC, hallucinogens, laughing gas and hard drugs (such as stimulants, cocaine, heroin) that someone used last month will be merged together and adjusted to a binary variable. This variable will indicate whether someone used at least one of the above mentioned hard drugs in the last month. These variables will be merged because of the low amount of observations for people who used drugs in the observed data. Merging these variables could perhaps ensure that there are enough observations. The variables sedatives, XTC, hallucinogens, laughing gas and hard drugs will also be adjusted to a binary variable and used for a separate regressions that will be available in the appendix.

3.2 Regression analysis

Below the regression that will be used to test the hypothesis can be seen. In this regression Y will stand for one of the different outcome variables in each regression.

$$\mathrm{Y} = \beta_0 + \mathrm{age}_{0} - {}_{6} * \beta_1 + \mathrm{age}_7 - {}_{12} * \beta_2 + \mathrm{age}_{13} - {}_{18} * \beta_3 + \mathrm{male} * \beta_4 + \mathrm{e}_2 * \beta_5 + \mathrm{e}_3 * \beta_6 + \mathrm{e}_4 * \beta_7 + \mathrm{e}_5 * \beta_8 + \mathrm{e}_6 * \beta_9 + \mathrm{e}_7 * \beta_{10} + \mathrm{e}_8 * \beta_{11} + \mathrm{a} * \beta_{12} + \epsilon$$

The independent variables in all the regressions will be dummy variables, except for one continuous variable. The first variable will be made with three different age categories. (0-6, 7-12, 13-18).

These three categories were chosen for various reasons. Firstly, the use of more than three categories could result in too few observations per category. In addition, all three categories indicate a different phase in the child's life when looking at school careers. The first category (0-6) consists of babies, toddlers and pre-schoolers. The second category (7-12) consists mainly of children in grades 3 to 8 of the Dutch primary school. The third category (13-18) consists of teenagers and adolescents. Often, these children are in pre-vocational secondary education (vmbo), senior general secondary education (havo), or the pre-university education (vwo) and in some cases they are in senior secondary vocational education (mbo) or higher vocational education (hbo/wo).

Each dummy variable will show at which age category the child was when his or her parents divorced. There will be a total of four dummy variables for the age categories, three age categories between 0-18 and one dummy with a category for people whose parents did not divorce or did divorce after they turned 19 as a reference category. For example, if your parents divorced when you were 11 years old, then the dummy variable for age category 7-12 ($d_{7\text{-}12}$) will be 1 and all other will be 0. β_1 indicates the effect of a parental divorce on age 0-6 compared with the effect of people whose parents did not divorce (before the age of 19) on the outcome variable. The variable male is a control variable which indicates 1 if the participant is a male and 0 if the participant is a female. β_4 indicates the effect of being a male on the outcome variable. The variable 'e' is a dummy variable and stands for education level with diploma, There are 8 educational dummy variables (primary school, vmbo, havo/vwo, mbo, hbo, wo, other, not (yet) completed any education/not yet started any education). Not (yet) competed any education and not yet started any education were separated options in the survey but are merged because of low observations with value 1 for both categories. This category will be called "no" from this point. The reference category will be the dummy for people were the highest education with diploma is primary school. e_2 will be 1 if the highest education a person completed with a diploma is vmbo, e_3 will be 1 if the highest education a person completed with a diploma is havo/vwo and so forth. β_{11} indicates the effect of people without/no education compared with persons with a primary school diploma as highest degree on the outcome variable. The variable a will indicate someone's age. ϵ is the error term.

3.3 Control variables

The extent to which a person suffers from/needs help after parental divorce depends to a large part on race, socioeconomic status, family structure, school, and parent-child relationships (Demir-Dagdas, Isik-ercan, Intepe-Tingir & Cava-Tadik, 2018). Not all of these variables are available from the data and therefore not all variables can be included in the model. The model above will look at the control variables education level, male and age. These variables were available from the data and an effect has been found from the literature.

(Higher) education level could reduce the effect of parental divorce on risky behaviour. Children in preparatory secondary vocational education (vmbo) drink more alcohol than children in pre-university education (vwo) (de Looze et al., 2014; van Dorsselaer et al., 2016). It is likely that this difference will remain in later life because early alcohol use is one of the strongest predictors of later alcohol use disorders, with early use usually taking place during puberty (Blomeyer et al., 2013). In line with previous findings, a study in the united states of America found that people who take academically advanced courses in high school have lower drinking and binge drinking rates during high school. However, these people have higher (binge) drinking rates when they are between 20 and 26 years old (Crosnoe & Riegle-Crumb, 2007). When looking at all ages, lower educational groups in the Netherlands are more likely to have excessive alcohol consumption (Droomers, Schrijvers, Stronks, Van de Mheen & Mackenback, 1999; Droomers, Schrijvers & Mackenbach, 2004).
The only problem with educational level as a control variable is that educational level might be influenced by parental divorce. Then education level is a mechanism. When this is the case, adding this variable as a control variable may cause the effect to be underestimated. Brand, Moore, Song & Xie (2019) did not found an impact from parental divorce on the education of the children. However, another study found that parental divorce has a net negative effect on children’s education on average and that this effect is stronger when divorce is more common (kreidl, Štípková & Hubatková, 2017). Nevertheless, I argue that this effect is small and therefore does not have to mean that people’s highest educational degree would differ when parents would not divorce. Therefore I think that highest educational degree with diploma is a good control variable.

4. Descriptive statistics

The descriptive statistics of the independent variables are presented in table 1. A few adjustments had to be made to the data of the panel. People who only filled in the survey about Health and not Family & Household or people who only filled in the survey about Family & Household and not Health were removed. Also people who did not know whether their parents divorced or people whose parents never had a relationship were removed. Next to that, all participants under the age of 18 were removed. In addition dummy variables were created and variables were adjusted to fit to the models. In the end, a total of 4518 observations remained.

Variable	Obs.	Dummy (%)	Mean	Std. Dev.	Min	Max
Age 0-6	4518	170 (3.76%)	.038	.19	0	1
Age 7-12	4518	147 (3.25%)	.033	.177	0	1
Age 13-18	4518	139 (3.08%)	.031	.173	0	1
Male	4518	2093 (46.33%)	.463	.499	0	1
Age	4518		54.516	17.617	18	103
1.primary school	4518	126 (2.79%)	.028	.165	0	1
2.vmbo	4518	910 (20.14%)	.201	.401	0	1
3.havo/vwo	4518	462 (10.23%)	.102	.303	0	1
4.mbo	4518	1101 (24.37%)	.244	.429	0	1
5.hbo	4518	1185 (26.23%)	.262	.44	0	1
6.wo	4518	593 (13.13%)	.131	.338	0	1
7.other	4518	82 (1.81%)	.018	.134	0	1
8.no	4518	59 (1.31%)	.013	.114	0	1
Dependent variables:						
Alcohol use last 12 months	4509		4.727	2.235	1	8
Cigarettes	4518	2236 (49.49%)	.495	.5	0	1
Soft drugs	4518	128 (2.83%)	.028	.166	0	1
Hard drugs	4518	162 (3.59%)	.036	.186	0	1

Table 1: Descriptive statistics of the independent variables (in all models) and dependent variables. The row Dummy indicates the number of observations that have value 1 for each dummy variable with percentage of total observations within parenthesis.

4.1 Representativeness of the sample

To check the representativeness of the sample, the statistics of the Dutch population are compared with the sample above.

For the Dutch population, the percentage of children whose parents are divorced is not known for the specific age groups used in this study. However, there is known that in 2017 about 30% of the fifteen-years-old children do not live with both parents at the same address. In 1997 this was around the 20% (Centraal Bureau van de Statistiek, 2018). However, since the average age of the population is higher than 50, and thus probably most of parental divorce with children happened more than 30 years ago. It is reasonable to say that it is more fare to compare the sample with the percentage of 1997. Still, the percentage of divorced parents in the Dutch population is much higher than that of the sample.

The percentage of males in the Dutch population is 49.7% (Centraal Bureau voor de Statistiek, 2020). This is almost the same as the percentage of males in the sample. The average age in the Netherlands is 42.2 years (Centraal Bureau voor de Statistiek, 2021). By way of comparison, the average age of the Dutch population is more than ten years younger than the average age of the sample.

Onderwijs in cijfers (2020) shows the statistics of the highest level of education of the Dutch population. The data below regarding the education level of the Dutch population is taken from this source. When looking at statistics of the highest level of education in the Dutch population, it appears that people are often grouped in a different way than what is done in this study regarding the highest level of education. Nevertheless, an attempt will be made to compare the sample with the Dutch population as closely as possible regarding highest educational level. Almost 8% of the Dutch population has primary school as highest degree. This is much higher then in the sample. Vmbo has been merged with havo- and vwo-superstructure and mbo-1 in the statistics of the Dutch population. 18.5% of people have achieved this as their highest education in the Dutch population. Even combined the percentage of the Dutch population is still slightly lower than the percentage that has vmbo as the highest education in the sample. Havo and vwo have been merged with mbo-2, mbo-3 and mbo-4 in the statistics of the Dutch population and 37.8% of the Dutch population has one of these diploma's as highest degree. If the percentages of havo/vwo and mbo from the sample are added together a percentage comes out that is close to the percentage of the Dutch population. The percentage of people who have a hbo or wo as highest degree (bachelor or master) is 34.2% for the Dutch population. This is lower than the percentages for hbo and wo as highest degree added up in the sample. For 1.6% of the Dutch population the highest degree is unknown. This is close to the amount of people with "other" as highest degree in the sample. However, in the statistics of the Dutch population people without educational degree are not mentioned. It is also important to note that these data of the Dutch population regarding educational level are from persons aged between 15 and 75 years (with some exceptions).

For alcohol use in the last 12 months, no data could be found from the Dutch population that could be compared to the sample.

In 2019, about 54% of the Dutch population has ever smoked (ANP, 2020). This is slightly higher than the percentage in the sample. This seems a small difference, but it should be kept in mind that the sample is on average older than the Dutch population and that smoking used to be considered more normal.

Last month, 4.9% of the Dutch population used soft drugs (trimbos-instituut, 2020). This percentage is slightly higher than the percentage in the sample. If we add up the use of different hard drugs in the Dutch population, it emerges that 2.4% of the Dutch population used hard drugs last month (Trimbos Institute, 2020). However, it could be that the same persons have used several types of hard drugs in the past month and therefore the actual percentage is lower. This is a bit lower than the percentage of hard drug use in the last month in the sample.

5. OLS

In order to get a clear picture of the data and possible results, OLS regressions will be performed for all dependent variables.

5.1 OLS on alcohol use last 12 months

Table 2 shows the OLS regression on the outcome variable alcohol use last 12 months. Males report on average 0.707 categories lower for alcohol use in the last 12 months compared with women, ceteris paribus. This is significant on a 1% significance level.

People who have vmbo as highest degree report on average 0.528 categories lower compared with people who have primary school as highest degree, ceteris paribus. This is significant on a 5% significance level. People who have havo/vwo as highest degree report on average 0.926 categories lower compared with people who have primary school as highest degree, ceteris paribus. This is significant on a 1% significance level. Meaning that people who have havo/vwo on average drink more alcohol. People who have mbo as highest degree report on average 0.607 categories lower compared with people who have primary school as highest degree, ceteris paribus. This is significant on a 1% significance level. People who have hbo as highest degree report on average 1.047 categories lower compared with people who have primary school as highest degree, ceteris paribus. This is significant on a 1% significance level. People who have wo as highest degree report on average 1.381 categories lower compared with people who have primary school as highest degree, ceteris paribus. This is significant on a 1% significance level. A lower category always shows that people report that they drink more alcohol on average.

People report on average 0.026 categories lower when there age increases with 1 unit, ceteris paribus. This is significant on a 1% significance level.

5.2 OLS on cigarettes

Table 2 shows the OLS regression on the outcome variables cigarettes and soft drugs and hard drugs. The coefficient plot of the results can be seen in figure 1. Firstly, I will discuss the results of the regression on cigarettes.

The variable d_{0-6} is significant on a 10% significance level. People whose parents divorced before they were younger than seven years old (0-6) are 8.74% more likely to have ever smoked compared with people whose parents did not divorce (before the age of 19), ceteris paribus. People whose parents divorced when they were between 7-12 years old are 15.8% more likely to ever have smoked, compared with people whose parents did not divorce (before the age of 19), ceteris paribus. This is significant on a 1% significance level. Table 2 also shows that people whose parents divorced when they were between 13-18 years old are 10.3% more likely to ever have smoked compared with people whose parents did not divorce (before the age of 19), ceteris paribus.

The chance that some has ever smoked increases on average 0.007% per additional year that someone lives, ceteris paribus.

5.hbo is significant on a 5% significance level. People who have hbo as highest degree with diploma are 12.3 percentage point less likely to have ever smoked compared with people who have primary school as highest degree with diploma, ceteris paribus. People who have wo as highest degree with diploma are even less likely to have ever smoked. These people are 17.6 % less likely to have ever smoked compared with people who have primary school as highest degree, ceteris paribus. This is significant on a 1% significance level.

5.3 OLS on soft drugs

The OLS regression on soft drugs that can be found in table 2 shows that people whose parents divorced when they were between 7-12 years old are 6.85% more likely to have used soft drugs in the last month compared with people whose parents did not divorce (before the age of 19). This is significant on a 5% significance level. Males are on average 2.81% more likely to have used soft drugs in the last month compared with woman on a 1% significance level. However, the chances that someone used soft drugs in the last month decreases with 0.001% per year of life. This is significant on a 1% significance level. A coefficient plot of the results can be found in figure 1.

5.4. OLS on hard drugs

Table 2 shows the results of the OLS regression on hard drugs use. This table shows that people whose parents divorced when they were between of 7-12 years old are 3.83% more likely to have used hard drugs in the last month compared with people whose parents did not divorce (before the age of 19), ceteris paribus. This is significant on a 10% significance level. However no other variable is significant in this model. Meaning that these variables do not explain hard drugs use in the last month for the observations in this dataset. A coefficient plot of the results can be found in figure 1. The OlS regressions on all the hard drugs variables separated can be found in the appendix in table 11A.

5.5 Assumptions & validation OLS regressions

OLS regressions was performed on all the dependent variables. A somewhat clearer interpretation of the variables can be given with this method in comparison with other methods. Some other models use log odds which are difficult to compare with other models or other variables. However, this clearer interpretation of OLS is a trade-off. Multiple assumptions of the OLS models do not hold in this case. Logit models were developed partly because OLS with categorical outcome variables violates some assumptions. The assumptions violated by OLS with categorical dependent variables will be discussed.

The first assumption that is violated is the linear regression assumption. The relationship between X and the mean of Y must be linear. However with categorical dependent variables this is not the case. Here, the outcome variables are categorical in all cases. To be precise, the outcome variables consist of three binary dependent variables and one dependent variable with eight categories.

The second assumption that is violated is that there is random sampling of the observations. The data is taken from the panel which is approximately a random sample from the Netherlands. However, some observations had to be removed for this study. Therefore we cannot be sure whether the sample is random. In section 4.1, it was shown that the statistics of the sample do not fully correspond to the Dutch population. Furthermore, parental divorce is not a random event. However, OLS will use this as if it parental divorce is a random event.

The third assumption that is violated is the conditional variance assumption or homoscedasticity. The OLS regression will suffer from heteroskedasticity as the mean changes. This will make the t-statistics biased.

Furthermore the predicted values must lie between 0 and 1. However, with a binary and categorical dependent variables these predicted values can be above 1 or below 0

	Cigarettes		Soft drugs		Hard drugs		Alcohol use last 12 months	
	OLS		OLS		OLS		OLS	
Age_06	0.0874**	(2.27)	0.0310	(1.61)	0.0221	(1.20)	0.132	(0.81)
Age_712	0.158***	(3.76)	0.0685***	(2.67)	0.0383*	(1.77)	-0.140	(-0.82)
Age_1318	0.103**	(2.43)	0.0215	(1.08)	-0.0140	(-1.10)	-0.0193	(-0.12)
Male	0.0210	(1.45)	0.0281***	(5.42)	-0.00333	(-0.58)	-0.707***	(-10.95)
2.vmbo	-0.0659	(-1.46)	0.00435	(0.30)	0.000386	(0.02)	-0.528**	(-2.32)
3.havo/vwo	-0.0883*	(-1.84)	0.00227	(0.14)	-0.0118	(-0.56)	-0.926***	(-3.95)
4.mbo	-0.0387	(-0.86)	-0.0151	(-1.05)	-0.0210	(-1.06)	-0.607***	(-2.72)
5.hbo	-0.123***	(-2.76)	-0.0180	(-1.28)	-0.0169	(-0.85)	-1.047***	(-4.69)
6.wo	-0.176***	(-3.73)	-0.0188	(-1.22)	-0.0219	(-1.06)	-1.381***	(-6.03)
7.other	-0.0864	(-1.25)	-0.0138	(-0.76)	-0.0109	(-0.39)	-0.0469	(-0.14)
8.no	-0.102	(-1.36)	0.0905*	(1.90)	0.0122	(0.33)	-0.252	(-0.71)
Age	0.00666***	(15.53)	-0.00142***	(-8.08)	-0.000200	(-1.12)	-0.0263***	(-13.76)
Constant	0.200***	(3.97)	0.0975***	(5.33)	0.0603***	(2.65)	7.296***	(30.09)
N	4518		4518		4518		4509	

Table 2: OLS regression on cigarettes, soft drugs, hard drugs and alcohol use last 12 months. First column shows the dependent variables and the second column shows the regression method. Statistics in parentheses. **** p<0.01, ** p<0.05, * p<0.10.*

6. Assumptions

Using STATA I will perform a gologit2, ordered logistic regression and three binary logistic regressions in addition to the OLS regressions. These models and methods must meet some assumptions. Below, the used models and assumptions will be discussed. Some models will be discussed several times because the dependent variable is different and therefore some assumptions need to be tested again.

6.1 Gologit2 on alcohol use last 12 months

To test the first hypotheses ordered logistic regression was chosen because this is one of the best ways to do a regression with a categorical outcome variable when you assume a natural order. A natural order can be assumed because the categories for alcohol consumption run from high to low (1. almost every day, 2.five or six days per week, 3. three or four days a week, 4. once or twice a week, 5. once or twice a month, 6. once every two months, 7. once or twice a year, 8. not at all over the last 12 months). Ordered logistic regression will probably give the most accurate values. However, this method has a few assumptions that must be met.

The first assumption for a Ordered logistic regression is that the dependent variable is ordered. For the ordered logistic regressions the variable for alcohol use in the last 12 months will be used as outcome variable. This variable is ordered and for this variables a natural order is assumed.

The second assumption is that at least one the independent variables is either continuous, categorical or ordinal. This assumption is also met.

The third assumption is that there is no multicollinearity. To test this the Variance inflation factor (from now on VIF) test will be used in Stata. The VIF test evaluates whether factors are correlated and therefore checks for multicollinearity. Normally, a VIF-value higher than 10 will be seen as a violation of the assumption. However, Rogerson (2019) concludes in his research that a VIF higher than 5 violates the assumption. Because it is not really clear whether the value 5 or 10 must be used to check whether the assumption is violated, there cannot be said if the assumption is really violated. In this study I assume that a VIF value lower than 10 does not violate the assumption. I will comment on this later. However, it is important to note that in the regression some variables have a VIF value higher than 5 and that this could mean that the assumption is violated. This can be seen in table 1A in the appendix. This could mean that the measured standard error of the regressions is higher than it should be. The p-values could therefore be higher and this could make the results less significant. Therefore it could be that a false null hypotheses will not be rejected for the variables were the VIF-test is higher than 5. Also a correlation matrix was made for both outcome variables. This correlation matrix can be seen in table 2A in the appendix. No value was above the lowest threshold of 0.7 was found. Unlike the VIF test, this does not give cause for concerns regarding the third assumption**.**

The last assumption for ordered logistic regression is that there are proportional odds. This is also called the Parallel regression assumption. The relationship between the lowest category versus all higher categories must be the same as the relationship between the next lowest category and all higher categories etcetera. To test the last assumption the Brant test will be performed. Table 3A in the appendix shows that the values of the Bant test are significant and thus the parallel regression assumption does not hold. Therefore ordered logistic regression cannot be performed because the model will not give a good output.

However, a user-written program called gologit2 offers a solution. This program is less restrictive than the ordered logistic regression and can therefore be performed because this program does not have the parallel regression assumption. Next to this, no extra assumptions needs to be tested. The disadvantage is that this method produces results that are less clear than with ordered logistic regression. The values of the dependent variable are irrelevant except that larger values are assumed to correspond to “higher” outcomes. Therefore, the ordered logistic regression will also be performed and will be compared with the gologit2.

Gologit2 was chosen over multinomial logistic regression because a Brant-test showed that some variables do not violate the parallel regression assumption. Gologit2 will only relax parallel regression constrain for the variables that do violate the assumption. Multinomial logistic regression would relax this assumption for all variables and this would not exploit the full potential of the data.

6.2 Binary logistic regression on cigarettes

For the hypothesis I will make use of binary logistic regression as the outcome variable is a binary variable with options 0 and 1. The assumptions will now be reviewed for the model that will be used. The first two assumptions, which indicate that you need a dichotomous (variable with two outcomes) dependent variable and that you need two or more independent variables, are not violated. The third assumptions is for the independence of observations. This assumption is also not violated. The fourth assumption states that there needs to be 50 cases per independent variable. This assumptions is satisfied.

The fifth assumption states that there needs to be a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. This was checked in STATA with the Box-Tidwell approach. By adding a interaction term which is the cross product of the independent variable times the natural logarithm (age*ln(age) to the model, there can be tested whether there is a linear relationship between the continuous independent variable and the logit transformation. This is called the Box-Tidwell approach or Box-Tidwell transformation. When the P-value of the transformed variable is not significant the assumptions holds. Unfortunately, as can be seen in table 4A in the appendix this assumption is not satisfied because the variable age*ln(age) is significant. Therefore this assumption does not hold. Because this assumption does not hold, the relationship between the independent variable and the logit transformation of the dependent variable is not linear. This could lead to unrealistic predictions. This will be covered in the discussion.

The sixth assumption is the assumption of multicollinearity. To check this assumption the VIF-test was performed. As explained before there is a chance that the assumption is violated. The fact is that in the regression some variables have a VIF value higher than 5. However, all values are lower than 10 as can be seen in table 5A in the appendix. Therefore for now there will be assumed that the assumption is not violated and the model can be used. Furthermore, no significant outlier were found in the data as is assumed by the last assumption.

6.3 Binary logistic regression on soft drugs

For the third hypothesis two binary logistic regression will be executed. Here, the assumptions will be reviewed for the regression on soft drugs use

The fist assumption is satisfied as the outcome variable for soft drugs is a binary variable. The independent variables in this regression are the same as for the binary logistic regression on cigarettes. Therefore the second, third and fourth assumption are satisfied.

To satisfy the fourth assumption a linear relationship between the continuous independent variables and the logit transformation of the dependent variable is necessary. In this model the only continuous independent variable is age. Again the Box-Tidwell approach was used. The results can be found in table 6A in the appendix. The table shows that the variable age*ln(age) is insignificant. Therefore the fifth assumption is satisfied.

The sixth assumption is the assumption of multicollinearity. To check this assumption the VIF-test was performed again. As discussed before there is a chance that the assumption is violated. The fact is that in the regression some variables have a VIF value higher than 5. However, all values are lower than 10 as can be seen in table 7A in the appendix. Therefore for now there will be assumed that the assumption is not violated and the model can be used. Furthermore, no significant outlier were found in the data as is assumed by the last assumption.

6.4 Binary logistic regression on hard drugs

Also for the regression on hard drugs, the assumptions for binary logistic regression will be examined. The fist assumption is satisfied since the outcome variable for hard drugs is a binary variable.

The independent variables in this regression are the same as for the binary logistic regression on cigarettes and Soft drugs. Therefore the second, third and fourth assumption are satisfied. The explanations for these assumptions can be found at section 5.2 and 5.3 as the outcome variable in this model the same properties when it comes to validating these assumptions.

The fifth assumption tells that there needs to be a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. In this model the only continuous independent variable is age. Again the Box-tidwell approach was used. The results can be found in table 8A in the appendix. The table shows that the variable age*ln(age) is insignificant. Therefore the fifth assumption is satisfied.

The sixth assumption is the assumption of multicollinearity. To check this assumption the VIF-test was performed again. All values are lower than 10 as can be seen in table 9A in the appendix. Therefore for now there will be assumed that the assumption is not violated and the model can be used. Furthermore, no significant outlier were found in the data as is assumed by the last assumption.

7. Results

7.1 Alcohol use last 12 months

7.1.1 Gologit2

In table 3 below the gologit2 regression on alcohol use in the last 12 months can be seen for the comparison of categories 1 vs 2-8 of the variable. In the regression the command autofit is used. This command makes use of the Wald test to test the proportional odds assumption. This test showed that the variables d_{0-6}, d_{7-12}, d_{13-18}, 2.vmbo, 5.hbo, 8.no education and male do not violate the proportional odds assumption. The categories for the variable alcohol in the last 12 months are: 1) almost every day, 2) five or six days per week, 3) three or four days per week, 4) once or twice a week, 5) once or twice a month, 6) once every month, 7) once or twice a year, 8) not at all over the last 12 months. All results for this Gologit2 regression assume that all other variables will be hold constant. The results of the whole regression can be seen in the appendix in table 10A. The coefficient plot of this regression can be found in figure 1.

In this model, 9 in-sample cases have an outcome with a predicted probability that is less than 0. This is a serious indication that some predictions might be wrong in this model. However, this is probably because most dummy variables only have a real small amount of observations for which the variable is one and a lot of observations for which the dummy variable is zero. McCullagh & Nelder (1989) stated that negative values are unavoidable because in non-parallel regression models because the lines must eventually intersect. They also stated that this does not have to be a problem if the intersection occurs in a sufficiently remote region of the x-space.

Table 9 shows that for men the log odds of being in a higher category regarding the number of days someone has been drinking is 0.592 points lower than for woman, which is significant on a 1% significance level. Men have higher log odds of being in a lower drinking category means that on average men have higher log odds to drink more times a week for the last 12 months, ceteris paribus. The log odds show that woman are more likely to be in a higher category, the categories go from drinking every day to not drinking. Because the log odds for woman are negative, this means that on average woman have lower change to be in a low category and thus lower chance to drink much alcohol compared with men, ceteris paribus. While men have a higher change to drink more alcohol. This is significant on a 1% significance level.

The ordered logit for people whose highest education with diploma is vmbo being in a higher category regarding the number of days someone has been drinking in the last week is 0.432 lower, and thus drinking on average more days a week for the last 12 months, compared with people whose highest education with diploma is primary school, ceteris paribus. This is significant on a 5% significance level. The ordered logit for people whose highest education with diploma is hbo in a higher category regarding the number of days someone has been drinking in the last week is 0.877 lower, and thus drinking on average more days a week for the last 12 months, compared with people whose highest education with diploma is primary school, ceteris paribus. The other significant variables do violate the proportional odds assumption according to the Wald test. Therefore the log odds of these variables change between categories and these variables will be interpreted per category. The results and coefficient for these variables can be seen in table 10A in the appendix. People who have wo as highest education as diploma are less likely to be in a higher category compared with people whose highest degree with diploma is primary school on a 1% significance level, ceteris paribus. This negative likelihood increases with the categories and the likelihood is the lowest in the highest category. Meaning that people with wo as highest degree do drink more on average compared with people with primary school as highest degree. Because these people tend to be in lower categories, which means that they drink more on average.

When the age of people increases, people tend to be more likely to be in a lower category, and thus people drink more when they get older, ceteris paribus. However, this effect decreases for higher categories (of alcohol use per week in the last 12 months) but is still significant.

The variables d_{0-6}, d_{7-12} and d_{13-18} were not significant on a 10% significance level. This means that there is probably no difference in the log-odds for the amount of drinking per week for the last 12 months between the three categories and the base dummy category not divorced (before age of 19). Thus there is no significant difference found for the amount of drinks per week for the last 12 months between the three age categories and the base category not divorced (before age of 19). This suggest that there is probably no effect of parental divorce in childhood on later alcohol use.

Variable	*Coefficient*	*Std. Error*	*P-value*
d_{0-6}	*0.148*	*0.141*	*0.296*
d_{7-12}	*-0.106*	*0.152*	*0.484*
d_{13-18}	*0.028*	*0.150*	*0.853*
Age	*-0.062*	*0.004*	*0.000****
Male	*-0.592*	*0.054*	*0.000****
Education with diploma:			
2. vmbo	*-0.431*	*0.171*	*0.012***
3. havo/vwo	*-0.490*	*0.232*	*0.034***
4. mbo	*-0.230*	*0.201*	*0.253*

5. hbo	*-0.877*	*0.169*	*0.000****
6. wo	*-0.757*	*0.220*	*0.001****
7. other	*0.063*	*0.257*	*0.807*
8. no	*-0.168*	*0.287*	*0.557*
Constant	*6.636*	*0.305*	*0.000****

*Table 3: Gologit2 on alcohol use last 12 months. Results of category 1 vs 2-8. Variables that not violate the parallel regression assumption have the same coefficient for every categoric comparison in this regression. Variables that violate the regression assumption do not have the same coefficient for every categoric comparison. For these coefficients check table 10A in the appendix. Pseudo R^2: 0.05. Observations: 4509. * p<0.10 ** p<0.05 *** p<0.01.*

7.1.2 Ordered logistic regression

Table 4 show the results of the ordered logistic regression on the categoric variable alcohol use in the last 12 months. The proportional odds assumptions is violated for some variables. However, the interpretation for gologit2 is harder for the variables that do not met the assumption and therefore this regression was performed. Meaning that the variables that violate this assumption do have an effect on the outcome variable that is different for each categories of this dependent variable. This model gives the same coefficient for all the categories meaning that the coefficient for some categories might be too high and for some categories the variables might be too low. To conclude, these variables are (slightly) biased. The coefficient plot of the results can be seen in figure 1.

The variable Age is significant on a 1% significance level. If the age of a participant increase with one year, the ordered log-odds of being in a higher drinking category decreases with -0.021, ceteris paribus. Older people have a bigger chance to end up in a lower drinking category. Meaning that older people do drink more often on average.

The ordered logit for men being in a higher category is 0.588 less than females. This means that on average men drank more often for the last 12 months compared with woman, ceteris paribus. This is significant on a 1% significance level.

People with vmbo as highest degree with diploma have an ordered logit that is 0.470 lower compared with people who have primary school as highest degree, ceteris paribus. This shows that people who have vmbo as highest degree are more likely to end up in a lower category and thus drink more often than people who have primary school as highest degree. This is significant on a 5% significance level. People who have havo/vwo as highest degree with diploma have an ordered logit that is 0.828 lower for being in a higher category compared with people who have primary school as highest degree, ceteris paribus. Meaning that people who have havo/vwo as highest degree are more likely to end up in a lower category and thus drink more often. The ordered log-odds for people who have mbo as highest degree for being in a higher category is 0.561 lower compared with people who have primary school as highest degree with diploma, ceteris paribus. Meaning that people who have mbo as highest degree are more likely to drink more often. This is significant on a 5% significance level. Also people who have hbo as highest degree have lower ordered log-odds of being in a higher category compared with people who have primary school as highest degree. The ordered log-odds for being in a higher category for people who have hbo as highest degree are 0.946 lower. This means that people who have hbo as highest degree are more likely to end up in a lower category and therefore drink more often, ceteris paribus. The ordered logit for people who have wo as highest degree being in a higher category is 1.195 lower compared with people who have primary school as highest degree, ceteris paribus. Meaning that people who have wo as highest degree drink more often on average compared with people who have primary school as highest degree.

In comparison with the gologit2 regression, It can be seen that the effect is usually in the same direction. Because gologit2 indicates coefficients and an ordered logistic regression log odds, it is not possible to compare them directly. he only clear difference is that the ordered logistic regression shows that people with educational levels 3.havo/vwo and 4.mbo drink on average more often per week in the past 12 months than people with primary school as highest degree, ceteris paribus. These effects were not significantly visible in the gologit2 regression.

7.2 Cigarettes

7.2.1 Binary logistic regression

In table 4 the results from the binary logistic regression with outcome variable cigarettes can be found. The coefficient plot of the results can be seen in figure 1. The variable $d_{0\text{-}6}$ is significant on a 5% significance level . Table 4 shows us that people whose parents divorced when they were between 0-6 years old have 1.465 times greater odds to ever smoke cigarettes compared with people whose parents did not divorce (before age of 19), ceteris paribus The variable $d_{7\text{-}12}$ is significant on a 1% significance level, therefore this variable is significant. People whose parents divorced when they were between the ages of 7-12 have 1.980 times greater odds to ever smoke cigarettes compared with people whose parents did not divorce (before age of 19), ceteris paribus. Also people whose parents divorced when they were between 13-18 years old have 1.561 times greater odds to smoke or have smoked cigarettes compared with people whose parents did not divorce (before age 18), ceteris paribus. This is significant a significance level of 5%.

The variable Age is significant on a 1% significance level. Meaning that when the variable Age increases with 1 unit then the odds that someone smokes or has smoked are 1.03 times greater, ceteris paribus.

If one looks at the highest level of education with a diploma, one can see that people who have havo/vwo as highest degree with a diploma have odds ratio of 0.677, meaning that these people are 32.3% less likely to smoke or have smoked compared with people whose highest degree is primary school, ceteris paribus. This is significant on a 5% significance level. People who have hbo as highest degree with a diploma have odds ratio of 0.587 meaning that these people are 41.3% less likely to smoke or have smoked compared with people whose highest degree is primary school, ceteris paribus. This is significant on a 1% significance level. People who have wo as highest degree with a diploma have odds ratio of 0.464, meaning that these people are 53.6% less likely to smoke or have smoked compared with people whose highest degree is primary school, ceteris paribus. This is significant on a 1% significance level.

The variables male, 2.vmbo, 4.mbo, 7.other, 8.no are not significant on a 10% significance level.

In conclusion, table 4 shows that people whose parents divorced before the age of 18 are more likely to smoke or to have smoked. This probability is the largest for people who were between 7-12 years old when their parents divorced. In addition, people with havo/vwo, hbo or wo as highest level of education with diploma are less likely to smoke or have smoked compared to people who have primary school as highest level of education with diploma.

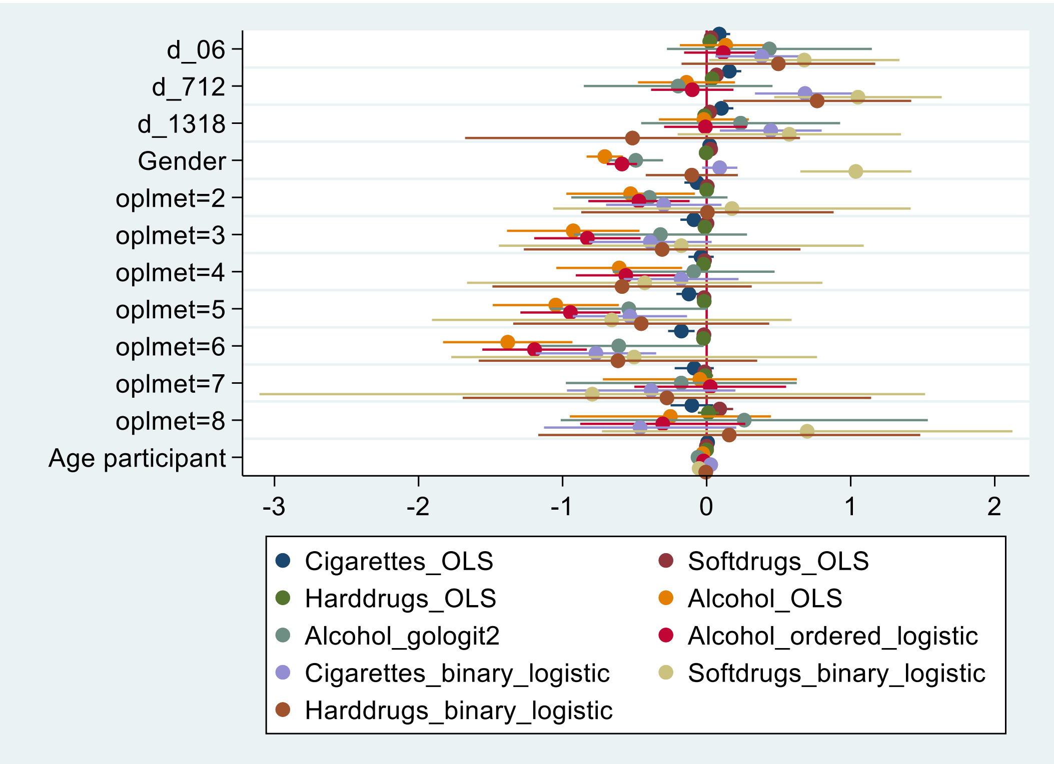

Figure 1: Coefficient plot of all regressions. Coefficient plot per regression can be found in the appendix. Oplmet: 2=vmbo, 3=havo/vwo, 4=mbo. 5=hbo, 6=wo, 7=other, 8=no.

	Alcohol use last 12 months		Cigarettes		Soft drugs		Hard drugs	
	Ordered logistic		Binary logistic		Binary logistic		Binary logistic	
Age_06	0.114	(0.83)	1.465**	(2.33)	1.969**	(2.01)	1.645	(1.45)
Age_712	-0.0999	(-0.68)	1.980***	(3.85)	2.859***	(3.54)	2.154**	(2.30)
Age_1318	-0.0086	(-0.06)	1.561**	(2.47)	1.775	(1.45)	0.598	(-0.87)
Male	-0.558***	(-10.97)	1.095	(1.46)	2.817***	(5.26)	0.902	(-0.63)
2.vmbo	-0.470**	(-2.62)	0.743	(-1.46)	1.192	(0.28)	1.005	(0.01)
3.havo/vwo	-0.828***	(-4.40)	0.677*	(-1.80)	0.839	(-0.27)	0.734	(-0.63)
4.mbo	-0,561**	(-3.16)	0.838	(-0.87)	0.651	(-0.68)	0.556	(-1.28)
5.hbo	-0.946***	(-5.34)	0.587***	(-2.63)	0.517	(-1.03)	0.635	(-1.00)
6.wo	-1.195***	(-6.46)	0.464***	(-3.60)	0.605	(-0.78)	0.540	(-1.25)
7.other	0.0249	(0.09)	0.680	(-1.29)	0.452	(-0.67)	0.759	(-0.38)
8.no	-0.0305	(-1.04)	0.630	(-1.36)	2.010	(0.96)	1.170	(0.23)
Age	-0.0213***	(-13.06)	1.029***	(14.52)	0.949***	(-8.68)	0.994	(-1.20)
cut1	-4.263***	(-20.49)						
cut2	-3.831***	(-18.60)						
cut3	-3.130***	(-15.41)						
cut4	-2.083***	(-10.41)						
cut5	-1.496***	(-7.51)						
cut6	-1.107***	(-5.56)						
cut7	-0.476*	(-2.39)						
N	4509		4518		4518		4518	

Table 4: Results regressions. First column shows dependent variable. Second column shows method. Statistics in parentheses. *** *p<0.01, ** p<0.05, * p<0.10.*

7.3 Soft drugs

7.3.1 Binary logistic regression

The results from the binary logistic regression can be seen in table 4. The coefficient plot regressions can be seen in figure 1. The odds that someone used soft drugs last are 1.979 times greater when your parents divorced when one were between 0-6 years old, compared with people whose parents did not divorce (before their 19th birthday), ceteris paribus. The significance level is 5%. The odds that someone used soft drugs last month are 2.859 times greater when your parents divorced when you was between 7-12 years old, compared with people whose parents did not divorce (before their 19th birthday), ceteris paribus. This is significant on a 1% significance level.

The odds that someone used soft drugs are 2.817 time greater for males, compared with females, ceteris paribus. This is significant on a 1% significance level.

When age increases with one year, the odds that someone used soft drugs last month are 5.1% lower. For example the odds that someone of 51 has used soft drugs the last month is 0.949 times the odds that someone of 50 (one year younger) used soft drugs last month, ceteris paribus.

The variable d_{13-18} is not significant. Next to that not a single dummy variable for education level with diploma is significant in this model. Meaning that drugs use between people with different educational levels is probably equal on average compared with people who have primary school as highest degree.

7.4 Hard drugs

7.4.1 Binary logistic regression

Table 7 below shows the results of the binary logistic regression on hard drugs. The coefficient plot of the results can be found in figure 1. One problem with this model is that the p-value for the overall model is 0.091. Therefore the conclusions, that can be drawn from the results of this model, should be handled with caution.

The only significant variable in this model is d_{7-12}. This variable is significant on a 5% significance level. The models shows that people whose parents divorced when they were between the ages of 7-12 have 2.154 times greater odds to have used hard drugs (sedatives, XTC, hallugcinogens, laughinig gas or hard drugs such as stimulants, cocaine, heroin) in the last month compared with people whose parents did not divorce (before age of 19), ceteris paribus. These people are thus more likely to have used hard drugs in the last month compared with people whose parents did not divorce (before the age of 19).

8. Conclusion

The main goal of this study was to find an answer to the research question: *What are the (long-term) effects of parental divorce* during childhood on risky behaviour such as drinking alcohol, smoking and drugs use for their children (in later life/adulthood)?*

This question was divided in four parts. Namely, the effect of parental divorce on:

1) alcohol use

2) cigarettes

3) soft drugs use

4) hard drugs use

In this study no effect of parental divorce on alcohol use was found with both the gologit2 and ordered logistic regression. This is contrary to the literature found earlier, which indicated that parental divorce causes an increase in alcohol consumption in their offspring compared with people whose parents did not divorce (Auersperg, Vlasak, Ponocny & Barth 2019, Kristjansson, Sigfusdottir, Allegrante & Helgason, 2009; Nayga & Wu, 2015; Thompson, lizardi, Keyes & hasin, 2008; Wolfinger, 1998). Several studies also indicated that children of divorced parents were more likely to consume alcohol later in life than children whose parents were not divorced (Arkes, 2013; Jeynes, 2001; Roger & Sartor, 2016). A similar result was expected with the used methods from the hypothesis: "*Individuals who were a child (0-18) when their parents divorced are generally more likely to drink alcohol, compared with individuals whose parents did not divorce when they were a child.".* Looking at the results of this study, it can be concluded that this hypothesis does not hold. This could be because the Dutch generally drink more and therefore divorce has little effect. It could also be that parental divorce actually has no effect on alcohol consumption in the long term.

The second hypotheses: "*Individuals who were a child (0-18) when their parents divorced are generally more likely to smoke (cigarettes), compared with individuals whose parents did not divorce when they were a child."* , this study found evidence for this hypothesis. The results from the binary logistic regression show that the odds for people whose parents divorced before they turned 19 have higher odds to have every smoked cigarettes compared with people whose parents did not divorce (before the age of 19). Respectively if we look at the age categories that indicate the age of the child when their parents divorce, there can be seen that the category 0-6 have 1.465 times greater odds, the odds are 1.980 times greater for people in age category 7-12 and 1.560 times greater for people in the age category 13-18. All compared with people whose parents did not divorce (before the age of 19). The total odds indicate the chance that someone ever smoked cigarettes. The OLS regression also shows that people who were a child when their parents divorced are more likely to have ever smoked cigarettes. Children of divorced parents were between 8 and

15% depending on age group more likely to have ever smoked compared to children whose parents were not divorced (before the age of 19). This is in line with previous literature discussed in the theoretical framework (Amato & Anthony, 2014; Auersperg et al., 2019; Gustavsen et al., 2015; Wolfinger, 1998). The largest effect was for cigarettes was seen in children who were between 7 and 12 years old when their parents divorced.

The results from the binary logistic regression on soft drugs also showed an effect of parental divorce on the risky behaviour of their offspring in later-life. People who were between the age of 0-6 when their parents divorced have 1.969 times greater odds and people who were between the age of 7-12 have 2.859 times greater odds to have used soft drugs in the last month. Both odds are in comparison with people whose parents are not divorced (before the age of 19). The OlS regression on soft drugs showed that people whose parents divorced when they were between 7-12 years old are 6.85% more likely to have used soft drugs in the last month compared with people whose parents did not divorce (before the age of 19).

The hypothesis about the effect of parental divorce on drug use was as follows: "*Individuals who were a child (0-20) when their parents divorced are generally more likely to use marijuana and/or hard drugs, compared with individuals whose parents did not divorce when they were a child.".* In this study evidence for this hypothesis was found for soft drugs as parental divorce has an effect on soft drugs use for two of the three age categories in the binary logistic regression and one of the three age categories in the OLS regression. This is in line with the previous studies (Arkes, 2013, Auersperg et al, 2019; Gustavsen et al, 2015; Skeer, McCormick, Normand, Buka & Gilman, 2009). The hypotheses also hold for hard drugs. However, there is only an effect present in the group that sees the highest effect of parental divorce on risky behaviour for alcohol use and cigarettes. In contrast to the study of Gustavsen et al. (2015) for both the binary logistic and OLS regression on hard drugs there is an effect found for people whose parents divorced when they were between the ages of 7-12 for using hard drugs in the last month. This in in line with previous literature (Arkes, 2013; Auersperg et al, 2019). For the other age categories there was no effect found from parental divorce on hard drugs use.

This study has shown that people whose parents divorced when they were between the age of 0-18 years are more likely to have ever smoked cigarettes and used soft and hard drugs in the past month compared to people whose parents did not divorced (before the age of 19). For soft drug use, there is only an effect found in this study for people who were between 0-6 (binary logistic regression and OLS) and 7-12 (binary logistic regression) when their parents divorced. For hard drugs this effect was only found for people who were between 7 and 12 years old when their parents divorced. In contrast to the literature no effect on alcohol use could be found. The ages 0-6 and 7-12 seems to be critical in the development in risky behaviour. This could be due to the mechanism that have been discussed in this study.

9. Discussion & limitations

In this study a few limitations were found. Also, in some models the assumptions may be violated. Moreover, with the data set used it was not possible to include every mechanism or to measure the outcome variables as desired or as was done before in previous literature. This will be discussed below.

One assumption that was made in this study is that a VIF-value above 10 would violate the multicollinearity assumption. However, as explained before Rogerson (2019) concluded that a VIF-value higher than 5 could violate the multicollinearity assumption. For all the binary logistic models and gologit2 some values from the VIF-test were above 5. If these variables violate the multicollinearity assumption this could mean that the p-values for highly correlated variables could be become too high. It could be that a false null hypotheses will not be rejected for the variables that have a VIF-value above 5. This could mean that in this study type 2 errors have occurred.

The gologit2 model has 9 in-sample cases with predicted probabilities less than zero. I assumed that this is because of the low observations with value 1 for the dummy variables. However, it needs to be mentioned that if this is not the cause of the problem then the gologit2 model might be biased.

For the binary logistic regression on cigarettes the linearity assumption does not hold. This could mean and thus probably means that the parameter estimates are biased in general and probably inconsistent. Therefore the predictions of the odds ratio for the variable age in this model is probably (a bit) biased. This might also affect the predictions for the other variables.

The OLS regressions have been added in order to provide a clearer link between parental divorce and risky behaviour. However, OLS is not really suitable to be used with binary dependent variables because it violates several assumptions as discussed. When looking at the results of the OLS regressions, it is important to realise that the model is biased. The OLS regressions therefore do not reflect reality as well as the gologit2 and binary logistic regressions. However, because the binary logistic and gologit2 models are difficult to interpret and translate into clear statistics or numbers, the OLS regressions have been added to clarify the effect of parental divorce on risky behaviour.

Having discussed all the problems with the models, we can now move on to the limitations of using the panel datasets. The dependent variable for alcohol consumption in the last 12 months was categorical and indicated the number of days a person drank alcohol on average in the last 12 months. Previous literature often looked at the amount of alcohol a person drank per week and this was not possible from the data. This is a limitation. A recommendation for follow-up research would be to look at the amount of drinking per week. Mainly because this is easier to compare with, for example, the Jellinek guidelines (Jellinek, 2020) and because these values are easier to compare with other literature.

Moreover, there were few control variables available from the panel that emerged from the literature review. This probably leads to omitted variable bias. Therefore the effect of parental divorce on risky behaviour is probably underestimated.

Follow-up research could also possibly take these mechanisms into account. An example of such a control variable that was not mentioned before could be the income of the parents just before the parents' divorce. Not including this variable could give upward bias since income of the parents could have an effect on risky behaviour as well.

A control variable that is used in all models is education level. I argued that the effect of parental divorce on education level is small and therefore would not underestimate the effect of parental divorce on risky behaviour. However, there is a chance that the effect of parental divorce on education is larger than I expect. Then educational level is a mechanism and the effect of parental divorce on risky behaviour is underestimated.

The external validity of this study is pretty high as most values of descriptive statistics are close to the real numbers in the Netherlands. However, some values are not that close. The average age for observations in this study is 54.5 years old. This is higher than the average age in the Netherlands and therefore does harm the external validity. Next to this, the percentage of children with divorced parents seems to be a lot smaller compared with the statistics from the Dutch population.

The results showed that parental divorce has the greatest effect on risky behaviour for people who were between the age of 7-12 when their parents divorced. A recommendation is to look closer at children whose parents are divorcing within this age range. These children seem to be the ones most affected by parental divorce and so additional monitoring these children could help to reduce them from falling into risky behaviours. This age range seems crucial in the development of risky behaviour. The additional monitoring of these children could counteract this risky behaviour. This monitoring could also help to clarify the exact causes of the risky behaviour, as parental divorce is certainly not the only cause. This does not mean that children in the age category 0-6 and 13-18 should not be monitored when their parents divorce as there is an effect found in this study for parental divorce on risky behaviour for all age categories. However, the effect in these groups only seems smaller from this study.

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11. Appendix

Variable	**VIF**
Age_{0-6}	1.02
Age_{7-12}	1.03
Age_{13-18}	1.02
Male	1.02
Age	1.16
Education with diploma:	
2. vmbo	6.57
3. havo/vwo	4.25
4. mbo	7.44
5. hbo	7.75
6. wo	5.06
7. other	1.62
8. no	1.47
Mean VIF	3.28

Table 1A: VIF-test for regression on outcome variable alcohol use last 12 months.

	2	3	4	5	6	7	8	9	10	11	12	**13**
1) *Alcohol_12months*												
2) *Age$_{0-6}$*	1.000											
3) Age7$_{-12}$	-0.0362*	1.000										
4) *Age$_{13-18}$*	-0.0353*	-0.0326*	1.000									
5) *Male*	-0.0107	0.0322*	-0.0251	1.000								
6) *2.vmbo*	0.0039	-0.0173	-0.0260	-0.0629*	1.000							
7) *3.havo/vwo*	-0.0147	0.0274	0.0352*	-0.0188	-0.1710*	1.000						
8) *4.mbo*	0.0279	0.0158	0.0004	0.0218	-0.2837*	-0.1924*	1.000					
9) *5.hbo*	-0.0362*	-0.0235	-0.0187	0.0133	-0.2979*	-0.2021*	-0.3353*	1.000				
10) *6.wo*	0.0020	-0.0006	0.0180	0.0476*	-0.1944*	-0.1319*	-0.2187*	-0.2297*	1.000			
11) *7.other*	-0.0012	-0.0156	0.0042	-0.0080	-0.0684*	-0.0464*	-0.0770*	-0.0809*	-0.0528*	1.000		
12) *8.*no	0.0357	0.0422*	0.0007	0.0107	-0.0595*	-0.0404*	-0.0669*	-0.0703*	-0.0459*	-0.0162	1.000	
13) *Age*	-0.1080	-0.1219*	-0.0961*	0.0747	0.2300*	-0.1138*	-0.0413*	0.0073*	-0.1483*	-0.0859*	-0.0859 *	1.000

Table 2A: correlation matrix for regression on alcohol use last 12 months. *p<0.01

Variable	Chi2	P-value
Age_{0-6}	8.29	0.218
Age_{7-12}	6.20	0.401
Age_{13-18}	4.13	0.659
Age	250.65	0.000***
Male	10.93	0.091*
Education with diploma:		
2. vmbo	8.90	0.179
3. havo/vwo	17.07	0.009***
4. mbo	9.79	0.134
5. hbo	15.45	0.017**
6. wo	21.02	0.002***
7. other	7.26	0.297
8. no	2.89	0.822
All	447.44	0.000***

*Table 3A: Brant-test for outcome variable alcohol use last 12 months. * p<0.10 ** p<0.05 *** p<0.01.*

Variables	Odds ratio	Std. error	Z	P-value
Age	1.243	0.063	4.32	0.000***
*Age*ln(Age)*	0.962	0.010	-43.77	0.000***

*Table 4A: Box-Tidwell test for linearity for binary logistic regression on cigarettes. Significant p-value for Age*ln(Age) shows that there is no linearity. * p<0.10 ** p<0.05 *** p<0.01.*

Variable	VIF
Age_{0-6}	1.02
Age_{7-12}	1.03
Age_{13-18}	1.02
Male	1.02
Age	1.16
Education with diploma:	
2. vmbo	6.57
3. havo/vwo	4.27
4. mbo	7.45
5. hbo	7.76
6. wo	5.08
7. other	1.62
8. no	1.47
Mean VIF	3.29

Table 5A: VIF-test for binary logistic regression on cigarettes.

Variables	Odds ratio	Std. error	Z	P-value
Age	1.231	0.194	1.32	0.193
*Age*ln(Age)*	0.947	0.031	-1.65	0.100

*Table 6A: Box-Tidwell test for linearity for binary logistic regression on soft drugs. Insignificant p-value for Age*ln(Age) shows that there is linearity. * p<0.10 ** p<0.05 *** p<0.01.*

Variable	VIF
Age_{0-6}	1.02
Age_{7-12}	1.03
Age_{13-18}	1.01
Male	1.02
Age	1.16
Education with diploma:	
2. vmbo	6.57
3. havo/vwo	4.27
4. mbo	7.45
5. hbo	7.76
6. wo	5.08
7. other	1.62
8. no	1.47
Mean VIF	3.29

Table 7A: VIF-test for binary logistic regression on soft drugs.

Variables	Odds ratio	Std. error	Z	P-value
Age	0.861	0.100	-1.29	0.197
*Age*ln(Age)*	1.030	0.024	1.24	0.215

*Table 8A: Box-Tidwell test for linearity for binary logistic regression on hard drugs. Insignificant p-value for Age*ln(Age) shows that there is linearity. * p<0.10 ** p<0.05 *** p<0.01.*

Variable	VIF
Age$_{0-6}$	1.02
Age$_{7-12}$	1.03
Age$_{13-18}$	1.02
Male	1.02
Age	1.16
Education with diploma:	
2. vmbo	6.57
3. havo/vwo	4.27
4. mbo	7.45
5. hbo	7.76
6. wo	5.08
7. other	1.62
8. no	1.47
Mean VIF	3.29

Table 9A: VIF-test for binary logistic regression on hard drugs.

	(1) Alcohol use last 12 months	
1		
d_06	0.435	(1.20)
d_712	-0.198	(-0.59)
d_1318	0.236	(0.67)
d_male	-0.492***	(-5.09)
oplmet2	-0.398	(-1.44)
oplmet3	-0.321	(-1.05)
oplmet4	-0.0898	(-0.31)
oplmet5	-0.541	(-1.94)
oplmet6	-0.610*	(-2.03)
oplmet7	-0.176	(-0.43)
oplmet8	0.261	(0.40)
Age	-0.0600***	(-15.78)
_cons	6.279***	(16.20)
2		
d_06	0.376	(1.28)
d_712	-0.296	(-1.17)
d_1318	0.303	(1.02)
d_male	-0.557***	(-6.78)
oplmet2	-0.425	(-1.66)
oplmet3	-0.514	(-1.85)
oplmet4	-0.241	(-0.93)
oplmet5	-0.740**	(-2.91)
oplmet6	-0.945***	(-3.50)
oplmet7	-0.368	(-1.01)
oplmet8	0.226	(0.39)
Age	-0.0546***	(-18.00)
_cons	5.667***	(17.15)
3		
d_06	-0.0442	(-0.23)
d_712	0.0473	(0.22)
d_1318	-0.00979	(-0.04)
d_male	-0.539***	(-7.89)
oplmet2	-0.536*	(-2.32)
oplmet3	-0.715**	(-2.89)
oplmet4	-0.440	(-1.89)
oplmet5	-1.001***	(-4.36)
oplmet6	-1.230***	(-5.11)
oplmet7	-0.125	(-0.37)
oplmet8	-0.303	(-0.71)
Age	-0.0389***	(-17.59)
_cons	4.157***	(15.34)
4		
d_06	0.231	(1.40)
d_712	-0.175	(-1.01)
d_1318	0.141	(0.78)
d_male	-0.642***	(-10.43)
oplmet2	-0.259	(-1.33)
oplmet3	-0.513*	(-2.46)
oplmet4	-0.410*	(-2.11)
oplmet5	-0.760***	(-3.93)
oplmet6	-1.014***	(-4.94)
oplmet7	0.201	(0.68)
oplmet8	-0.0978	(-0.29)
Age	-0.0173***	(-9.31)
_cons	1.723***	(7.78)
5		
d_06	0.173	(1.05)
d_712	-0.0859	(-0.48)
d_1318	-0.153	(-0.82)
d_male	-0.668***	(-10.32)
oplmet2	-0.369	(-1.91)
oplmet3	-0.785***	(-3.77)
oplmet4	-0.496**	(-2.58)
oplmet5	-0.872***	(-4.53)
oplmet6	-1.288***	(-6.17)
oplmet7	0.0751	(0.26)
oplmet8	-0.315	(-0.98)
Age	-0.0110***	(-5.67)
_cons	0.956***	(4.32)
6		
d_06	0.0174	(0.10)
d_712	-0.218	(-1.08)
d_1318	-0.0686	(-0.35)
d_male	-0.610***	(-8.77)
oplmet2	-0.348	(-1.77)
oplmet3	-0.886***	(-4.11)
oplmet4	-0.583**	(-2.97)
oplmet5	-0.868***	(-4.41)
oplmet6	-1.325***	(-6.10)
oplmet7	0.225	(0.78)
oplmet8	-0.253	(-0.77)
Age	-0.00803***	(-3.87)
_cons	0.416	(1.82)
7		
d_06	0.190	(0.94)
d_712	0.0131	(0.06)
d_1318	-0.0633	(-0.27)
d_male	-0.550***	(-6.64)
oplmet2	-0.574**	(-2.76)
oplmet3	-1.258***	(-5.25)
oplmet4	-0.793***	(-3.78)
oplmet5	-1.118***	(-5.30)
oplmet6	-1.595***	(-6.55)
oplmet7	0.0693	(0.23)
oplmet8	-0.137	(-0.39)
Age	-0.00309	(-1.22)
_cons	-0.294	(-1.16)
N	4509	

*d_06= Age_06, d_712= Age_712, d_1318= Age_1318

*Table 10A: Results Gologit2 on alcohol use last 12 months. T statistics in parentheses. * p<0.05, ** p<0.01, *** p<0.001.*

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Sedatives	XTC	Hallucinogens	Laughing gas	Hard drugs
Age_06	0.00744	0.00112	0.00823	0.0114	-0.00158
	(0.0133)	(0.00874)	(0.00839)	(0.00970)	(0.00614)
Age_712	0.0151	0.0144	0.0154	0.0122	0.0321**
	(0.0153)	(0.0132)	(0.0114)	(0.0111)	(0.0161)
Age_1318	0.000131	-0.0102***	0.00368	-0.00543***	-0.00715***
	(0.0126)	(0.00220)	(0.00697)	(0.00170)	(0.00178)
Male	-0.0136***	0.00868***	0.00497***	0.00654***	0.00455**
	(0.00483)	(0.00265)	(0.00180)	(0.00197)	(0.00228)
2.vmbo	0.0122	-0.00375	0.00246	-0.00679	-0.0117
	(0.0171)	(0.00813)	(0.00163)	(0.00794)	(0.0113)
3.havo/vwo	0.000110	-0.00576	0.00591	-0.00336	-0.0150
	(0.0174)	(0.00914)	(0.00385)	(0.00916)	(0.0120)
4.mbo	-0.00230	-0.0114	-0.00128	-0.00957	-0.0183
	(0.0163)	(0.00831)	(0.00121)	(0.00833)	(0.0115)
5.hbo	-0.00445	-0.00387	0.00104	-0.00801	-0.0133
	(0.0163)	(0.00847)	(0.00134)	(0.00830)	(0.0115)
6.wo	-0.0137	-0.00399	0.000103	-0.00966	-0.0152
	(0.0164)	(0.00948)	(0.00260)	(0.00874)	(0.0121)
7.other	-0.00600	0.00332	-4.66e-05	-0.00834	-0.0163
	(0.0232)	(0.0143)	(0.000767)	(0.00799)	(0.0112)
8.not (yet) completed any education/not yet started any education	-0.00650	0.0150	0.0113	0.0350	-0.00873
	(0.0231)	(0.0248)	(0.0165)	(0.0287)	(0.0203)
Age	0.000419***	-0.000436***	-0.000180***	-0.000285***	-0.000345***
	(0.000138)	(9.81e-05)	(5.88e-05)	(7.72e-05)	(8.11e-05)
Constant	0.0103	0.0318***	0.00826***	0.0225**	0.0353***
	(0.0177)	(0.0113)	(0.00315)	(0.0106)	(0.0135)
Observations	4,518	4,518	4,518	4,518	4,518
R-squared	0.007	0.015	0.012	0.023	0.017

*Table 11A: Results OLS regressions on outcome variables for (hard) drugs separated. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

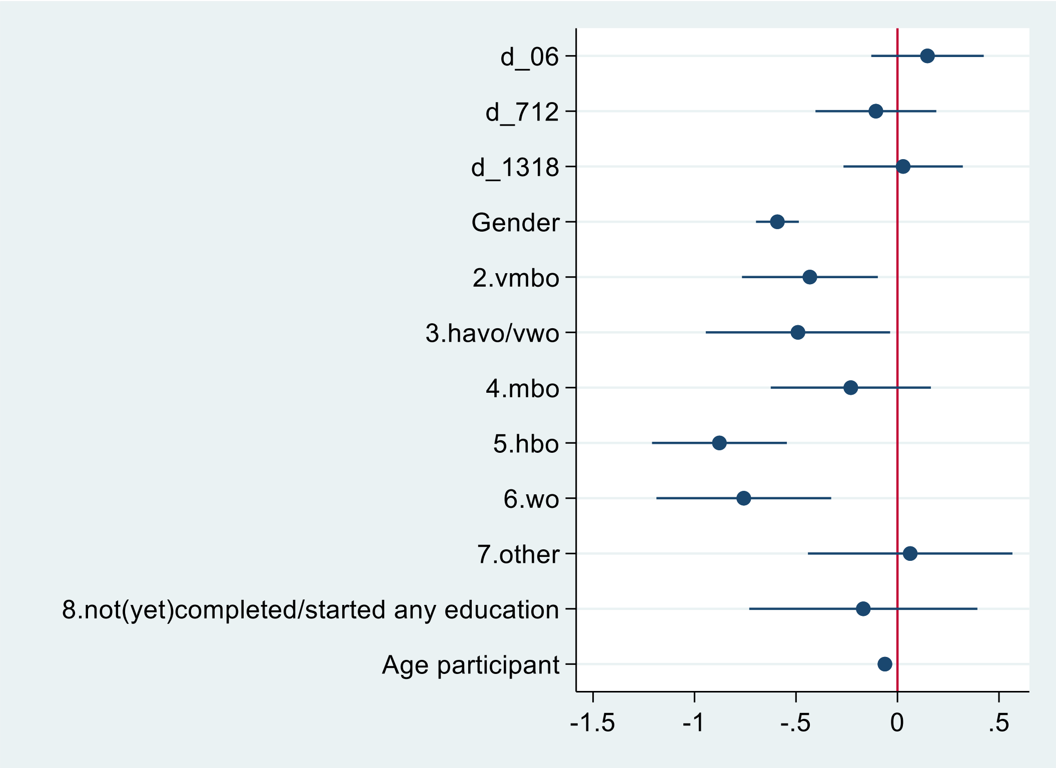

Figure 2: Coefficient plot of results Gologit2 on alcohol use last 12 months.

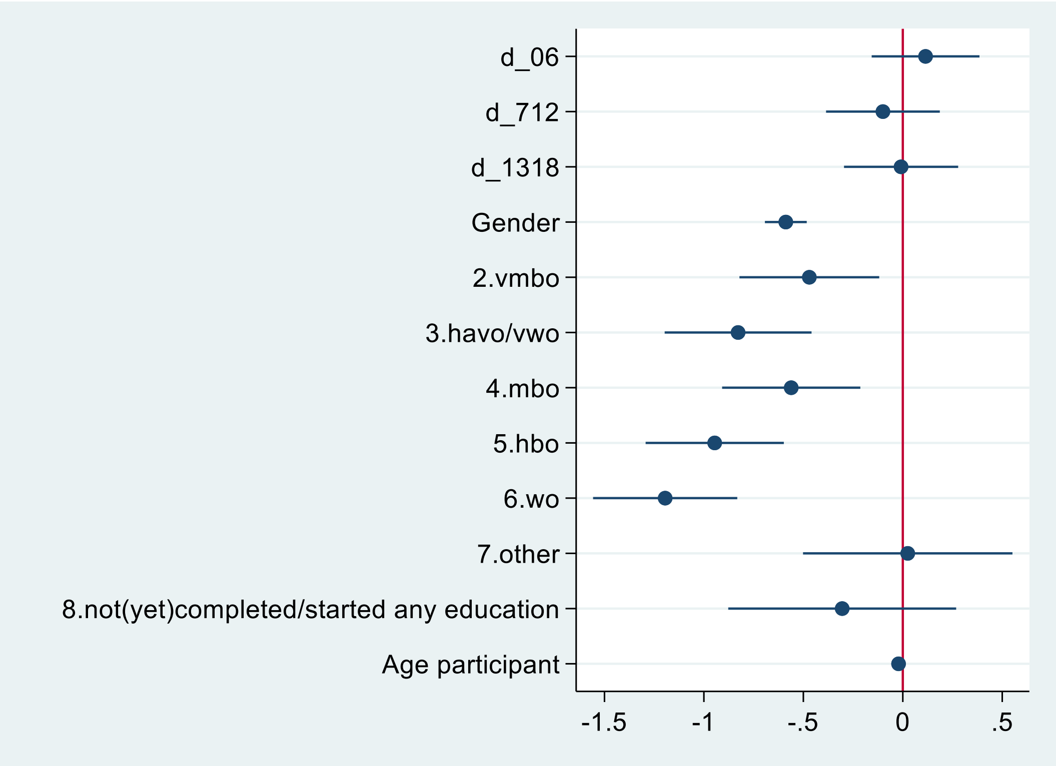

Figure 3: Coefficient plot of results ordered logistic regression alcohol use last 12 months.

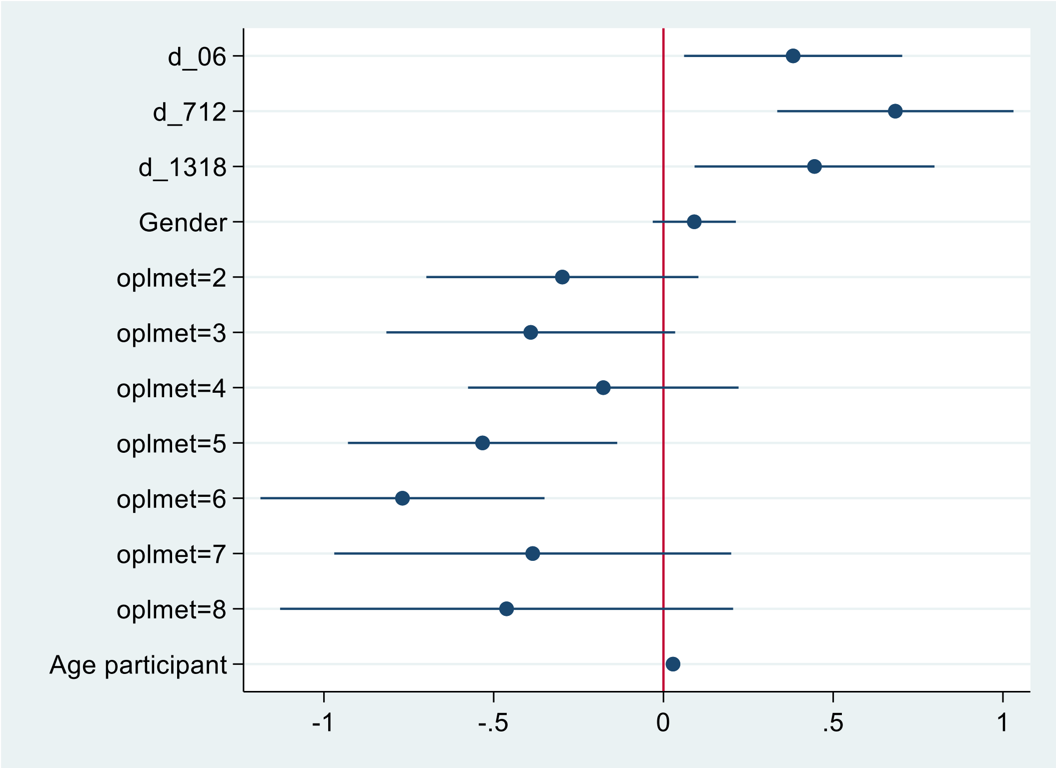

Figure 4: Coefficient plot of results binary logistic regression on cigarettes.

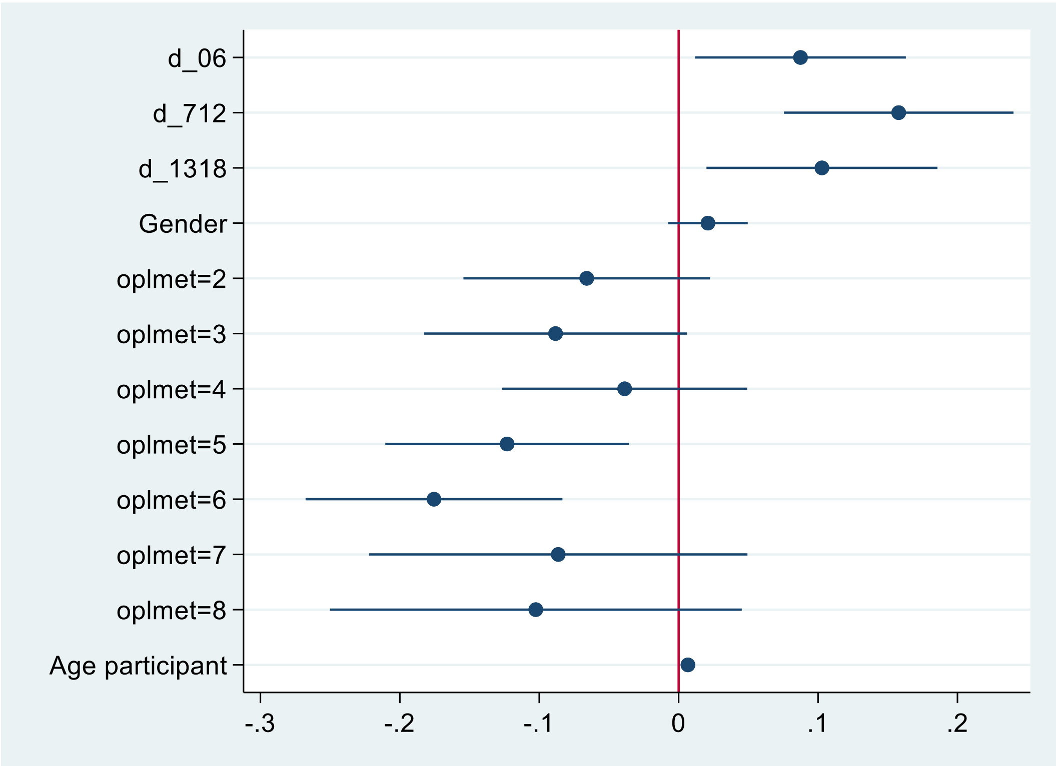

Figure 5: Coefficient plot of results OLS on cigarettes.

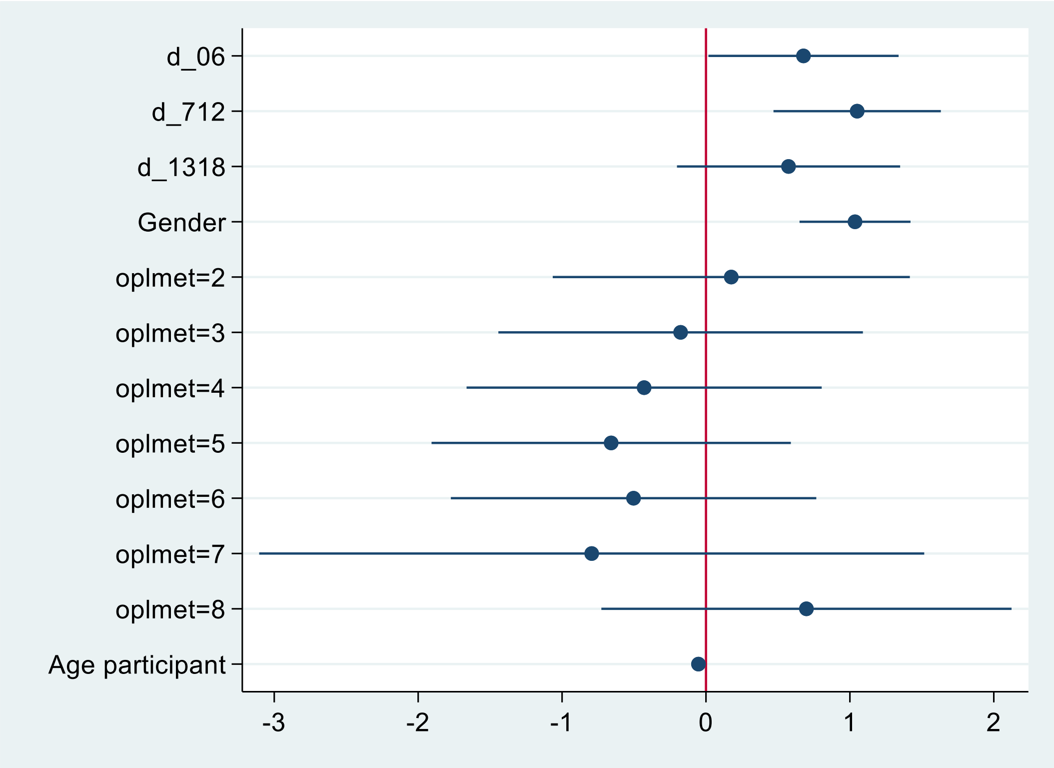

Figure 6: Coefficient plot binary logistic regression on soft drugs.

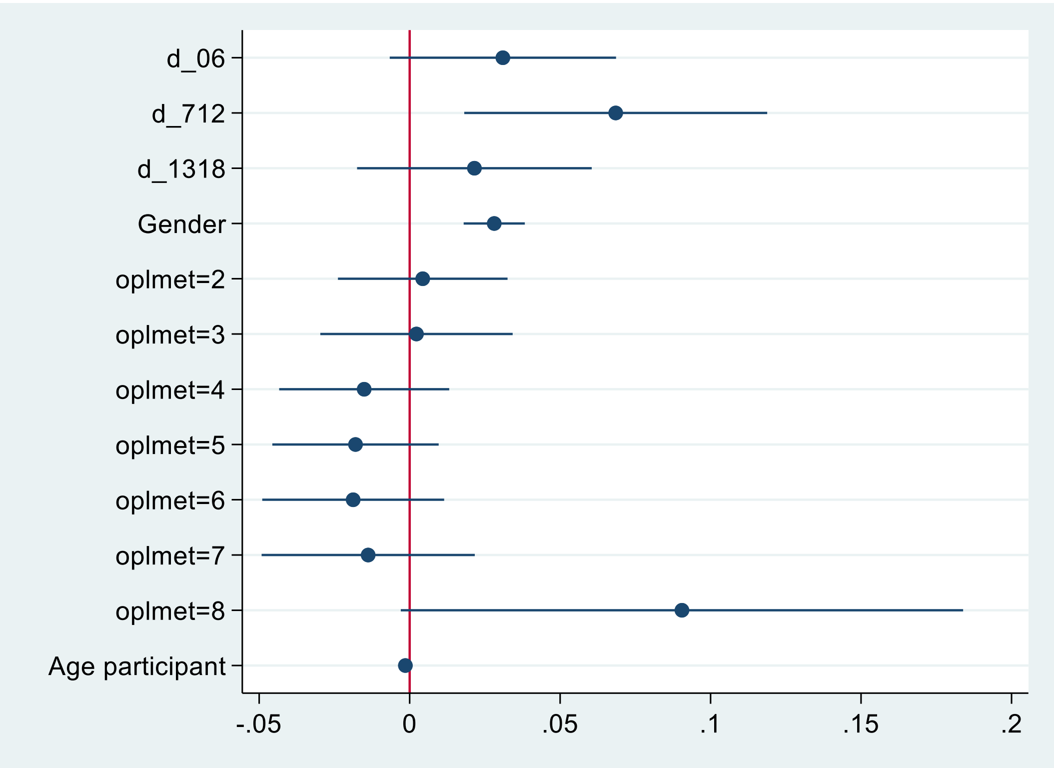

Figure 7: *Coefficient plot of results* OLS on soft drugs.

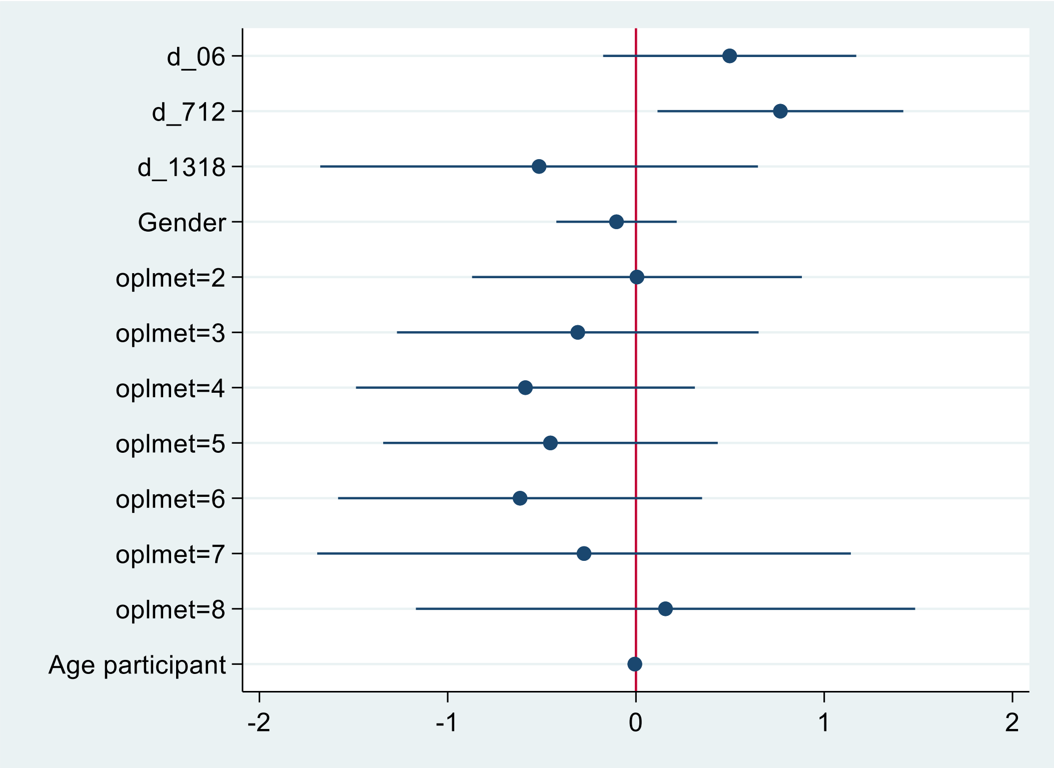

Figure 8: Coefficient plot of results binary logistic regression on hard drugs.

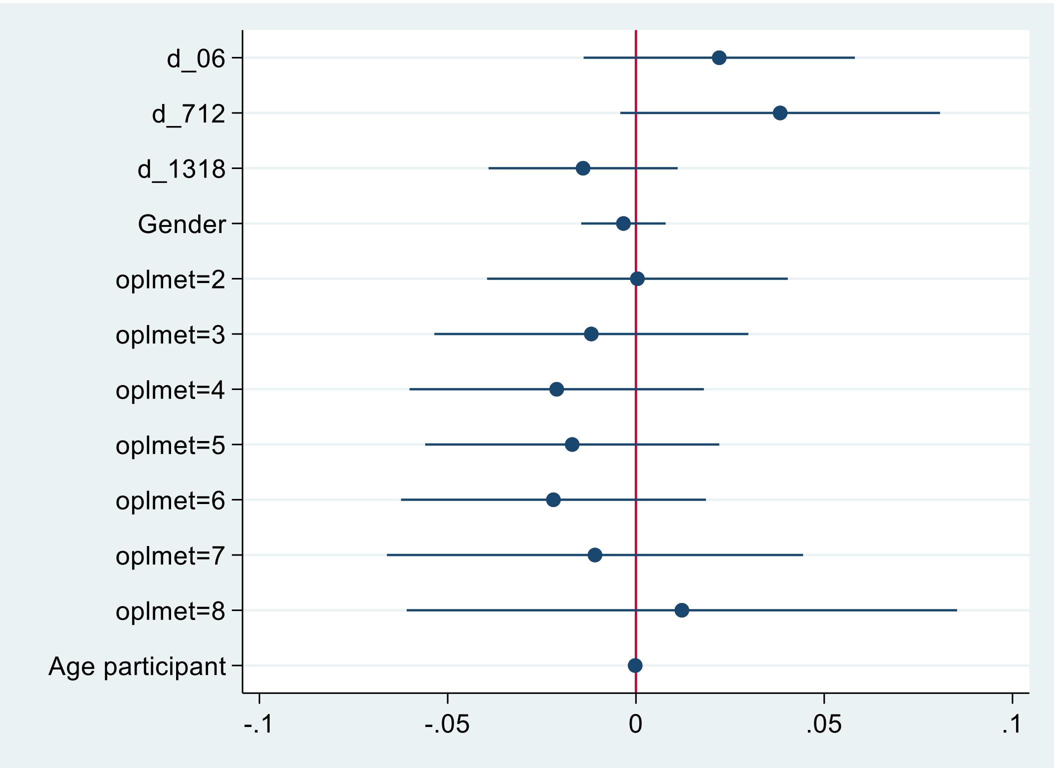

Figure 9: Coefficient plot results of OLS on hard drugs.