The study of substance use in longitudinal research

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to Mario, an old friend of mine,
who I hope to see again.

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Introduction

Drug use is widely considered a major problem in modern western societies that equally involves individuals and social actors. Drug use has been largely associated with several types of psychological and social harm such as health problems, reduced educational achievement and job perspectives, and also deviant behavior, involving thus not only the single users, but also the broader societal context around them such as family, communities, social and health care as well as the criminal justice systems (Macleod et al., 2004). Drug use is also a strongly heterogeneous behavior, ranging from legal to illegal substances, and from experimental to addictive consumption; accordingly, it is also heterogeneous in its consequences on the individual and the society around him/her (Hser, Longshore, & Anglin, 2007).
For these reasons, over the last century, drug use have been the target of many scientific research. Epidemiological studies, concerned with the distribution of the various manifestations of drug use in the population, and etiological studies, concerned with the causes, have produced a large amount of valuable knowledge about the distribution of the phenomenon and the risk and protective factors associated with it (Kandel, 1980).
Epidemiological research have highlighted some important recurrent findings. Over the last fifty years, since the outbreak of the hippie movement in the 1960s, marijuana has been the most common and widespread illegal substance in the western society. To date, 29% of the American youths between 8th and 12th grade reported having used marijuana at least once in life. Any other drug has reportedly been used by 16% of the surveyed youths (Johnston, O'Malley, Bachman, & Schulenberg, 2010). Similar trends have also been observed in Europe. In Germany, for instance, surveys on representative samples of the youth population report that about 7% percent of the adolescents between the age of 14 and 17 have ever tried marijuana; however, the figures change when looking at young adults between 18 and 25: here, 35% of the subjects have used cannabis at least once in life (Bundeszentrale für gesundheitliche Aufklärung, 2011b).
Marijuana use is also a strongly age-related phenomenon. The average age of onset is often located in early/mid adolescence, around the age of 14; thereafter, both prevalence and frequencies of use increase rapidly throughout adolescence, and starts to constantly decline only in the early twenties (Kandel, 1980; Reuband, 1999; Hser et al., 2007). According to this well accepted findings, marijuana use finds its roots early in life and undergoes important changes over a short period of time. The existence of such a development should not rise great concern, since the phenomenon tends to disappear with the youths entering adulthood. However, heterogeneity exists within the general youth population, and although the above mentioned bell-shaped trajectory well represents the average development, some concern have been raised about the existence of different developmental paths. For instance, smaller groups of chronic users and late-starters have

also been identified, and their developments have been correlated to negative outcomes in life, such as poor health, psychological problems, low achievement at work, and also use of other illicit drugs (Brook, Lee, Brown, Finch, & Brook, 2011). The latter association has been a widely discussed issue within the field of drug use research. Although the causal mechanisms behind it has not yet been defined, it is well accepted that marijuana acts as a gateway drug for more dangerous illegal substances; in fact, although not every marijuana user gets in touch with harder drugs, the vast majority of harder drug users have previously used, and continue to use, marijuana (Yamaguchi & Kandel, 1984). Furthermore, a more general stage sequential hypothesis has been formulated where legal substances act as a gateway for marijuana, followed then by other illegal substances (Kandel, 1975, 2002).

In sum, marijuana, at the present day in western societies, represents the most used illegal drug among youths, and also a necessary, but not sufficient condition for the use of other illegal substances. Its consume patterns are strongly age-related and undergo important developmental changes form early adolescence, where commonly use starts, to young adulthood, where the use reach a peak and decline thereafter.

These propositions highlight some major tasks for the research on drug use. A better understanding of the development of marijuana use in its early forms during adolescence and its role as a gateway drug might help to better understand the phenomenon and thus define ad hoc intervention strategies (Hser et al., 2007). It is, however, necessary to put together simple epidemiological facts within a more theoretical structure. This is possible if we understand the development of marijuana use during adolescence within the framework of the life-course perspective (Elder, 1985) and the criminal career paradigm (Blumstein, Cohen, Roth, & Visher, 1986). According to the latter, a career describes the development across an individual's life of his/her drug use habits, regardless of the types and the amount of substances used. In order to describe a career, key concepts have to be measured such as onset, escalation, frequency, continuity, and desistance. However, the criminal career paradigm remains an atheoretical instrument to measure behaviors over time; in its original form nothing is said about how a criminal career interacts with the social environment in which they develop. The life-course perspective offers a possible solution to this shortcoming. Within its framework, a career is considered a trajectory through life as much as any other human behavior; beside a drug use trajectory there are, for instance, educational and work trajectories that describe how these life domains evolve with the passing of time: for example, from elementary school to university, or from one job to another, for each person a life history can be described within each of these realms of life. All possible human trajectories have a start and an end, but also evolve over time interacting with each other. These interactions, together with individual and societal factors, might produce transitions and turning points that influence the onset, the course and the end of a particular trajectory. A prominent role is played in this case by the social environment in which the subject lives, and in particular by the societal informal control which is also a determinant factor in creating turning points and shaping trajectories in life (see Laub & Sampson, 2003). For example, a positive social environment around the individual might support him/her into getting a job; as a consequence, the normative social context associated with a stable working situation might create a turning point in the drug using trajectory of an individual, and eventually lead him/her to desist from use. A career can also be characterized by what is known as escalation: from minor experimental use of legal substances through abuse of more dangerous illegal drugs. In this case a drug use career will be characterized by transitions (socially and psychologically determined) among different substances. The gateway hypothesis, as proposed by Kandel (1975), offers a theoretical framework in which to understand transitions as a stage sequential development in substance use; according to this approach, substance use generally starts in adolescence with legal substances like alcohol

and cigarettes, is followed by alcohol abuse, then marijuana, and only thereafter by other illicit drugs. Earlier substances in the sequence act as gateway drugs for substances later in the sequence; being in an earlier stage is a necessary but not sufficient condition to move to a successive stage (Kandel, 2002).
Since no human behavior develops alone, the combination of these three paradigms into an integrated life-course approach will allow a better understanding of how drug use dynamically develops across time and life-phases, and how it interacts with other developmental processes that are also part of the individual's personal and social life.
The purpose of this work, in fact, is to empirically measure and describe some of the principal aspects of an integrated life-course approach to the study of marijuana use in adolescence, using longitudinal data from a German sample of pupils between 13 and 17 years of age (Boers, Reinecke, Mariotti, & Seddig, 2010). Improvements in the methodological approach over the last twenty years have also made it possible to measure, quantify, and describe many of the developmental processes specified above by means of complex statistical techniques. Latent growth model (LGM) (Bollen & Curran, 2006) and growth mixture models (GMM) (Muthén, 2004) will be used to estimate both intra- and inter-individual trajectories of marijuana use. By means of these modeling techniques drug use careers can be estimated within the sample and described using important life-course parameters such as age of onset, continuity, development of the frequency of use, and desistance. Furthermore, subjects can be grouped in classes with similar development over time, allowing to identify also different representative careers. Beside the measurement of quantitative development in marijuana use over adolescence it is also possible to empirically measure qualitative changes as suggested by a stage sequential involvement in substance use. Latent transition analysis (LTA), a longitudinal combination of latent class analysis and Markov models (Graham, Collins, Wugalter, Chung, & Hansen, 1991), allows to test whether specific substance acts as a gateway for other drugs. This technique will be used to test the gateway hypothesis of substance use (Kandel, 2002) during adolescence, and in particular a cumulative sequence going from abstinence to alcohol abuse, to marijuana, and then to other illicit drugs.
Chapter 2 of this work will give an overview over the actual research on marijuana use in adolescence. After a general historical introduction, the single paradigms of an integrated life-course approach to drug use will be presented, followed by the more recent results of trajectories and latent transition analysis about marijuana use. Chapter 3 will introduce the study design and representativeness issues of the data used for this work. In Chapter 4 general descriptive statistic will give an overview on the distribution of drug use in the sample and on the main variables that will be later used in the models. Chapter 5 and 6 will respectively present GMM and LTA models and their results. Finally, Chapter 7 will present conclusive remarks, limitations, and possible future research.

Chapter 2

The study of substance use in longitudinal research

The aim of this work is to empirically study stability and change in marijuana use during adolescence. In this chapter I will first present an overview over the history of marijuana use in the western society. Secondly, I will discuss the importance of a longitudinal approach, emphasizing its validity both for theory testing and empirical analysis. Thirdly, I will introduce a theoretical framework that can be used to understand different aspects of marijuana use development across adolescence; this will be an integrated approach based on paradigms well known to criminological and drug use fields of research. Finally, I will present the main working hypothesis that will later build the basis for my empirical research. However, before I start, I deem it necessary to introduce the definitions of the two main objects of this work: marijuana and adolescence.

Definitions

Marijuana, also known as cannabis, is a psychoactive substance derived from the cannabis sativa, a particular species of the hemp plant. Its psychoactive effects are primarily caused by the pharmacologically active component tetra-hydro-cannabinol, also THC, which is obtained from the leaves and flowering tops of the plant. These are dried, chopped and then generally smoked, although other forms of consumption are possible, for instance, in form of food or drink. Cannabis preparations vary also in quality and property, according to three grades: bhang, the cheapest and least potent, ganja, taken from selected plants and characterized by higher quality and effects, and finally hashish, which is obtained from the tops of mature plants and is stronger in its properties (Grinspoon & Bakalar, 1992). Concerning its psychic effects, marijuana has been often defined under the category of hallucinogen, although its consciousness-altering qualities are by no mean similar to those of more strong substances such as LSD, mescaline, and so on. Among the more common effects, cannabis intoxication generally produces an enhanced sensitivity to external stimuli, distorted body perception, spatial and temporal distortion, increased sensitivity, and also heightened suggestibility among others (Grinspoon & Bakalar, 1992, p. 238).

Adolescence can be technically defined as a particular phase in the life-cycle characterized by the emotional and behavioral states associated with becoming adult (Marshall, 1998). It is both a physically and socially determined status. For what concern the former, adolescence is associated to the physical changes that follow puberty and lead to sexual maturity; by this time youths are physically able to take over adult roles. However, this period of life has also been strongly socially influenced, so that over the centuries, the length and the meaning associated to it has rapidly changed, coupled, for instance, with changes in the family structure and in the labor market (Coleman & Hendry, 1999). In the past, the acquisition of physical maturity was rapidly associated with the acquisition of adult roles and privileges; the transition from puberty to adulthood was rapid and considered an early part of adulthood where adult roles were learned and responsibilities taken. Socially accepted drugs were also part of this new role learning process. In the modern society adolescence has become a longer and well distinct phase of life, due to radical social changes, especially connected with a prolonged educational time and thus a longer dependence from the family. The physical maturation process has lost importance as a marker, and the process of acquisition of adult roles and independence has been prolonged late into the twenties in many western countries (Bukstein, 1995). However, the prolonged gap between physical maturation and adult-status acquisition has led to a definition of adolescence strongly related deviant behaviors and the societal concern; Being physically grown, but not socially recognized as such, adolescents tend to engage in adult and risky behaviors as a way of identity formation and to prove their independence (Moffitt, 1993). Illegal and legal substance use, the latter of which is an accepted adult behavior, are typical examples.

2.1 An overview over substance use research

Drugs and society: historical perspective and development

Psychotic substances[1] have always been part of human social life throughout the history of mankind. The role they played within the society has always been closely linked to the characteristics and historical period of the particular society considered. It is thus acknowledged that along the centuries, and still today, the societal reaction to drug use, whether formal or informal, have ranged from acceptance and incorporation into a normative lifestyle to total rejection. Societal reaction to substance consumption can thus be seen as a continuum between these two extremes, whereas a distinction must be drawn between coexisting formal and informal reactions. These two latter aspects often differ from each other within the same society. As a consequence, the reaction to this issue is strongly related to the society in which it occurs, as much as the research conducted on it (Reuband, 1994).

The societal and political changes occurred in the western civilized countries over the last two centuries have not left aside the problem of substance use. It is within this framework that most of the available research has been conducted and, as a consequence, where most valuable studies and theories have been developed to explain the phenomenon.
The earliest record of marijuana use has been found in a Chinese compendium of medicine, dated, according to different sources, between 2737 BC and 400 BC (Grinspoon & Bakalar, 1992). As a drug with intoxicating properties cannabis was already known in the western society during the 19th century. Until the beginning of the 20th century cannabis was in part used for medical reasons to cure different types of psychosis, sleep disturbance, asthma, migraine, and also rheumatism, but never superseded opiates and other similar substances within the medical field. By this time, marijuana was still considered a medicament, the dangers connected with its use not yet challenged, and its consumption beside medical purposes as a recreational drug were seldom and confined (Reuband, 1994).
At the beginning of the twentieth century a general shift occurred concerning the overall societal concern about psychotic substances. Where earlier the big societal problem was represented by alcohol consumption, new substances such as opiate were emerging as a

[1]The term substances will be used here as a general term defining all psychotic substances, both legal and illigal.

threat. In fact, before that time the use of opiates and opioid (i.e., cannabis in particular) were confined to small groups of adults and young adults who became addicted after being prescribed the drug for medical purposes (Bukstein, 1995). For instance, above all other drugs, opium was considered as an universal everyday medicine, able to cure the more general diseases, and was easily prescribed by the most common physicians; it should not surprise that, at the beginning of the 20th century, opium was also used to cure alcohol addiction (Rosenberg, Gerrein, & Schnell, 1978). Although relegated to a small portion of the society, the addictive nature of these substances became clear and the concern associated with their spread grew steadily in the society. The pathological aspect characterizing these group of users and their limited number witnessed a change already in the 1930s in the USA, where marijuana in particular - a drug that to that date was common especially among low-class Mexican-American communities and only to a lesser extent to the white population - attracted the attention of the media, and turned in a sensationalization of the dangers for the society involved in its use (Bukstein, 1995). Fear spread in the public that marijuana could be responsible for stimulating violence and also being sold to children in the schools (Musto, 1992). This influenced, nonetheless, states' legislations to prohibit its diffusion and culminated with the Marihuana Tax Act of 1937 (Grinspoon & Bakalar, 1992), although, especially at that time, less were known about the real diffusion of the drug and its real dangers. However, marijuana use remained relegated to subgroup of the general population. Outside the USA, cannabis remained nearly unknown to the general public until the 1960s. In Germany, for instance, during the first half of the 20th century, concern about drug use was confined to drugs such as cocaine, heroin and above all opiates, that were prescribed for medical reasons; for instance, in the mid-1950s, two thirds of the addicted population in Germany (or the average picture of a drug user) were an adult who became addicted as a consequence of medical treatment (Reuband, 1994).

It is however only in the 1960s in the USA - and shortly after also in other western countries and Europe - with the emergence of the hippy movement and other related youth subcultures that marijuana became popular and known to the general public. In a relatively short amount of time the number of people using illegal substances grew dramatically, involving in particular young people and adolescents. For the first time, the problem was not merely relegated to lower-class and treatment communities, but rather involved a large proportion of middle and upper-class youths. The latter, in fact, are for the first time the large majority of the consumers. Although delayed compared to the USA, marijuana reached also other western countries in the mid-1960s. In Germany, for instance, a similar development was observed. In Hamburg, for example, cannabis consumption increased at a dramatic rate: from 160 youths between 14 and 17 years of age reported to police for cannabis use in 1967, to 330 in 1968, to 568 in 1969, and finally to about 1884 in 1970 (Reuband, 1994). Thus, especially after the second world war, the topic of youth's consumption of psychoactive substances received particular attention both by the media and the public. This sensationalization was perceived and presented in many cases as a problem. Two important issues contribute to its perception as a threat and prompted the consequent reaction.

First, a problem that shortly before was relegated to the side of the society was now emerging and threatening what was perceived as an important, but weak, societal group: the adolescents. Although not yet proven scientifically, concern raised about possible health consequences of marijuana use early in life and the subsequent harm for society. Furthermore, drug use was quickly associated to deviant behaviors and perceived as increasing the rate of criminality among youth (Bukstein, 1995).

Second, until that time drug users and addicted persons were not really blamed for their conditions, since drug abuse was a mere consequence of medical treatment, and thus considered a byproduct of the health care systems - which also took care of them and provided the drugs. By now, drug use became not only widespread to the general youth population, but also a matter of personal choice (Reuband, 1994). People were not forced by doom into drug use, but chose rationally. This new form of consumption, which was totally different from what had been seen so far, was perceived as out of control. The societal reaction to such a change led to substantial modification in societal reaction to the drug. “Out of the ghetto” (Reuband, 1999, p. 8) meant also the need to rethink the approach to the problem; marijuana had become part of the society.

These concerns were also supported by general data about the prevalence of use of licit and illicit substances, and especially the age of onset. Over the last fifty years some stable patterns have found their roots in the western society. For instance, for what concerns the age of onset, it is well accepted that alcohol and tobacco have an earlier age of onset than illegal substances and a longer time span in which they are used. It is also proven that marijuana use does not generally start before the age of 14, with the higher risk of initiation between 15 and 17 years (Kandel, 1980). Constant use of such substances can be still present in general population until the mid-twenties, when it decreases sharply. The picture for alcohol abuse shows a wider age range with an earlier age of onset and a general use that last into the thirties (Kandel, 1980, p. 242). Gender differences are relatively negligible; however, it should be noticed that generally both periods of higher use and age of onset occur for males a year later than for females. For the latter, in fact, a peak is reached between 18 and 19, whereas for males between 19 and 20 (Kandel & Logan, 1984).

However, trends in the prevalence of substance use have not remained the same over the last fifty years, but have seen recurring shifts all across USA and Europe. Prior to the 1960s less than 2% of the general population and 5% of college students reported use of marijuana. Since then, the picture has changed dramatically: for instance, in 1977, 25% of the population and about 60% of college students reported having tried marijuana (Kandel, 1980, p. 242). According to the Monitoring the Future Study (MTF, Johnston et al., 2010), a long standing research on health behaviors among youths carried out in the USA over the last three decades, marijuana remains the most widely used illicit drug in the USA since study begin 35 year ago. A closer look at the development of the prevalence rates over the last thirty years, as measured by MTF, marijuana use has seen a peak in 1979 where 51% of the 10th graders (14-15 years old) reported having used that substance at least once in life. Prevalence decreased steadily thereafter through the 1980s and the early 1990s to 22%, and then showed a new increase with a peak at 37.8% in 1997. Since then marijuana consumption among 8th, 10th, and 12th graders (between 13 and 18 years of age) has decreased constantly, although since 2008 signs of a new increase have been spotted; in 2009, the prevalence rate was at 29%. At the same time, also 54.6% have tried alcohol and 31.2% have tried tobacco, whereas only a 16.5% have tried any illicit drug other than marijuana.

Similar trends can also be observed in other western countries. For instance, in Germany since 1973 the Bundeszentrale für gesundheitliche Aufklärung (BZgA) has conducted regular representative measurements of licit and illicit substance use among youths and young adults. After a slowly growth in the lifetime prevalence during the 1970s and the 1980s, the 1990s and the beginning of the last decade witnessed a sharp increase in cannabis consumption among both youth and young adults. In 2004 the highest prevalence rates were measured: 18.2% of the male youths aged between 12 and 17, and 47.4% of young adults aged between 18 and 25, reported having used cannabis at least once in life, whereas female respondents reported lower values. Since then, a constant reduction in lifetime prevalence has been witnessed in Germany; at the time of the last measurement in 2010 (Bundeszentrale für gesundheitliche Aufklärung, 2011b), 9.6% of male youths and 41% of male young adults reported having use marijuana. A closer look at the mid-adolescent time, between 14 and 17 years of age, shows that in 2010, 10.2% of the respondents (male

and female together) have used that substance. Similarly, by 2010, 31.9% of youths and 71.1% of young adults have tried tobacco (Bundeszentrale für gesundheitliche Aufklärung, 2011c), 42.8% of youths and 78.6% of young adults have used alcohol in the last 30 days (Bundeszentrale für gesundheitliche Aufklärung, 2011a), and 6.6% of all interviewed subjects between 12 and 25 years of age have tried illicit substances other than marijuana (Bundeszentrale für gesundheitliche Aufklärung, 2010).
Also at cross-national level trends in substance use have been measured over the last two decades. The European School Survey Project on Alcohol and Other Drugs (ESPAD) is an ongoing project that started in 1995 with the goal of monitoring substance use habits among European youths aged between 15 and 16. Similarly to the German results, also overall in Europe a similar trend in the consumption of cannabis can be seen; marijuana and illicit drug use increased over the first years of the last decade to reach a peak in 2003. By that time 21% of the interviewed youths reported having used illicit drugs. However, in 2007 at the last measurement, the prevalence of illicit drug use sank to 18%, showing a general decreasing trend. In that year, 19% of the sample reported lifetime use of cannabis, whereas only 7% have ever tried any illicit substance other than marijuana. For what concerns licit substances, alcohol remains widely used, with 82% of sample having drunk alcoholic beverages in the last twelve months; regular smoking is also widespread, with 29% reporting having smoked at least once in the last month (ESPAD, 2009).

Marijuana, in particular, remains the most widely used illicit substance in the western society. National and Cross-national reports, both in the USA and in Europe, confirm a general slow reduction in marijuana use rates over the last decade. However, still 29% of the USA adolescents and 19% of their European counterpart are involved in cannabis use. As a consequence, concern is high about the societal and health consequences of this behavior.

Explaining drug use: classical theoretical approaches

Like almost every human behavior, and especially those which are considered a threat for the society itself, people have sought to explain them and find their causes. This is of course also the case for drug use related behaviors. Before the 1960s drug use research sought to explain the use of illegal substances using explanations which ranged from moral failing to a pure desease. Not only was drug use seen as a pathological problem, but also the target populations of many researches on the topic were drawn from small sample groups of extreme consumers (ghetto and low-class areas, patients from treatment institutions, addicted, convicted, etc.). Until the early 1970s most longitudinal data on drug use were, in fact, collected on follow up of clinical population of heroin addicted (see Stephens & Cottrell, 1972), which represented, and still represent, the last extreme segment of the larger user population (Kandel, 1978, p. 3). The nature of these studies involved a biased research population, since in reality the drug-use phenomena is more widespread in the general population in other forms than addiction. Furthermore, the design of these studies precluded an adequate analysis of possible antecedents and consequences of drug use. Indeed, although much was known about addicted users, very few was known about the causes of initiation and the consumption habits of the younger segment of the population, which was known to be particularly at risk of initiation.
With the societal changes occurred in the 1960s, and the observation that consumption of illegal drugs was not merely a subcultural problem, the academic world witnessed an important shift in the race to find the causes of substance use. In fact, larger parts of the society - and especially middle and higher class youths - were now involved in the use of illicit drugs, especially marijuana. As a consequence, the academic community witnessed important changes in its research focus; from small clinical groups to population-representative

samples[2] , from mere institutional information to self-reported questionnaires, and from narrow focused researches to broader survey projects which involved also background psychosocial and structural information connected with the consumption of drugs (Kandel, 1980). Due to the acknowlegment that drug consumption was a more widespread phenomenon than what could be measured in rehabilitational and correctional facilities (thus not only addiction and crime related consumption), researchers focused on use patterns observable in the general public (Kandel, 1980; Bukstein, 1995).

Accordingly, the many explanations given to the phenomenon are strongly associated with the time specific public and political reaction and perception of particular substances. This is clearly reflected in the ways scholars, from many different disciplines, have attempted to explain consumption. Over the last century a great amount of research has been produced in association with all possible aspects of substance use; from legal to illegal substances, from small to larger samples, from qualitative to quantitative studies. Most of the research on drug use has been concerned with the epidemiology of the phenomenon and the identification of risk and protective factors rather than with the development of structured theories (Kandel, 1980). In fact, research in these fields has provided important knowledge about risk and protective factors associated with alcohol and substance use within the framework of prevention oriented studies (Hawkins, Catalano, & Miller, 1992).

However, attempts have also been made to create theories of drug use; they can be roughly divided into four main groups: (a) disease-model theories, (b) biological theories, (c) psychological theories, and (d) socio-psychological theories (or behavioral-oriented theories) (Bukstein, 1995).

The term “disease model” is an umbrella term used to define a wide range of approaches to drug use. It is primarily concerned with the end stadium of substance use disorder, i.e. addiction, and has found widespread application within the treatment community. It considers addiction as a disease “which is not an explanation so much as a statement of fact about the maladaptive use patterns and the risk of repetition of these patterns throughout the life of the addict” (Bukstein, 1995, p. 11). This approach, however, finds less application within the field of marijuana consumption, where still today its addictive effects have not been scientifically proven (Grinspoon & Bakalar, 1992).

Biological theories are closely related to the disease model. Some researchers, in fact, have argued that biological inherited traits might be the cause for drug use predisposition, independent of or in interaction with external influences (such as the social context). Although many of these findings remain controversial, possible causes have been proposed to be connected with neurological and metabolic abnormalities; for example, studies in molecular genetics have found a link between the D2 dopamine receptor gene and risk for alcoholism (Blum, Noble, & Sheridan, 1990) and substance abuse, especially for what concern poly-drug use and substances like cocaine and amphetamines (S. Smith, OHara, & Persico, 1992; Comings, Muhleman, Ahn, Gysin, & Flanagan, 1994). Twin studies and adoption studies have also been conducted to determine genetic influences on drug use controlling for the social environment. Although limited in number, these studies confirmed an increase in the likelihood of both alcohol and substance use for children with substance using biological parents (Cadoret & Gath, 1978; Hrubec & Omenn, 1981; Heath, Meyer, Eaves, & Martin, 1991). However, the lack of consistent evidences on biological heritage makes it improbable that a single genetic predisposition is responsible for drug use behavior alone. More likely, biological predispositions could interact with psychological and societal factors such as parental attitudes, monitoring, and closeness to

[2]As an example, Kandel (1980, p. 240) shows how the modal age for male alcoholics taken from clinical samples in the 1970s reported an age of between 40 and 49; however, the same values taken from a general population survey reported that the problem drinking occurred mainly in the early twenties.

determine an increased risk for substance abuse (Bukstein, 1995). Experimental use of legal and light illegal substances, as it is mostly the case in adolescence, could be largely more socially determined than advanced substance abuse, where more psychological and, perhaps also biological factors, might play a role (Kandel, 1975).
Especially after the marijuana hype of the 1960s and early 1970s, psychological theories have found widespread consensus both within the academic community and the policy makers. According to Bukstein (Bukstein, 1995, p. 11), “psychological theories support the role of internal processes such as feelings, emotions, and personality as the primary causes of pathologic behavior, including substance use”. Within this perspective drug use, independently of the frequency and the drug used, is considered an individual psychological reaction to the more general problems in life. Life strain theory, for instance, sees drug use as a symptom of deeper psychological problems, and used as a coping strategy to overcome unpleasant situations in life such as life strain, major life events, and also more general everyday problems (Allison, Edward, & Donna, 1997). In particular life strains, defined as perceived stressful conditions connected with specific roles in the society, play a central role in explaining drug use among adolescents (see Wills & Shiffman, 1985). Also the self-medication theory has been one of the most prominent. According to this theory, drugs are used to cope with unpleasant affective states, that, in the eyes of the subject, cannot be overcome with other means; for instance, depression, boredom, need for integration, etc. (Hurrelmann & Hesse, 1991; White & Labouvie, 1994). However, mere psychological approaches might fail to explain more socially oriented typologies of substances and way of use, as it is the case for marijuana during adolescence.
Socio-psychological theories are concerned with the explanation of drug use behavior within the social contest in which it takes place. They have taken over old sociological approaches concerned mainly with the influence of the societal structure on drug use (see Anomie theory for instance), to concentrate on individual attributes and their interaction with the social contest (Kandel, 1980). They also depart from psychological theories inasmuch as they understand drug use not as an individual isolated incident, but as occurring within a social environment; it is in this context that such a behavior is primarily learned and then performed, especially in the early stages of consumption during adolescence (Bukstein, 1995).

None of the theories presented above, however, seems to be exclusive, and evidences suggest that many different psychological, sociological and also biological factors might be at work in determining drug use behaviors. It is also true, that the term drug use includes a large variety of different behaviors; from experimentation with a substance to addiction, and from legal substances to illegal hard drugs. On these continuums, different factors could be at play at different stages of drug use involvement. As Kandel (1975) stated, earlier stages in drug use, such as onset and legal or light drugs, are more socially determined, whereas later stages are more psychologically influenced. From this point of view, over the last thirty years learning and interactional processes have found large consensus among scholars, especially for substances like marijuana and other related light drugs, which are relatively widespread among the population and especially among youths. The consumption of these drugs, in fact, has strong roots in the social context, especially the peer group, where learning behaviors are at play, and it should not surprise that all recent theories concerned with these drugs are social and behavioral oriented (Reuband, 1999).
Socio-psychological theories attempt to explain drug use as a behavior which is learned and performed in constant interaction with the social environment around the subject, and include many concepts inherited from more general theories of deviance, such as differential association (E. Sutherland, 1947), social learning (Akers, 1998), social control (Hirschi, 1969), and interactional processes (Krohn, Lizotte, Thornberry, Smith, & McDowall, 1996). Indeed, many attempts have been made to explain drug use by means of the classical criminological approaches. However, among the more established classical

theories applied to address the use of licit and illicit light drugs such as marijuana in the lager population few stand out in the literature; these are, social learning theory as developed by Akers (1998), problem behavior theory (Jessor & Jessor, 1977), and Kandel's adolescent socialization theory (Kandel, 1978, 1980). I have choosen these three theories since they focus on particular aspects important for the topic of this work. In fact, compared to more classical theories of deviance, which are general in purpose, the above mentioned theories are unique in their approach to drug use since they: (a) focus on psychosocial aspects, which are determinant during adolescence; (b) are concerned with either particular deviant behaviors that manifest themselves primarily in adolescence, or specifically in connection with drug use itself; (c) combine theoretical aspects that suite at best early stages in the use of substances like marijuana. Furthermore, substantive empirical materials have been published over the last fifty years.

Since Sutherland's differential association theory (E. Sutherland, 1947), social learning processes have been included in many criminological theories. More recently Akers (1998) proposed an elaborated new form of what is known as social learning theory, which included Sutherland's sociological approach and also other psychological aspects such as imitation (Bandura, 1973). Although developed to explain deviant behaviors in general, the theory has been successfully applied to substance use (Akers & Cochran, 1985; Akers & Lee, 1996; Lee, Akers, & Borg, 2004). According to Akers, variations in the social structure, culture, and location of individuals and groups in the social system explain variations in drug use rates, principally through their influence on differences among individuals on the social learning variables; these are differential association, differential reinforcement, imitation, and definitions favorable and unfavorable to this behavior (Akers, 1998, p. 322). A subject then is more likely to engage in substance use if he/she is differentially associated with individuals that promote specific drug use behaviors, if he/she has the chance to learn models of behavior associated with drug use, if this behavior is perceived as desirable within the reference group, and finally if the rewards associated with substance use are greater than the negative aspects.

Such a model is easily applied to the study of marijuana use among youths, which rates reach a peak in late adolescence, and where the use occurs mainly within the peer group (Kandel, 1980). Social learning theory remains probably the most accepted socio-psychological theory to explain substance use among youths, either applied in its entirety, or only as part of integrated theories. It bridges the gap between old sociological and psychological approaches by including both the societal and contextual influences, and individual learning processes in acquiring a new behavior.

Another socio-psychological approach, known as problem behavior theory (PBT), was developed by Jessor (Jessor & Jessor, 1977) to study youth deviant behaviors such as marijuana and alcohol use, smoking, sexual precocity and other behaviors in youth considered deviant by the larger society. Its main structure integrates variables form three levels of analysis: first a macro structural level which includes the larger social environment in which the subject lives with his/her norms; second, the perceived proximal environmental structure, that includes family, peer group and other relevant primary socialization actors; finally the personality system, which includes personal beliefs, personal self-control, and motivational variables (Jessor & Jessor, 1978). The balance within each of these levels of analysis between risk factors for and protective factors against deviant behavior determines what is called "problem-behavior proneness": this is an individual characteristic that determines the propensity to engage in a particular behavior at a particular point in life. In fact, the PBT also includes a developmental approach to particular age-related deviant behaviors across different phases in life, and particularly during adolescence. Jessor and Jessor (1978) argue that each society has a system of expectations related to age-specific behaviors; more specifically, for instance, alcohol use and sexual intercourse are accepted after a particular age, but sanctioned before. Adolescents often tend to engage

in behaviors that are not yet appropriate for their age, and are thus considered deviant. According to the PBT age-specific modifications in “problem-behavior proneness” can also be understood as “transition proneness” to engage in age-specific deviant behaviors. The higher the score on “transition proneness”, the higher the likelihood of a developmental change through the display of age-graded, deviant behaviors (Donovan, 1996).
Kandel’s adolescent socialization theory is the result of a long standing experience in the field of substance use among youths, which is also confirmed by the amount of literature that has contributed to advances in the field (see Kandel, 1978, 1980, 2002). Over the last forty years this theory has evolved to become a new approach to the etiology of substance use in adolescence. Its focus is mainly concentrated on the interplay between the individual and the primary socialization agents, especially family and peers, and their role in determining behavior. Furthermore, being the interplay between them stronger during adolescence, her approach concentrates only on that particular phase of life. According to Kandel peers and parents interact with each other in shaping an individual drug use behavior by means of three main processes: through imitation and social reinforcement, as already specified by the classical social learning theory (Akers, 1998), and through commitment, i.e. the quality of bond between parents and child, as stated by Hirschi’s control theory (Hirschi, 1969). Thus, parents and peers, providing drug related behavioral models, contribute to the learning of substance use behavior, whereas the quality of the relationships with the parents, independently of parental behaviors and moral values, will influence the children’s deviant behavior (Kandel, 1980). Although similar to learning and control theories, the particularity of Kandel’s approach consists of two issues that previous cross-sectional research had overseen and that contributed to overstate peers influence. First, parents play an important indirect role in influencing the kinds of peer with whom the children associate; thus, a poor relationship with parents might exert an indirect important influence on the choice of delinquent, drug using peer (Kandel, 1980). Second, peer relationships, and thus learning processes, are bi-directional: some studies suggest that both socialization and selection processes are at play in influencing, for instance, marijuana use (Kandel, 1978). Finally, Kandel’s approach provides important guidelines for further research on the topic; in particular, she stresses the necessity of understanding the important role of parents and the separation of learning from selection processes in peer relationships. Concerning the latter, Kandel suggests that research concerned with the role of peers in socialization processes should rely more on self-reported information from the peers themselves, rather than on superficial perception provided by the interviewed subjects (Kandel, 1978; Kandel & Davies, 1991).

The above mentioned theories, to my opinion, better represent the classical approaches to the study of legal and illegal light substance use in the larger youth population. Beside them, however, other theories, many of which classics of the sociology of deviance, have been adapted to and tested for drug use. Among the many studies conducted over the last fifty years, control theory (Matsueda, 1982; Brook, Brook, Gordon, Whiteman, & Cohen, 1990), self-derogation theory (H. Kaplan, 1975), and the theory of planned behavior (Marcoux & Shope, 1997; J. Kam, Matsunaga, Hecht, & Ndiaye, 2009) represent, as an example, attempts to test other theories, all well known in the criminology field. Also many attempts have been made to integrate different theories to explain drug use behavior. For instance, Marcos, Bahr, and Johnson (1986) integrated bonding and association theory, Elliot, Huizinga, and Ageton (1985) integrated bonding, association and strain theory, and the social development model (Hawkins & Weis, 1985) combined control and social learning theory with the main purpose of developing preventive measures.
However, most of the above mentioned theories do not take into account the developmental nature of human behavior, especially in a period of life like adolescence, where a lot of change is expected. Although some of them, such as Jessor’s problem behav-

ior theory, includes some developmental aspects in their structure, they still rely on a static conception of the behavior under study. Drugs use is understood and measured in its happening at a particular point in time, focusing on inter-individual differences rather than intra-individual development. Only the latter, however, can allow a precise measurement and understanding of stability and change in a subject's development over time; only the latter, goes beyond the mere distinction between user and non-user to focus on other important characteristic of substance use such as age of onset, continuity, and desistance. These characteristics, among other, are fundamental to the etiology of drug use and need to be incorporated in new "developmental" approaches to the subjects. With regard to this issue, the last three decades have witnessed a steady increase in longitudinal studies concerned with drug use. The inclusion of the variable "time" in the research has allowed, beside unprecedented new analytical perspectives, the slow development of new theoretical approaches, that include now the developmental aspect among their main propositions. By means of longitudinal epidemiological studies have become clear that behaviors such as drug use, especially early in life, undergo dramatic changes in a short period of time. New theoretical approaches should take it into account.

2.2 The shift from a cross-sectional to a longitudinal/developmental approach to the subject

During the last three decades a major shift has occurred in drug use research. Although cross-sectional analyses had already documented age-specific trends in drug use, they were biased by the fact that their results relied on different cohorts, "and therefore confound two possible processes: maturational change associated with chronological age, and historical differences among cohorts with different life experiences, in this case different rates of opportunities to use drugs in adolescence" (Kandel & Logan, 1984, p. 660). Cross-sectional data fail in two major ways.

First, longitudinal data go beyond cross-sectional data for what concern the amount of information they carry; where the latter contain only aggregate information about differences among individuals (for instance, they distinguish between user and non-user), the former allow also the measurement of intra-individual differences; in other words, they allow to move from the aggregate to the individual level of analysis (Farrington, Loeber, Yin, & Anderson, 2002). This means that, concerning the use of drugs for example, it is now possible to distinguish both between user and non-user and also to see how individual habits change over time, and this in many different ways: new information are now obtained such as time of onset, period of continuity beside period of no use, changes in the frequencies, and also desistence. In fact, like most other behaviors, individual patterns of drug use change over time; people might continue for years or simply experiment with illegal substances only for a short period of time. Even in the latter case, substance use is not a mere incident but also the result of interconnected events and behaviors in life that have developed before, and will develop together with drug use. Thus, only longitudinal observation of individuals over long periods of time allows to define and measure both the mere development of substance consumption and the stability and change of all those behaviors, personality and environmental traits that are deemed important for the explanation of drug use. For instance, among the well accepted evidences from cross-sectional studies are the age of onset, which is found in early adolescence, the peak in use of illegal drug in the early twenties, and the steady decline thereafter (Kandel & Logan, 1984); similar in shape to the well accepted age-crime curve in criminology (Blumstein et al., 1986). The bell-shaped curve describing the development of drug use differs only for the

fact that it is shifted from late adolescence to young adulthood in the early twenties. For instance, Kandel (1980, p. 247) reports that "rates of current use of the socially accepted drugs remain constant, while current use of illegal drugs declines from the younger to the older cohorts, especially beginning with persons at age 25.". However, "how far does the observed peak of the aggregate age/crime curve reflect changes within individuals as opposed to changes in the composition of offenders?" (Blumstein & Cohen, 1987, p. 51). This question could only be answered by means of longitudinal studies that allow, beside the analysis of aggregate information, also the definition of intra-individual change in drug use over time. It is only by following single subjects over time that it is possible to determine whether the bell shaped developmental curve proposed above is the mere result of an increase in the prevalence rate (different subjects at different times), or the true individual development.
Second, it is well known that a necessary condition for causal relationships between variables is time (Blalock, 1964). Causality can be determined when the influencing factor occurs at an earlier point in time with respect to the influenced one. Longitudinal data are thus both an instrument to determine real individual change and a necessary condition for researching the causes of drug use involvement at any particular age. Another important aspect is that also causal factors can be studied in their developmental process, allowing thus to define dynamic causal processes, where a change in a risk factor can influence a change on a dependent variable (see S. Duncan, Duncan, & Hops, 1996; Bentler, Newcomb, & Zimmerman, 2002).
Cross-sectional data, in the past decades, have been largely used and have provided knowledge of incomparable value about risk and protective factors for drug use (see Kandel, 1980; Hawkins et al., 1992). However, in many cases, they have been misused to explain both individual behavior and causal relationships (Farrington, 2005).

The first longitudinal studies on drug use behavior were carried out already in the 1950s, although they were mainly concerned with subpopulations of high risk consumers (see Vaillant, 1966; Stephens & Cottrell, 1972). These studies, often limited in time, in most cases analyzed addicted consumers or selected minorities in deprived areas of large cities (Bukstein, 1995). However, as a consequence of the increase in use among youths and in the wider population in the 1960s (Johnston et al., 2010), the most important feature of modern longitudinal research on drug use is the possibility to achieve a more precise and representative epidemological measurement of the phenomenon within the wider social contex in which it happens (Kandel, 1980). All this has been possible thanks to the first self-reported prospective longitudinal studies based on large representative samples, many of which started in the late 1960s/ early 1970s in the USA (Kandel, 1978, pp. 6-11). They focused, for the first time, on representative populations, including both users and non-users, and thus allowing group comparisons and more accurate search for the causes. They covered a time span from school to young adulthood, and included many other contextual information other than drug use such as personality traits (G. Smith & Fogg, 1979), parents and peers information (Kandel, 1978), as well as focusing on important moments in young people lives such as high school time (G. Smith & Fogg, 1978), the transition from high school to adult life (Johnston, O'Malley, & Eveland, 1978), college time (Jessor & Jessor, 1977), and also studies on Vietnam war veterans (Robins, 1978).

Although very informative and important for the research, longitudinal studies are expensive and time consuming. To my knowledge, the exact number of longitudinal studies on drug use is unknown, due to their heterogeneity in designs and measurements; there are, in fact, many studies which include some variables about drug consumption, but do not focus entirely on that, and comparably less exists concerning only the study of drug use behavior. For instance, Kandel (1980) reported that 35 longitudinal studies had been identified, most of which were initiated between 1969 and 1971 as a legacy of the widespread concern about drug use among youths associated with the hippie culture. A recent review conducted in the USA by Macleod and associates (Macleod et al., 2004) identified 48 relevant longitudinal studies on cannabis use. More precisely, these studies were concerned both with the developmental measurement of marijuana use in adolescence (a search condition was to have 25 years or younger) and the correlated psychological and sociological consequences. For instance, among the early studies conducted in the 1970s, the Boston School Project (Guy, Smith, & Bentler, 1993), and the Children in the Community Project (Brook, Cohen, & Brook, 1998) were population based studies concerned about the distribution of cannabis use in the general population and its consequences; they found a relationship between cannabis use and drug use in adulthood, but they also found no sign of psychological health problems connected with marijuana use. The Central Harlem Study (Brunswick & Messeri, 1986), also conducted in the early 1970s, found however that cannabis and cocaine use were associated with greater reported psychological problems. More recent studies conducted in the 1990s, such as the National Longitudinal Study on Adolescent Health (Resnick, Bearman, & Blum, 1997) and the East Harlem Study (Brook, Balka, & Whiteman, 1999), found evidence of an association between marijuana use and problem behaviors. It is evident from the few examples reported above, that the large heterogeneity in sample construction, study design, measurement of drug use, and covariates considered, is reflected in the general inconsistency of the results. In their review, Macleod and associates (Macleod et al., 2004) conclude that, although the large heterogeneity among the studies, marijuana consumption seems to be associated, among others, with reduced achievement in school and subsequent illicit drug use; it is also unclear, and in some case contradictory, whether cannabis use is associated with psychosocial problems and delinquent behaviors. Although longitudinal studies offer unprecedented advantages for the analysis of causal relationships, concrete causal factors important for the understanding of drug use have not yet been clearly identified. In any case, “cross-sectional evidence cannot clarify questions of causality; longitudinal or interventional evidence is needed” (Macleod et al., 2004, p. 1579), since only longitudinal studies are able to measure the individual development in drug use and thus highlight specific facotrs influencing the use of drugs at a particular time in life. This is especially true when studying behaviors, such as marijuana use for instance, among children and adolescents, where developmental processes are at work and a lot of change is expected (Flory, Lynam, Milich, Leukefeld, & Clayton, 2004). More should be done to identify study designs suitable for more precise causal testing, where the effect of possible confounding variables and mechanisms are taken into account (Macleod et al., 2004, p. 1585).

Research on drug use has always been strongly influenced by and interconnected with the more general research on deviance and criminal behavior. This is not surprising since in most cases illegal drug consumption is considered a deviant behavior and treated alike. This is also well reflected in the classical theories on drug use, which are taken from the sociology of deviance. By looking at the development of longitudinal research in the field of substance use, two main streams can roughly be distinguished, which have developed mostly independently from each other, and this regarding both the theoretical perspective and the analytical tools used. First, from a theoretical point of view Kandel (1975) set a milestone in the longitudinal research on substance use when she first produced the gateway hypothesis of drug use and advocated for more and more longitudinal data in order to better understand the phenomenon (Kandel, 1980). Her pledge was picked up years later by Collins and colleagues (Graham et al., 1991; Collins & Wugalter, 1992) who also developed and applied special analytical techniques to the analysis of longitudinal data concerned with testing the qualitative progression through different stages of drug use. The gateway hypothesis remains an important perspective on the development of substance use across specific time, and latent transition models are the actual more advanced statistical tool to measure it by means of longitudinal data. Second, as a consequence

of the increase in longitudinal studies in the criminological field during the 1960s and the 1970s, the criminal careers and "career criminals" report produced by Blumstein in 1986 (Blumstein et al., 1986) set the beginning for what will become the developmental life-course criminology in the successive decades (Farrington, 2003). Amongst the new features of this approach is the concept of careers, which can be also applied to the study of substance use; by means of latent curve models it is in fact possible to statistically define individual and aggregated developmental trajectories for a specific behavior measured over time. This technique, although primarily employed in the study of more general deviances, was also in some cases utilized for describing drug use careers.
Thus, the advantages of a longitudinal approach to the study of human behavior is clear, and also the necessity to apply the right analytical technique to the right longitudinal data. Over the last three decades important steps have been made in the field of quantitative methods, first due to the unprecedent fast development of computing capabilities, and second in order to satisfy the growing need of empirically testing long established theories in the social science. As outlined above - considering drug use among youths - great interest has been shown in two main research areas: (a) the mere epidemiological measurement of the rates of consumption, and (b) the distribution in the youth population of different types of substances. Coupling these topics with the recent availability of longitudinal information about both aggregate data and the career of the single consumers, it is possible to expand and test established theoretical questions within a longitudinal framework.

In the next sections the above mentioned longitudinal approaches to the study of substance use will be described in more detail. First, the life-course perspective will be presented as an umbrella paradigm to understand drug use behavior in its development across different life-phases and adolescence in particular. Second, within this framework, recent results concerning the existence of different drug use trajectories in adolescence and young adulthood will be presented. They reflect the interest in quantifying the more common developmental patterns of use present in the actual western society. Finally, a more qualitative approach to the development of substance use will be presented in the form of the gateway hypothesis of substance use, focusing on the identification of sequential stages of development.

2.3 Life-course perspective and criminal career paradigm on drug use

Classical and more "static" theories have failed to account for the developmental aspect of drug use behavior. Drug use, in fact, is generally not an isolated incident, but develops with its own specific patterns across different phases of human life. Furthermore, even in its mere experimental form, it is in part the result of a web of interrelated psychosocial factors that develop over time and interact with each other.
A general trend in marijuana use has been identified in the broader population, which progresses from initiation in middle adolescence, reaches a peak in young adulthood, and tends to decrease in the early twenties (Kandel & Logan, 1984; Hser, 2002; Brook et al., 2011). Furthermore, many other studies have suggested the existence of different developmental paths (Ellickson, Martino, & Collins, 2004; Tucker, Ellickson, Orlando, Martino, & Klein, 2005; Jackson, Sher, & Schulenberg, 2008), which differ, for instance, according to the age of onset, frequency levels, duration, age of desistance, and prevalence in the population. Moreover, similar studies have pointed out how different paths at different ages are strongly correlated with specific risk factors (Flory et al., 2004) and outcomes later in life (J. Guo et al., 2002; Schulenberg et al., 2005).
It is thus important to approach the study of drug use behavior from a new perspective,

which involves long-time observations of individual development and its interaction with all possible risk factors.
Although a lot has been done in the sociology of deviance with the development of the developmental life-course criminology (DLC) (see Farrington, 2003), little has happened within the drug use research field (Hser et al., 2007). However, two important paradigms within the DLC can be used to formulate an integrated life-course/developmental approach to the study of substance use. On the one hand the criminal career paradigm (Blumstein et al., 1986), and on the other hand the life-course perspective (Elder, 1985).

With the publication in 1986 of the report on Criminal Careers and "Career Criminals" (Blumstein et al., 1986) a milestone was set for the future development of the discipline. A coherent new approach was codified and proposed to the research community. The criminal career approach understands a deviant behavior not as a static incident, but rather as a developmental process that involves correlated antecedents and outcomes (such as repeating the same behavior in the future). Deviant behavior is better described as a career, which is the "characterization of the longitudinal sequence of crimes committed by an individual offender" (Blumstein et al., 1986, p. 12). The novelty of this approach is that Blumstein codifies and provides the instruments to measure and describe each specific criminal career, shifting the interest from the aggregate to the individual. Thus, a deviant career, in its broader terms, is defined by a beginning, a period of continuity, and its end. Other important parameters that characterize the criminal career approach are, for instance, the frequency of crime, escalation from light to serious crimes, and the severity of the committed actions (Blumstein et al., 1986). Measurements over time of the same subjects are strictly necessary, so longitudinal studies become the key tool for the DLC paradigm. In fact, being it a paradigm and not a theory itself, the main goal is to measure and describe from a new perspective a specific behavior; as Blumstein pointed out, "the construct of the criminal career is not a theory of crime. Rather, it is a way of structuring and organizing knowledge about certain key features of offending for observation and measurement." (Blumstein, Cohen, & Farrington, 1988, p. 4).
The criminal career approach remains, however, an atheoretical perspective (Laub & Sampson, 2001). It is in fact necessary to include deviant careers within a more general developmental framework, that should include both individual and sociological factors. The link is offered by the life-course perspective (Elder, 1985).

The concept of career is thus the key feature of this new approach to the study of human behavior, and particularly deviant behavior. It can be tracked back to studies on developmental processes proposed by Elder (1985), and it is also known as the life-course paradigm. This approach sets new standards to the study of human behavior; the latter, in fact, in order to be properly understood has to be measured and studied in its dynamic development across time and, especially, across different phases of a person's life. Each behavior, in its development, is described by a trajectory, which is defined as a pathway of development during life and can describe different realms of human life, such as work, education, parenthood, and also deviant behavior. Trajectories, thus, in the conception of Elder (1985), are long term patterns of specific behaviors, strongly interrelated with each other and with the societal, environmental, and psychological context in which they exist and go through. Trajectories are also marked by particular events in life that are responsible for changes, and that constantly reshape them, giving them new forms and new meanings. These events, that evolve over shorter time spans than trajectories, are called transitions and refer to particular situations such as changing job, entering or leaving school, committing a new crime, etc. The constant interaction between trajectories and transitions across different phases in human life can generate important changes in the individual course of life; they are called turning points (Elder, 1985, p. 32), and are responsible for major changes in the development of a particular trajectory. Thus, "the long-term view embodied by the life-course focus on trajectories implies a strong connec-

tion between childhood events and experiences in adulthood. However, the simultaneous short-term view also implies that transitions or turning points can modify life trajectories - they can redirect paths" (Sampson & Laub, 1992, p. 66). Thus, Elder (1985) defines a trajectory as the particular path a behavior follows across its development and, transitions and turning points as the events in life that change a particular behavioral trajectory. For instance, a general representative trajectory of marijuana use during adolescence can be described by an age of onset around 14 years of age, followed by an increase and a peak in the frequencies around the end of adolescence, and, finally, a decrease thereafter (Kandel & Logan, 1984). Transitions might be represented by consumption of more dangerous substances, or also a sharp increase in the frequency of use. Turning points could be considered, for example, getting a job or a stable relationship which might contribute to desistance from drug use (Kandel, 1980).
The new approach of the life course introduces a new dynamic way to study and understand behaviors, which imply not only a new theoretical perspective but also a new empirical approach. Similar to the criminal career paradigm, also the life-course perspective is not a theory itself but it is rather an instrument for the researchers to organize knowledge about the development over time of a particular behavior.

The combination of the two above mentioned approaches, together with the important knowledge gained over the last fifty years about risk and protective factors in criminology (Farrington, 2000), led to the development of the DLC (Farrington, 2003).
In a similar fashion, the two paradigms can also be applied to the study of drug use. It is in fact well known from recent longitudinal studies, that the consumption of drugs, especially between early adolescence and young adulthood, undergoes important developmental changes and does not always remain an isolate behavior in the life history of the majority of the population. Independently from the typology of substance used - it can be alcohol, but also marijuana - consumer careers can be measured with the tools provided by the criminal career approach (Blumstein et al., 1986). Individual trajectories of use across specific time spans can be described by the age of onset, the period of continuity and possible escalation, and in many cases also by the time of desistance. Furthermore, all these processes, summarized in a single trajectory, can be better understood within the framework of the life-course perspective (Elder, 1985); indeed, behavioral developments (trajectories) are shaped by particular events in life, which are age-specific and influenced by both internal and external factors, and eventually are the markers that define each specific individual path. For instance, many researchers have pointed out the importance of the peer group for the involvement in drug use (Kandel, Yamaguchi, & Chen, 1992; Akers & Lee, 1996); transition in life like entering school, as an example, can bring a subject in contact with peer that use drugs and therefore act as a turning point for the beginning of a new path in the child's life. Similarly, entering adulthood, and thus acquiring new adult roles in the society is strongly correlated with - and thought to be one of the main causes of - desistance from use (Kandel, 1980; Schulenberg et al., 2005).

Two main features of a life-course approach to the study of drug use are concerned with the epidemiology of the phenomenon, and are of paramount importance for the correct development of drug use policies. On the one hand, a great role is played - at the moment (Brook et al., 2011) - by the definition of drug use trajectories concerned with the development of specific substances across specific life phases. On the other hand, another important feature concerns the definition of specific sequences of use among different substances and the role of gateway drugs. These two topics will be discussed in the following two sections.

2.4 Developmental trajectories: a "quantitative" approach to the development of drug use

The interest in the epidemiology of drug consumption in the wider population has characterized most of the drug use research to date (Kandel, 1980). Important aspects such as age of onset, development of the incidence, and desistance over adolescence are strictly connected to the paradigm of the developmental life-course criminology. This paradigm can be successfully applied to substance use in all its forms.
Hand in hand with the establishment of the DLC as a leading approach in the study of deviance and the availability of more longitudinal data, the last twenty years have witnessed the development of ad hoc statistical techniques for the analysis of behavioral patterns, i.e. careers. The latter, in fact, represent the main innovative parameters introduced by the criminal-career paradigm - and the DLC in turn - for the study of a specific deviant behavior. Latent growth models within the framework of structural equation models (Bollen, 1989), firstly proposed by Meredith and Tisak (1990), allow the estimation of both intra- and inter-individual differences in the developmental pattern of a behavior across a well-defined time span. In other words, individual "careers" regarding the frequency of a specific behavior can be estimated and mathematically described by a trajectory; furthermore, the average development of the sample is also calculated by means of an aggregated trajectory. Being able to measure developmental curves is also the first step toward explaining that particular development by means of theoretically defined covariates (risk factors). The latter, in fact, can be introduced in the model to explain a particular development. However, latent growth models imply the existence of an homogeneous population which shares a single particular development. Among the many contributions of the DLC and longitudinal research to the field of criminology the most important is by large the assumption that different groups of deviants exist, anyone with its own specific development, and requiring specific risk factors and theoretical prepositions (Moffitt, 1993). The existence in the sample of an heterogeneous population regarding the behavior under study, can be explored by means of growth mixture models (Muthén & Shedden, 1999), which are able to statistically estimate - if present - different developmental trajectories for different groups of subjects. Also in this case, model specifications allow to include covariates (risk factors) and outcomes for more advanced theory testing (Muthén, 2004).

Although these models have been mainly used for the study of deviant behaviors in general (see Nagin, Farrington, & Moffitt, 1995; Nagin, 1999; Kreuter & Muthén, 2008b) they have also been applied to the study of substance use. Among the first to apply latent growth models to the study of substance use behaviors in adolescence were T. Duncan and Duncan (1995). For instance, they followed a sample of youths aged 14 for three years and measured the development of the frequency of alcohol consumption. Although significant variance for the developmental parameters suggested high variability in the developmental pattern, the model resulted in a linear development with a constant increasing trajectory across time, suggesting a constantly increasing individual frequency of use from early into late adolescence. In a similar study, S. Duncan et al. (1996) found that the linear positive development in substance used by adolescents was strongly correlated with peer and family factors such as peer and parents drug use, and parent-child conflicts. Also Walden, Iacono, and McGue (2007) found an important association between the trajectory of substance use and specific risk factors; as an example, an acceleration in the development of substance consumption during adolescence was associated with parental substance use. Bentler (Bentler et al., 2002) used a cross-lagged growth model for alcohol and illicit drugs to test whether initiation and development in alcohol use could influence the same parameters for marijuana, using a representative sample taken from local American schools and assessed for a period of 3 years. The results suggested that the increasing trajectory in marijuana use was strongly influenced by similar patterns of development in alcohol consumption.

These studies focused on the identification of a single trajectory, implying a heterogeneous population with individual differences captured by random effects (e.g. variance on the trajectory's parameters). There is however large interest in the identification of subgroups concerning particular problematic behaviors. This has already been done in the field of criminal behavior, where, since the seminal work of Moffitt (1993), many attempts have been made to identify different classes of deviant subjects with their own developmental trajectory. For what concern substance use, research findings on longitudinal data have shown that individual development of drug use habits across time are extremely heterogeneous (Hser et al., 2007) and, as a consequence, this heterogeneity needs to be taken into account both theoretically and empirically. Furthermore, marijuana use at different stages in life has been associated with a variety of psychosocial problems in particular areas of adult life, such as health, work, partnership and also parenthood (Ellickson et al., 2004). The ability to distinguish among individuals with different developmental trajectories, characterized by different age of onset, duration and intensity of use, might help policy makers to better define timing and targets of specific interventions.

The first studies concerned with the definition of subgroups for substance use (Weber, Graham, Hansen, Flay, & Johnson, 1989; Tarter, Kirisci, & Mezzich, 1997) were limited by the use of cross sectional data, and attempted classifications using combinations of constructs including not only drug use but also other structural and individual variables. Only recently, with the introduction of growth mixture models (Muthén, 2004), a definition of subgroups based only on longitudinal individual information about substance use has been possible. Below are presented some studies employing growth mixture models, that have been carried out in the last decade.

To start with legal substances, Wiesner, Weichold, and Silbereisen (2007) used a representative sample of youths followed from age 14 to 18 and found four distinct developmental trajectories of alcohol consumption. Furthermore, although the same number of groups were estimated for both genders, some remarkable differences were also noted. For instance, the regular user class represented the largest group and the normative pattern of consumption among male respondents with 76%. Their development across time started with high frequencies of use at age 14 and increased moderately until the last measurement. The other patterns represented smaller group of subjects with different developments such as the late escalators, who started later and increased sharply the amount of alcohol used, the rare users, who maintained a very low profile across adolescence, although few in number (8%), and finally the early peaker class, who showed a peak in use at age 16 and decreased sharply thereafter. Female respondents differentiated themselves from their male counterpart mainly for the smaller number of regular users, who represented only the 56%. However, also for them, the rare user class was strongly underrepresented with only 9%. The results confirm that alcohol use in adolescence is a normative and well established behavior, which by the age of 18 does not seem to decrease in intensity. In a similar study (Wiesner, Silbereisen, & Weichold, 2008), the same model was re-estimated adding covariates for etiological purposes. Again, the four trajectories were also confirmed in this more complicated application of the growth mixture models, although no striking evidence was found of differences among classes regarding control variables and deviant peer association.

Some major studies on marijuana use are reported below. They are all concerned with defining developmental trajectories using longitudinal data ranging from early adolescence to the late twenties.

One of the first studies on trajectories of marijuana use was carried out by J. Guo et al. (2002) using a representative sample in Seattle, USA. The children were interviewed

annually from age 10 to age 18, and the best fitting model for marijuana use estimated four different trajectories: a large group of nonusers, comprising 73% of the participants and reporting no use all across the time span; an early-highs group (3%), which started using marijuana at the age of 10, increased during adolescence and tended toward no use at the age of 18; two more classes, the late onsetters (19%) and the escalators (5%), that reported a similar developmental pattern characterized by a common late start around the age of 15, and a constant increase in use thereafter. The escalators, however, showed a more remarkable increase in use compared to the other group.
Brook et al. (2011) followed a sample of African-American and Puerto Ricans youths at four time points between the age of 14 to 29, collecting information on both the consumption of marijuana and other related factors like personality traits, work, and partnership in adulthood. Also in this case four trajectories were estimated. The majority of the sample (72%) belonged to the non-/low-user group, with frequency values close to zero all over the time span. The three remaining classes were equal in size (about 9%) but showed different developmental curves: the late-onset user class reported a sharp increase in consumption from late adolescence onward; the maturing-out group showed a peak around the age of 19 and a sharp decrease toward zero thereafter; finally, also a group of chronic users was identified that reported a constant increase throughout adolescence, and stabilized at high level in adulthood. Interesting results were also reported for the association between trajectories and later outcomes; for instance, compared to low/non users all other trajectories were associated with negative outcomes in adulthood, such as engaging in deviant behaviors, unemployment, low work achievement, no marriage and partner marijuana use.
Jackson et al. (2008) used a representative sample of the USA youth population taken from the long standing project Monitoring the Future (Johnston et al., 2010), and examined the development of substance use into young adulthood, from the age of 18 to 26. For what concern marijuana use they found four trajectories of development. The vast majority of the sample (80%) belonged to the low- and non-user group, which reported sporadic low use all across the time span covered. The second largest trajectory was the developmentally-limited users (9%), that already by the age of 18 began to desist from consumption. Two remaining smaller classes included the chronic users (7%), with constant high frequencies of use, and the late-onset users (4%), which showed a rapid increasing pattern that started around the age of 18 and continued into adulthood matching the chronic class level by the age of 26.
In a similar fashion Schulenberg et al. (2005) used a sample from the Monitoring the Future study and searched for possible trajectories in the development of marijuana use form the age of 18 to 24. Also in this case the focus laid on the transition from adolescence into young adulthood. They identified 6 trajectories, although three of them, abstainers, low users and fling, accounted for the 80% of the sample and showed low level patterns of consumption. The remaining three groups included chronic users (5%), increasers (5%), and desisters (7%), the latter representing desistance form marijuana use from the age of 18 onwards.
Ellickson et al. (2004) analyzed the development of marijuana use from early adolescence (age 13) to young adulthood (age 23), covering in this way a large time spam yet rarely seen in trajectory analysis on the topic. They found that the majority of the participants (53%) were included in the occasional-light-user class, which showed an onset between the age of 13 and 14, and remained at a constant low level through the measured time span. The two second-larger classes included a group of stable light users (17%) and a group of steady increasers (25%), the latter showing a constant increasing rate from the onset at the age of 13 throughout young adulthood. A last small class (5%) was identified comprising individuals who started with high rates at the beginning and slowly decreased thereafter. It is worth of notice that occasional light users and stable light users showed

a very similar trajectory, with the only relevant difference that the latter reported marijuana use before the age of 13. The same results using the same sample were obtained also by Tucker et al. (2005), although using different covariates and late outcome variables in analysis.
In a study conducted by Flory et al. (2004), based on a community sample in the USA, pupils drawn from local schools were interviewed six time between the age of 11 and 21. For what concern marijuana use three trajectories were found, and separated trajectories were defined for boy and girls. However, both groups showed similar developmental patterns: a non-user class (38% of the men and 46% of the females), where no use was measured all along the covered time span; an early-onset group (6% of the men and 11% of the females), which reported a bell-shaped development over the ten years with an early start at the age of 11; and finally a late-onset class (56% of the men and 42% of the females), where the subjects initiated consuming marijuana around the age of 14/15 and increased sharply thereafter.
Brown, Flory, Lynam, Leukefeld, and Clayton (2004) conducted a trajectory analysis on a subsample of Afro American and Caucasian youths. The subjects were regularly interviewed between the age of 11 and 20. For both races a three classes solution was found with similar developmental trajectories. Among the Caucasian youths, 41% belonged to the nonuser class, 46% to the late-onset group, and finally 13% showed a bell-shaped development during adolescence. The Afro-American subjects were differently distributed among the classes: 70% belonged to the non-/low-user class, 24% to the late-onset group, and the remaining 6% reported an adolescence limited pattern.
Windle and Wiesner (2004) used a four waves representative school sample in Germany to identify trajectories of marijuana use. They interviewed the subjects at 6 month intervals from the age of 15 to the age of 17, covering what is considered to be the age in adolescence more at risk for marijuana use. They identified five trajectories: an abstainers (82%) and an experimental users (9%) group that represented the majority of sample and showed no or sporadic use of the substance; a group of chronic users (2%), who showed a constant high level of marijuana use; a decreasers (3%) and a increasers (4%) group, which respectively reduceed and started using marijuana in the two years of observation.
Table 2.1 summarizes the trajectories found by the studies presented above. The names used for the classes are those given by the authors in each study.

Table 2.1: Summary of the major studies on trajectories of marijuana use

Study	Groups/Classes	%
Brook et al., 2011	Non-/low users Maturing-out users Late-onset users Chronic users	72% 9% 9% 10%
Brown et al., 2004	Non-/low users Adolescence limited Late onset	C. 41% A. 70% C. 13% A. 6% C. 46% A. 24%
Ellickson et al., 2004	Occasional light users Early highs Stable light users Steady increasers	53% 5% 17% 25%
Flory et al., 2004	Non users Early onset Late onset	♂38% ♀46% ♂6% ♀11% ♂56% ♀42%
Guo et al., 2002	Nonusers Early highs (ad. lim.) Late onsetters Escalators	73% 3% 19% 5%
Jackson et al., 2008	Low users Developmentally limited users Late onset users Chronic users	80% 9% 4% 7%
Tucker et al., 2005	Triers Early increasers Stable highs Steady increasers	53% 5% 17% 25%
Schulenberg et al., 2005	Abstainers Rare users Decreased Increasers Chronic Fling Remaining	47% 28% 7% 5% 5% 6% 2%
Windle & Wiesner, 2004	Abstainers Experimental users Decreasers Increasers High chronics	82% 9% 3% 4% 2%

The studies presented above show how much has been learned in the last ten years about the development of marijuana use among adolescents and young adults. Looking at the trajectories that have been found, at least four specific patterns have emerged: a non-user/ low user group, an early-onset persistent or chronic consumer group, an adolescence-limited group (maturing out of the substance in young adulthood), and a last class of late-onset users (see Jackson et al., 2008; Brook et al., 2011).
Although there is some heterogeneity in the results of the above mentioned studies - in many cases due to differences in sample choice and time span covered - these four resulting patterns of development share a common substantive interpretation.
The non-user or experimental low-user group, which on average represents the 70% of the analyzed samples, is also a good picture of the general trend of marijuana use found in the

larger population. It represents the majority of youths that either never use marijuana or simply try it occasionally in life; occasional experimentation seems to be a widespread phenomenon within the youth population, age-related, and of no societal concern. In fact, if compared to the remaining 30% of the sampled youths, who represent those with a more continuative and frequent use of the illegal substance, beside differences in the developmental trajectories they also show important differences concerning risk factors and developmental outcomes related to their drug habits. For instance, Brook et al. (2011) found out that compared to the non-/ experimental-user group all other trajectories scored higher on psychosocial outcomes such as anxiety, interpersonal difficulties and depressive symptoms. Similar results were also obtained for the work domain, educational career, and partner relationships. J. Guo et al. (2002) also found significant differences among marijuana use trajectories in risky sexual behaviors during adolescence. All user classes, independently of their development, scored higher for all outcomes compared to the non-user group. Also for what concerns early risk factors substantial differences have been found between users and non-users; for instance, Flory et al. (2004) reported that the non-user trajectory group scored higher than the user groups on school achievement, self-esteem, family relations, and peer pressure resistance.

About one third of the consumers show a bell-shaped age-use curve, a well-known developmental pattern in criminology (Blumstein et al., 1986); this group, called adolescence limited, but also referred to as maturing out or simply desisters, shows a developmental pattern of use that grows from early adolescence into young adulthood and decreases thereafter. Although the timing is sometimes different among the studies, this trajectory well represents a normative age-related development of marijuana use in adolescence; for many users, in fact, marijuana use begins in early adolescence, grows into young adulthood reaching a peak between the age of 16 and 18, and decreases thereafter, when the influence of the peer group fades and the youths enter adult roles (Kandel & Davies, 1991). For what concerns group related risk factors and outcomes, adolescence-limited users also reported significant differences compared to other groups. For instance, considering early predictors Flory et al. (2004) found that adolescence-limited users (AL) had lower school achievement rates, self-esteem, and resistance to peer pressure than other groups. However, results concerning group specific outcomes were less clear and often study-specific; in general, adolescent-limited users scored somehow between non-users and chronic users for many outcomes such as employment, educational achievement, and quality of partner relationships (Brook et al., 2011).

Another group among the users is composed of those who report constant high frequencies of marijuana use all across the considered time span. They are common to many studies and, although small in numbers (on average about 6%), these chronic users present a pattern that starts very early in adolescence, reaches rapidly a high level, and remains constant throughout young adulthood and the early twenties; what happens afterwards is not yet clear, since none of the studies reported above cover a longer period of time. This group also differentiates itself from the other classes concerning specific life-outcomes measured later in life; for instance, Ellickson et al. (2004) and Schulenberg et al. (2005) found that later in life chronic users had significantly lower earnings, health, and educational attainment than the other classes. Brook et al. (2011) also found that chronic users were the category of users more at risk to engage in criminal behaviors and, in general, they were more at risk than others to suffer from negative outcomes later in life. Also specific risk factors were associated with this group; for instance, Schulenberg's results showed that chronic users were more likely to have poorer school achievement in high school, were mainly male, and spent more time out with peers compared to non-users (Schulenberg et al., 2005). Also Jackson et al. (2008) found that chronic users were more at risk for delinquency and showed higher level of risk seeking attitudes compared to other classes. Similarly, Windle and Wiesner's chronic gruop was associated with delinquency, lower

academic achievement, more drug using friends, and more stressful life events (Windle & Wiesner, 2004).
Finally, a last recurrent group of marijuana users is represented by the late onsetters. This class, which includes on average about 5% of the samples and has been found in every analysis so far, represents those subjects whose use starts later in adolescence - between the age of 16 and 18 - and increases sharply throughout the time span covered by the single studies; indeed, in Jackson et al. (2008) and Schulenberg et al. (2005) their frequencies were still increasing by the age of 26. The consequences of such a developmental trajectory later in life were studied, for instance, by Ellickson et al. (2004); they found that late-onset users, although having significantly better educational and work achievement than chronic users, were also at higher risk of using harder drugs than simple occasional or low-level users, especially because of the high level of consumption reached in the mid-twenties. Brook et al. (2011) noted that late-onset users, together with chronic users, were the two groups more at risk for low achievements at work, and had a reduced probability of being married later in life. Flory et al. (2004) analyzed also differences among groups in risk factors. For instance, late-onset users scored between the non-users and the chronic users for what concern school achievement, family relations, and peer pressure resistance. Similarly, Windle and Wiesner (2004) found that late-onset users were more at risk to suffer from depression than the other groups.
The four typical trajectories presented above are simply a general overview of the more common developmental patterns identified so far in the literature. Some trajectories, in fact, such as the non-user, the chronic, and the late-onset are commonly found in nearly every study, whereas other, for instance the adolescence limited show slightly different shapes and are not always found (in many cases they are also labeled differently). An overview is given in Table 2.1. In any case, the necessity of differentiating among different marijuana use trajectories, especially early in life, is paramount. Although the above mentioned studies are still small in number and limited in the amount of covariates included in the analysis, not only the existence of substantive different groups of users has been proved, but also the necessity to differentiate among them in terms of risk factors and outcomes later in life.

Another important application of the notion of a developmental perspective to the study of substance use is a stage sequential approach to the consumption of different substances. A developmental perspective, in fact, such as that one specified by Jessor and Jessor (1977), define drug use as an age-graded behavior, which is specific to particular phases in life and marks particular transitions among these. Furthermore, they argue that the acquisition of a specific behavior is often associated with changes in the probability of initiating a similar behavior (Kandel, 1980). Ellickson et al. (2004), for instance, suggested that all four marijuana use trajectories found in his study had between two and four times higher risk of hard drug use than the abstainers group. Thus, developmental sequences for substance use have been identified and will be discussed in the following section.

2.5 Gateway hypothesis of substance use: a "qualitative" approach to the development of drug use

The gateway hypothesis can be considered part of a life-course approach to the study of drug use. In fact, although it has evolved on its own to answer specific questions about the epidemiology of substance use, it addresses issues that can be legitimately included in the more general framework of the life-course perspective; parameters characterizing the life-course/drug career approach such as onset, escalation, and desistance can be properly analyzed using the stage-approach of the gateway hypothesis (Hser et al., 2007, p. 529). It is a well established fact that adolescents do not generally experiment with only one substance, but get in contact with different drugs, both legal and illegal (Yamaguchi & Kandel, 1984). It is also well accepted that some kind of substances are used before others, and that a fairly stable order of experimentation can be drawn among such substances (Kandel, 2002); for instance, cigarettes and alcohol, and thus legal drugs in general, generally precede illegal substances. Similarly, it is also accepted that marijuana is the first illegal drug people get in touch with. Thus, the gateway theory emphasizes that certain drugs serve as a gateway for other substances and that involvement with various typologies of drugs is not opportunistic but follows a precise pathway. Similar processes are also measured for other behaviors that, especially during adolescence and childhood, undergo rapid changes and developments (Kandel & Jessor, 2002). The notion of stages, in fact, can be tracked back to early works of developmental psychologists that tried to empirically test the child's moral development across theoretically defined stages (Kohlberg, 1969, 1980), and it is also in line with the research field known under the umbrella term "stage theories of health behavior" (Weinstein & Rothman, 1998). The latter assumes the existence of qualitative different stages in a particular health behavior, and that individuals move across such stages over time. Stages have to be ordered, and being in an earlier stage should facilitate the access to the next one. The increasing interest in developmental processes has risen the interest in stage-sequential models, which have also been applied to cognitive development (Piaget, 1971, 1972), reading development (D. Kaplan & Walpole, 2005), sexual development (Kandel & Jessor, 2002), and delinquent behavior (Loeber & Hay, 1997).

Within this framework, it can also be distinguished between stages and sequential models; the former are concerned with the phases involved in a particular behavioral development, such as for example the transition from experimental use of cigarettes to regular smoking (see B. Guo, Aveyard, Fielding, & Sutton, 2009), whereas the latter involves the transition from one behavior to another, thus focusing specifically on transitions in a broader sense (Bentler et al., 2002). In particular, a relevant problem is posed by the definition of stages in a sequential model. Bentler et al. (2002) identified three possible definitions: (a) use versus nonuse of a substance, (b) level of consumption, and (c) definition of problematic use/abuse. As a consequence, depending on the choosen definition, empirical research has sometimes shown contradictory results. The mostly used definition has been the first, mainly due to its semplicity, althought less informative than the other. Most of the researches using this definition have reported a sequence where people begin with nonuse, move to alcohol and cigarette, then marijuana, and finally harder drugs. In other cases, a preciser definition of drug use has been chosen; Kandel and Faust (1975), for instance, used ten or more times as cutting point for the definition of users, and the results proved to be similar to those mentioned above. Another important feature of the gateway hypothesis model is that it involves a cumulative process. That means, each time a new substance is used, the previous ones are not dismissed, but still used. Thus for instance, people who start using marijuana, according to the gateway hypothesis, continue to drink alcohol and smoke cigarettes (Collins & Wugalter, 1992).

Pioniering work was conducted by Kandel (1975), who tested empirically the hypothesis of the existence of stages in the use of drugs by means of cross-sectional data, and found a sequence going from beer and wine, to hard liquor and cigarettes (that held interchangeable positions), to marijuana, and finally to other illicit drugs. On the basis of her work Kandel (Kandel, 1975; Kandel & Faust, 1975) was the first to propose a sequential model of drug use which supports the notion that the use of one drug precedes the use of another in an established sequence. Other authors also came to similar results using different samples (see O'Donnell & Clayton, 1982; Donovan & Jessor, 1983), and a subsequent review (Werch & Anzalone, 1995) on the major findings of the sequential model also confirmed the hypothesized sequence starting with nonuse, progressing to legal substances, and then to illegal ones, where the first to be experimented is always marijuana.

Learning from nearly three decades of empirical and theoretical research the current formulation of the gateway theory is defined by two main propositions; the temporal sequence, and the association among drugs (Kandel & Jessor, 2002; Fergusson, Boden, & Horwood, 2006).

The first proposition is concerned with the epidemiological evidence that a sequence can be identified, as already mentioned above. Especially during adolescence, a period in life which has been particularly endeavored in drug use research, many empirical studies have found that specific drugs precede the use of others; in the typical sequence licit drugs are tried first, followed by marijuana, and finally by harder illicit substances. Although the sequence is socially and historically determined, this progression is well established in most western societies (Adler & Kandel, 1981; Kandel et al., 1992; Kandel & Jessor, 2002), and particularly in those countries that share common patterns of substance availability and consumption (Degenhardt et al., 2010).

The second proposition assumes a strong association between substances which are close to each other in the sequence. In fact, the use of drug earlier in the sequence should increase the likelihood of using another drug later in the sequence. For instance, those who use marijuana are at increased risk of using harder drugs compared to those who never used marijuana. Alcohol and tobacco users are, similarly, more at risk than abstainers to try marijuana and progress in the sequence. Many epidemiological studies have also confirmed this proposition; for example, among the earlier studies Yamaguchi and Kandel (1984), using longitudinal data for a cohort of high school students, found that in more than 90% of the cases alcohol preceded marijuana and other illicit drugs, marijuana preceded other illicit substances and prescribed psychoactive drugs, and that cigarettes also preceded all illicit substances. Two sequences, however, were less clear: in only 60% of the cases cigarettes preceded marijuana, and in 80% of the cases alcohol preceded cigarettes. Also Donovan and Jessor (1983) confirmed the nature of this association using a Guttman scale; their analysis suggested that "use or abuse of a less common drug is accompanied by experience with all of the more commonly-used drugs. Such a pattern of involvement suggests the following ordering: nonuse, nonproblem use of alcohol, use of marijuana, involvement in problem drinking, use of one or more of the pills, and use of either or both of the hard drugs" (Donovan & Jessor, 1983, p. 545).

There are, however, two main critical issues embedded in this definition of the gateway hypothesis.

The first problem is concerned with the exact sequence and association among drugs. Although much is known about the role played by marijuana as a gateway substance for harder drugs, less is known about the real sequence between alcohol and tobacco, and among more advanced drugs. Although drunkenness is one of the main predictors of subsequent marijuana use (see Graham et al., 1991; Maldonado-Molina & Lanza, 2010), confusing results have been obtained about whether alcohol use precede tobacco or vice versa (see Graham et al., 1991; Lanza & Collins, 2002; Patrick et al., 2009). The majority of the studies, in fact, propose a sequence where both legal substances are equally considered entry drugs, so that their role and position in the sequence is not yet clearly defined (Kandel & Faust, 1975). In their review, Werch and Anzalone (1995, p. 92) concluded that "the exact sequence of alcohol and tobacco products in the progression of other drug use is equivocal". Similarly little is known about the sequence among hard drugs after marijuana. For instance, Ellickson, Hays, and Bell (1992) using longitudinal Guttman scaling technique found that although the initial sequence involving legal substances and marijuana held, less stable results were obtained concerning the location of pills, cocaine and other illicit drugs in the sequence; experimentation of cocaine and other illicit substances was generally combined with regular use of marijuana, whereas pills were found

to follow the initial use of marijuana. Similarly, Flisher, Parry, Muller, and Lombard (2002) using a sample of South African youths, found that marijuana was followed by either crack or ecstasy, but a clear sequencing between the last two substances was not possible. In any case, marijuana remains the entry drug for illegal substance use, and no agreement has been found so far about the successive sequence (Kandel, 2002).
The second major problem is concerned with the question of what is responsible for the above mentioned associations, and more precisely with both the existence of a causal relationship between two adjacent substances in the sequence, and the mechanisms that determine movement across stages (Kandel, Yamaguchi, & Klein, 2006). The causal mechanism behind these associations can be explained in two ways: directly, by means of neurophysiological conditions, or indirectly through the social environment (Macleod et al., 2004). In the first case, some studies suggest the existence of a causal relation between two adjoining drugs (Fergusson et al., 2006). In this situation, for example, the consumption of marijuana might cause biochemical changes in the brain that would promote the subsequent use of other specific drugs, such as opiates. Schenk (2002) conducted an animal study to test the hypothesis that gateway drugs like marijuana could enhance sensitivity to the pharmacological properties of other drugs. She found that repeated exposure to gateway substances such as tobacco, alcohol and marijuana produced a significant sensitization to cocaine. However, causal relationships of this type on humans have not yet been scientifically proven (Kandel & Jessor, 2002) and the current research supports the second hypothesis about the existence of different external factors that might influence specific associations among drugs in the gateway sequence. For instance, an underlying predisposition - such as risk taking behavior, or a general predisposition to use drugs - might be responsible for the stage sequential process, and only external factors like availability, social support, and opportunities would account for the position of a specific drug in the sequence (Fergusson et al., 2006). The discussion is yet open (Degenhardt et al., 2010), and for these reasons, as Kandel and Jessor (2002) suggest in the formulation of the main hypothesis of the gateway hypothesis, the existence of a developmental sequence should not be considered a causal process. On the contrary, the use of a gateway drug is necessary but not sufficient for moving to the next stage. This definition implies that other factors are at play in determining movement across stages. Furthermore, different factors operate at different stages, so that earlier stages are more socially determined, whereas later stages are more psychologically influenced (Kandel, 1975). The gateway hypothesis only suggests that those at a particular stage are more likely to move further than those who have not yet entered the sequence.

Over the last fifty years of research on stage sequence in drug use, many different analytical tools have been used (see Kandel, 2002). For example, among the earlier works, Kandel (1975) and Donovan and Jessor (1983) used Guttman scale to analyze cross-sectional data. However, the most important shift in research on the gateway theory - as pointed out before - was the introduction of longitudinal individual data. With the availability of longitudinal datasets also life event history analysis (Kandel et al., 1992) and structural equation models (Newcomb & Bentler, 1986; Bentler et al., 2002) have been used. For instance, Bentler et al. (2002) compared the cross-lagged influences of tobacco and marijuana use using the frequencies of drug use. The results of their latent growth model showed that tobacco was the gateway drug for other licit and illicit substances. Alcohol use was also found to be a gateway drug for marijuana and other illicit substances, although cross-lagged effects showed how an increase in marijuana use influenced a similar trend in the consumption of alcoholic drinks. Using the same modeling strategies S. Duncan et al. (1996) reported similar results. In another study, Donovan and Jessor (1983) found that problem drinking was successive to the use of marijuana and other illicit drugs. Newcomb and Bentler (1986) also found that prolonged and increased smoking led to an increase in marijuana use and vice versa.

Only recently Collins and Wugalter (1992) developed an ad hoc method of latent class analysis to test sequences of change among different qualitative stages. This method, known as latent transition analysis (LTA) (Graham et al., 1991), estimates the probability of transitioning from one state to another in a specific sequence, and allows statistical inference on the estimated parameters. This method has only recently found application in modern statistical softwares, and it is now available to the practitioners. It represents, so far, probably the better way to test stage sequences, although it can only deal with nominal and categorical ordered variables. In most cases the simple distinction between user and nonuser of a substance are used.

Among the many advantages offered by LTA is the possibility to test the two main propositions of the gateway theory at the same time in a single model (Fergusson et al., 2006). LTA, in fact, allows both to specify and test every possible stage sequential model - and thus to empirically test the existence of a specific development - and also to estimate probability of transition from one stage to another and thus to measure the amount of association between two adjacent stages. This characteristics make it probably the most suited instrument so far to test the gateway hypothesis.

Mainly due to the studies conducted by the working group around Linda Collins, the gateway hypothesis has been intensively tested using different drugs, different samples, and also controlling for covariates.

Among those studies, the analysis conducted by Graham et al. (1991) can be considered the first application of latent transition analysis to test the validity of the gateway hypotesis of substance use. Different stage sequential patterns were tested against each other. In the best resulting model both alcohol and tobacco were equally considered as possible entry-substances for the non-user population. After initiating with one of them, the next stage was represented by alcohol and cigarettes at the same time, followed by alcohol abuse (drunkenness), and finally marijuana. The cumulative process specified in this model did not allow, however, for inverse processes (i.e. going back from one stage to one earlier in the sequence), thus was not possible to discern, whether subjects might also desists from showing particular drug use habits.

In another study Collins (2002) tested the hypothesis that marijuana is a gateway substance for cocaine, and that legal substances in general precede the use of illegal drugs. In doing so she estimated a model where marijuana preceded cocaine, and where the path to marijuana use was equally defined by both alcohol and tobacco use. Two stages preceded illegal substance: either alcohol and being drunk or alcohol and tobacco use could be the necessary condition for the use of marijuana. The results confirmed the hypothesis that tobacco use and experiencing with drunkenness (or alcohol abuse) can be also considered gateway conditions for the use of marijuana. However, the specified model did not allow for developmental reversals in the transition matrix, suggesting that in the analyzed two years' time span none of the subjects receded from a previously acquired status.

Collins and Flaherty (2002) also considered the stage sequential process involved in marijuana use. They found that both alcohol and tobacco acted as starting substances in the progression, although tobacco users seemed to be more likely to move to the next stage where both substances were used at the same time. This stage, at last, acted as a gateway to marijuana use. Thus, both legal substances preceded the use of illicit drugs - in this case marijuana - although tobacco seemed to have stronger effects than alcohol alone. Similar results were also obtained by C. Kam and Collins (2000) using a different sample. Furthermore, they also observed no significant difference between male and female respondents for what concerned the stage-sequential process indicated above. Also Tang, Lanza, and Collins (2001) provided support for the above mentioned stage-sequential process using a different sample, and confirming that no gender differences could be measured. Furthermore, their analysis suggested that a better model fit was achieved when also developmental reversals were allowed in the transition matrix. In other words, subjects were statistically allowed not only to progress from a previous status to the next one (or simply to remain in the same status), but also to step back to a prior stage.

Lanza and Collins (2002) investigated the gateway theory on a sample of adolescent females and tested whether the pubertal timing played a role on the chances of progressing through the sequential stages. The model they found was rather complicated compared to other studies and was characterized by eight stages. The first step included alcohol or tobacco use, both equally representing entry substances. Then the subjects moved either to use both, or cigarette and marijuana. At this point, for some subjects tobacco use was the gateway substance to illicit drug use. However, another path was possible: from tobacco and alcohol to alcohol abuse, and then marijuana, although those who used already marijuana and tobacco had the possibility to use alcohol at a later stage.

Maldonado-Molina et al. (2007) analyzed the stages that led to illegal substance use in a subsample of Hispanic Puerto Ricans in the United States. In this study the focus laid on stage sequential use of legal substances that preceded the use of illegal drug, where the latter were included in a single category and no distinctions were made. The resulting model suggested that five stages were sufficient to describe the process: non users started using alcohol, then cigarettes, and the combination of both became the gateway condition to later involvement with illegal substances. Heavy drinking (experiencing drunkenness), also estimated in the model, although preceded by alcohol and to a lesser degree by tobacco use, was not a gateway substance for later illicit drugs consumption.

Patrick et al. (2009) were also concerned with the process behind the onset of marijuana use, and they further investigated the effects of using marijuana on the subsequent use of inhalants. Using a sample of black South African adolescents aged between 14 and 15, this study analyzed whether the progression from non-use to illegal drugs was facilitated by alcohol and cigarettes. The results showed that both alcohol and cigarettes represented the initial step, followed by both, then marijuana, and finally inhalants. It should be noted that also in this case no reversal processes were allowed in the model.

Maldonado-Molina and Lanza (2010) tested the hypothesis that different legal substances act as gateway drugs for marijuana use. More specifically, they found out that a model with seven transition stages was the best representation of the observed data. The statuses consisted in no use, alcohol only, cigarette only, alcohol and drunkenness, alcohol plus cigarettes and drunkenness, and all the mentioned substances plus marijuana. Furthermore, they also found that in some cases youths moved to use marijuana directly from smoking, without being involved in any form of alcohol use. In any case, this study confirmed the sequential process where legal drugs, and in this case different combinations of them, act as gateway substances for marijuana use.

All the studies presented above represent applications of the gateway hypothesis to sequential models, that is, models concerned about transitions among different, but related, behaviors. These typology of studies, although fundamental to the original formulation of the gateway hypothesis, is not the only one; stage models have also been tested in order to define transition across stages of a single behavior. An interesting example is J. Guo, Collins, Hill, and Hawkins (2000), that used LTA to test transitions among stages in alcohol consumption. They compared a group of youths diagnosed with alcohol abuse dependence (AAD) with a group who were not. The aim of the study was to identify whether differential sequences were at work within the two groups. Different age periods were also taken into account, measuring development from elementary school to young adulthood. Four stages were identified for both groups: nonuse, initiation only, current use only, and heavy episodic drinking. No differences between groups were found in elementary school, and only relatively small ones in middle school. Indeed, the more evident differences were found during high school, where most members in the AAD group were already in the heavy episodic drinking stage, whereas the majority of the non-AAD members were still in the initiation and current-use status. This study, beside confirming the existence of within-substance stage sequential processes, also suggested that specific life- or age-phases might be more at risk for the development of specific substance abuse habits. Table 2.2 summarizes the sequences found in the studies presented above.

Table 2.2: Summary of the major studies on the gateway hypothesis

Study	Sequence
Collins, 2002	AD or AT $\rightarrow M \rightarrow HD$
Graham et al., 1991	A or T $\rightarrow AT \rightarrow ATD \rightarrow ATDM$
Patrick et al., 2009	A or T $\rightarrow AT \rightarrow M \rightarrow HD$
Maldonado-Molina & Lanza, 2010	A or T $\rightarrow ADorATD \rightarrow ATDM(alsoTM)$
Lanza & Collins, 2002	A or T $\rightarrow ATorTM \rightarrow ATDorATM \rightarrow ATDM$
Collins & Flaherty, 2002	A or T $\rightarrow AT \rightarrow M$
Kam & Collins, 2000	A or T $\rightarrow AT \rightarrow M$
Tang & Collins, 2001	A or T $\rightarrow AT \rightarrow M$

(A “alcohol use”; T “tobacco use”; D “drunkenness”; M “marijuana use”; HD “hard drugs use”)

The results presented in the table above are taken from a “representative sample” of actual studies on the gateway theory. On the one hand they confirm the existence of a general sequence of stage development of drug use especially during adolescence. Indeed, although some sequences (especially concerning legal drugs) are not the same for all studies, a general trend can be identified where legal substances are entry drugs, followed by alcohol abuse, marijuana, and only after more dangerous illegal substances. On the other hand, although some of these differences could be led back to different measurement procedures and study designs, the sequence among legal substances and among harder drugs is still unclear and less understood (Kandel, 2002).

There is an ongoing debate about both the validity of the gateway hypothesis, and its contribution for the development and implementation of substance use prevention programs. Knowing the sequence with which drug use develops can help policy makers to target populations at risk for specific gateway drugs, and thus prevent the use of substances more advanced in the sequence. Recent efforts made in the USA to combat the diffusion of illicit drugs, especially in the youth population, have strongly relied on such a generalized interpretation of the gateway hypothesis. Many researchers doubt that the simple prevention of alcohol and tobacco use could lead to a significant reduction in illegal drug use (see Golub & Johnson, 2002). Such an application of the theory fails to take into account other important factors that might be at play in defining a specific stage sequential development in drug use. In fact, two major points should be considered.
The first problem was mentioned already, and is concerned with the validity of the sequence proposed by the gateway theory. It should be kept in mind, especially when developing prevention strategies based on the gateway hypothesis, that if on the one hand a lot is known about the role of marijuana, on the other hand less is known about sequences among hard drugs, and it is still unclear the real sequence among legal substances. More intercultural and cross-national studies might help to identify population specific sequences, but also support the idea that social and cultural factors, among others, are at play in defining time and place of specific sequential developments.
A second problem concerns the causality assumption that can be deducted from the two main propositions of the gateway theory. In fact, the presence of a given sequence, and the association among different stages could suggest that a substance in an early stage is the principal cause for the use of another substance at a more advanced stage. However,

already Kandel and Jessor (2002) warned about taking causality into the gateway hypothesis. The existence of a progression does not directly imply a causal mechanism; the empirical results clearly suggests that being in an early stage is necessary to progress to a more advanced stage, but not all those who are in a particular stage do progress. The rates of progression through the sequence, in fact, can be easily represented by a pyramid, where the higher a substance is in the sequence, the less subjects use it. Furthermore, other empirical studies have also showed that reversal movements on the sequence are possible; only few move forward, many remain, and also many - especially in the more advanced stages - recede to a previous stage.
So far, no causal mechanism between drugs have been proven. There is instead strong support to the hypothesis that stage sequences, as found in the last thirty years, are strongly cultural determined. Other factors, in fact, concur to define a specific development within a specific culture. Drugs use, both legal and illegal, remain primarily a socialization process that is learned within specific socializing contexts, such as the family for what concern mainly legal substances, and the peer group and the school for the abuse of legal substances and illegal drugs. So it is highly probable that societal use and availability of particular substances might strongly influence their sequence.

Concluding, the gateway hypothesis offers a valid instrument to identify gateway drugs, especially in a developmental phase of life like adolescence. It has been proven, in fact, that the onset of a specific substance use is age specific. Knowing the existence of gateway substances might also help defining more accurate drug prevention programs. However, it should be kept in mind that no causality processes are alone at work, and that a sequence that works for one society, might not work for another. A valid approach to the practical implementation of the gateway theory suggests that at first, the exact existence and form of the sequence should be found within the target population. Thereafter, external socio-psychological factors as well as influences of the setting (availability and social acceptance of a substance) should be included in the sequence to test for spurious effects. Only when an overall view over the influencing mechanisms is gained, prevention measures can target specific contextual factors related to specific gateway substances.

2.6 Hypothesis

There is a general consensus about some main results of the first longitudinal studies on marijuana use, concerned both with quantitative and qualitative development. This can help to formulate some hypothesis for the empirical analysis. From an epidemiological point of view, the following statements can be made.

Drug use, in particular cannabis use, generally starts during adolescence around the age of 14, and reach a peak in late adolescence/early adulthood, between the age of 18 and 21 (Kandel, 1980). By then, its rates of consumption (both frequencies and prevalence) decline to very low levels within the general population (Hser, 2002; Hser et al., 2007). Keeping in mind that the time span covered in the data used for this empirical analysis covers only transitions from early into late adolescence (13-17), a similar general trend in the surveyed population is expected.
H1) *By means of latent growth models I expect to find clues of a bell-shaped trajectory in the individual development of marijuana use across adolescence. This, in fact, should show an increasing frequency pattern that tends to stabilize at the end of adolescence (i.e., by the last measurement point, at the age of 17, I expect a still increasing trajectory or a stabilizing one).*

Empirical research in DLC and drug use development have shown that more than a single developmental pattern is to be expected, also for what concern marijuana use. In fact, research on drug use careers suggests that multiple patterns are present at every stage of drug use developmental process (Hser et al., 2007). More precisely the literature

suggests that at least 4 trajectories are generally found for marijuana use (Brook et al., 2011).
H2) *By means of growth mixture models I expect to estimated different developmental trajectories of drug use. They should resemble four different typologies of development across adolescence: non-users/low users, chronic users, late-onset users, and an adolescence-limited group.*

Research on the gateway hypothesis on the development of drug use in adolescence has shown that a sequence exists that represents the stages at which different drugs are taken (Kandel, 1975; Kandel & Faust, 1975). Initiation with legal drugs is generally the first step; smoking cigarettes and drinking alcohol are equally considered entry substances. In successive steps subjects experience alcohol abuse (such as binge drinking and drunkenness), followed by marijuana use, and only after other illicit substances. For all these transitions a cumulative process is expected, for which the previously used substance is not dismissed, but rather used together.
H3) *By means of latent transition analysis a cumulative model should be specified in which the following sequence is tested: use and abuse of licit substances precede marijuana use, which in turn is followed by hard drug use. I also expect that subjects will not skip stages but move always to the next in the sequence in a sequential fashion.*

Some studies have also shown that not only forward progression through stages is possible, but also backward movements are possible (Tang et al., 2001; Collins & Flaherty, 2002). Subjects, in fact, especially in a period like adolescence where many changes are expected, could also temporally experiment with a substance and then give up its use. In this case one would step back from an advanced substance in the sequence to a previously used one.
H4) *LTA model should also include the possibility of backward movements in the stage sequential process. I also expect that not all subjects will move forward, but that many would remain in a given stage across time, and some would also recede to a previous one.*

These four hypothesis will be tested in the following chapters using empirical data taken from the longitudinal study Crime in the Modern City, a panel study on youth delinquent behavior conducted over the last decade in the German town of Duisburg (Boers et al., 2010). Before the empirical analysis using growth models and latent transition analysis, two chapters will deal with the presentation of the study design and some important descriptive statistics.

Chapter 3

Sample and design

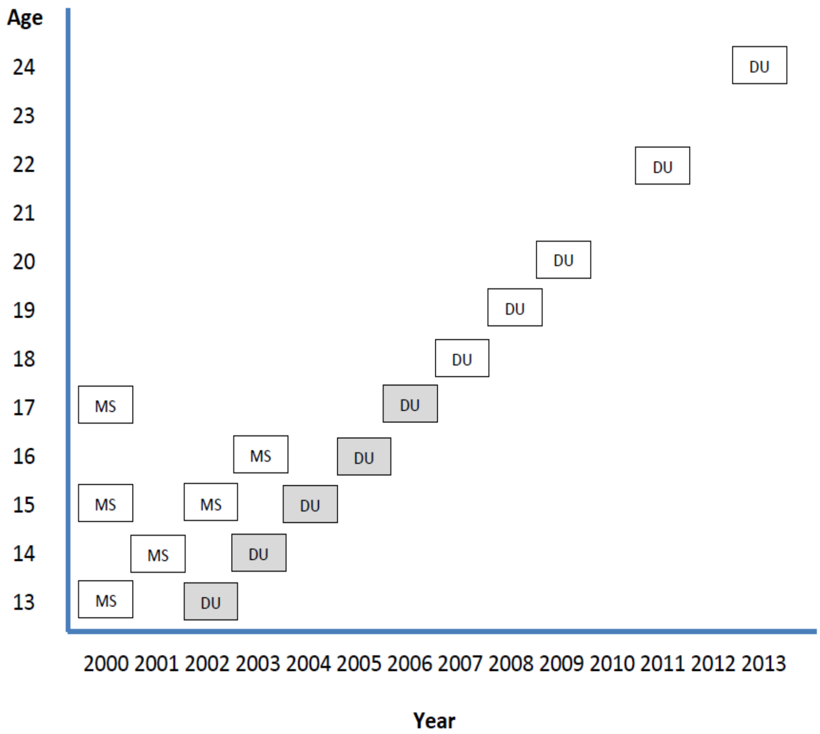
3.1 General information

The empirical basis of the following analysis is taken from the longitudinal research project Crime in the Modern City (CriMoC). The main focus of the study is the emergence and development of deviant and delinquent behaviors of juveniles, and the social control surrounding them. With social control is here meant both the formal - meaning the police and the judiciary - and the informal control - referring to school, family, and peers (Boers, Reinecke, Motzke, & Wittenberg, 2002).

The panel data contains the responses to self-administered interviews of pupils from the town of Duisburg, located north of Cologne in West Germany. Duisburg, with a population of about 500,000, is among the fifteen largest towns in Germany, it is a former renowned industrial and mining centre in the Ruhr district, and, as a consequence of the large immigration of "guest-workers" in the post-war period, still maintains a heterogeneous population with a large proportion of foreign citizens and a marked level of social inequality. According to recent statistics (2005) one third of the Duisburg population has immigrational background, whereas 14.7% are registered foreign citizens, among which the majority (8.5%) is Turkish (see Kunadt, 2011). All these characteristics make Duisburg an appealing research field.

The initial survey was conducted in 2002 with pupils from the 7th and the 9th grade considering all relevant school types in the community. Measurements on one cohort (7th grade) have been conducted annually until 2009, and will be conducted at biannual intervals until 2013. Figure 3.1 shows the study design. In grey are shown the surveys used for this study.

Figure 3.1: Study design



Before the beginning of the panel in Duisburg (DU) a similar study was conducted also in Münster (MS), Germany, from 2000 to 2003. This preliminary study was concluded in 2003 and the results published in Boers and Reinecke (2007).

With the regard to the Duisburg study, in the following sections some important infomation about the distrubition, the representativeness, and the sample attrition will be presented to help the successive interpretation of the results.
A first interesting aspect is the distribution of the response rates of the first five waves. These data constitute the basis for the analysis presented in this work. For each time point the following information are reported: (S_t) the whole number of pupils registered in the schools that agreed to participate in the study; (Q_t) the number of pupils actually interviewed each year; (P_t) the size of the five wave panel (i.e., those who participated in all five measurements which constitute the data set used in this paper).

Table 3.1: Sample construction (five time points)

	t1 (2002) $7^{th}Class$	t2 (2003) $8^{th}Class$	t3 (2004) $9^{th}Class$	t4 (2005) $10^{th}Class$	t5 (2006) $11^{th}Class$
S_t	3910	3763	3925	3543	4016
Q_t	3407	3390	3339	3243	3367
P_t	1552	1552	1552	1552	1552
Average age Q_t	13	14	15,1	16	17,5
s.d.	0.8	0.8	0.8	0.8	0.9
Average age P_t	12.9	13.9	14.9	15.9	17
s.d.	0.7	0.7	0.7	0.7	0.8

Although much attention was paid to the preservation of the original panel sample, every year was attempted to reach the largest number of subjects belonging to the whole school population in Duisburg. In this way, beside the panel sample, which is composed of subjects who were interviewed at all five time points, the project collected important cross-sectional information every year (see Pöge, 2007).
The relatively high response rate is in part the result of the confidentiality restrictions applied during the interviews. In order to guarantee the veracity of the given responses, all the questionnaires are anonym, so that it is impossible for the researchers to identify the respondent. This is made possible by the use of an encryption code, which is composed of questions about easy-to-remember personal characteristics (for example, questions about specific letters of respondent's eye and hair colours, and numbers of the respondent's birthday datum), and should be reproduced every year at the beginning of the questionnaire. Additional information (e.g., change of class, school, etc.) were collected to avoid equal codes belonging to different persons. It is in fact expected, that the participant exactly reproduces his/her own code each year, and thus allows the researchers to match his/her questionnaires over time (see Pöge, 2005, 2008).
A particularity of the German school system is that pupils attending professional schools obtain their certificate already at the end of the 10th class. After that, they are scattered around to other different institutions which provide them with practical working experiences and introduce them into the labour market. As a consequence, a large proportion of participants, who in the 10th class were easily accessible in the schools' premises, cannot be interviewed anymore so easily. To overcome this problem, that would have caused a high rate of panel attrition, already in the 9th and 10th class the permission to collect the private addresses of all participants was asked, in order to be able to reach by mail those who would have left school in the next years. This strategy included all pupils without distinction of the attended school, with the purpose of creating a data base for the time to come when all of them will leave school and a complete mail-survey will be necessary[1]. Thus, in 2006 a portion of the interviews were conducted per mail, and the return rate of the questionnaires was about 66%.

In order to further clarify the composition of the sampled cohort, the modal age of the respondent at each measurement point is reported in Table 3.2.

[1]This is exactly what has been done from 2008 onwards.

Table 3.2: Statistics for age at each time point

	t1 (2002) $7^{th}Class$	t2 (2003) $8^{th}Class$	t3 (2004) $9^{th}Class$	t4 (2005) $10^{th}Class$	t5 (2006) $11^{th}Class$
Mean	12.89	13.87	14.92	15.88	16.95
Mode	13	14	15	16	17
Std.Dev.	0.688	0.683	0.695	0.685	0.806
Minimum	12	11	12	14	12
Maximum	19	17	19	19	25

The age distribution in the sample is fairly normal at all measurement points. The mean age is very close to the modal age. These results allow to assign to each time point a specific age; from the 7^{th} class where the subjects are centred around the value of 13 years, to the 11^{th} class where they are on average 17 years old.

Concluding this short introduction to the study design, it can be seen that two sampling methodologies are present at the same time in the survey: on the one hand, each year a complete cross-sectional sample is obtained, including all possible pupils attending one of the participating schools; on the other hand, great attention is paid to the preservation of the main panel, i.e., the sample of those who attended to all five measurements so far. The latter consists of 1552 subjects, which is still a good sample size for the analysis of complex statistical models.

3.2 Sampling and attrition rates

This section will give a closer look to the sampling distribution of the interviewed pupils. This is especially important for the assessment of the representativeness of the sample compared to the whole school population in Duisburg. More precisely, this section will address the problem of sample attrition and panel construction, the distribution of the male and female populations, and the different school types. Similar data for immigration background and other demographical variables are not yet available. The problem of representativeness, in fact, is an important issue for the successive interpretation and generalisation of the model's results.
The information in the following tables are taken from Pöge (2007) and Bentrup (2007). The former includes information on the first four waves from 2002 to 2005. The latter reports statistics for the fifth wave in 2006.

As clearly visible in Table 3.1, a particularity of this study is that at each measurement point cross-sectional data were collected on the basis of the available school population. Thus, the panel sample (P_t) is not based on a baseline sample defined at t_n and then followed at the subsequent t_{n+1}, t_{n+2}, t_{n+i}, but rather it is constructed using the information available from the single cross-sectional samples. Furthermore, the panel sample (P_t) is composed of those who participated to all measurements across the considered time span. To further clarify the composition of the panel sample (P_t) Table 3.3 reports the evolution of this sample across time, with respect to the number of time points considered.

Table 3.3: Panel construction (five time points)

	t1 to t2 (2002 to 2003) 7^{th} to 8^{th} Class	t1 to t3 (2002 to 2004) 7^{th} to 9^{th} Class	t1 to t4 (2002 to 2005) 7^{th} to 10^{th} Class	t1 to t5 (2002 to 2006) 7^{th} to 11^{th} Class
P_t	2472	2012	1715	1552
Retention Rate	-	81.4%	85.2%	90.5%

The size of the panel sample (P_t) decreases over time due to "wave nonresponse" type of missingness. The retention rates are calculated on the basis of the size of the preceding panel.

The fact that the panel size decreases over time, however, is only in part the result of panel mortality in its strict sense. In fact, not taking part at a single measurement point is sufficient for being excluded from the panel sample. However, due to the fact that each year a complete cross-sectional sample is collected, subjects might reappear but are not included again into the panel sample.
The data below are very informative with regards to the most common "wave nonresponse" patterns of missingness in the whole sample across five time points (Mariotti & Reinecke, 2010). If we consider all those who participate at least twice in the study (n=3909) the following missing patterns are the most common found over a time span of five years (from 2002 to 2006). In Table 3.4 a question mark (?) is used to represent missing information, whereas a x is used to represent the observed ones. The percentages are referred to the whole sample of 3909 subjects.

Table 3.4: Most common missing data patterns

Patterns	t1 (2002) $7^{th}Class$	t2 (2003) $8^{th}Class$	t3 (2004) $9^{th}Class$	t4 (2005) $10^{th}Class$	t5 (2006) $11^{th}Class$	N	%
1.	x	x	x	x	x	1563	40
2.	?	x	x	x	x	403	10
3.	x	x	?	?	?	289	7
4.	?	?	x	x	x	275	7
5.	x	x	x	?	?	150	4
6.	x	?	x	x	x	134	3
7.	?	?	?	x	x	114	3
8.	x	x	?	x	x	109	3

It can be observed that the majority of partecipants took part at least in more than two measurement occasions, but were not present at some of the others. Having a closer look at the most common patterns, it can also be notice that the majority of the subjects missed only one interview and were present at all the remaining four. The second largest missing pattern, in fact, with 403 cases is composed of those who were not present at the first measurement point, but attended all others.

Another important issue is the representativeness of the panel sample compared to the general population and the cross-sectional sample. For this purpose the following

two tables report representativeness statistics for gender and school-type for the first four waves (see Pöge, 2007). More detailed information on sampling and representativeness for the fifth wave in 2006 are described by Bentrup (2007) and are not reported here.
Table 3.5 reports sample statistics for male and female, and are divided into school sample (S_t), interwieved cross-sectional sample (Q_t), and panel sample (P_t).

Table 3.5: Sample and population statistics for four time points (from 2002 to 2005)

		Male		Female		Total$N$
		N	%	N	%	(100 %)
t_1	S_{t_1}	2 003	51,2	1 907	48,8	3 910
	Q_{t_1}	1 728	50,7	1 679	49,3	3 407
	$P_{t_{1,2,3,4}}$	751	43,8	964	56,2	1 715
t_2	S_{t_2}	1 927	51,2	1 836	48,8	3 763
	Q_{t_2}	1 703	50,2	1 687	49,8	3 390
	$P_{t_{1,2,3,4}}$	762	44,4	953	55,6	1 715
t_3	S_{t_3}	1 999	50,9	1 926	49,1	3 925
	Q_{t_3}	1 635	49,0	1 704	51,0	3 339
	$P_{t_{1,2,3,4}}$	756	44,1	959	55,9	1 715
t_4	S_{t_4}	1 760	49,7	1 783	50,3	3 543
	Q_{t_4}	1 627	50,2	1 616	49,8	3 243
	$P_{t_{1,2,3,4}}$	760	44,3	955	55,7	1 715

Although the cross-sectional sample is fairly close to the school statistics for what concern gender proportions, the panel sample is clearly biased and shows a higher proportion of female respondents; as a consequence females are overrepresented in the panel sample. This trend remains constant across the four time points, where males represent about the 44% of the sample and female about the 56%.
Table 3.6 reports the sampling statistics for the different school types included in the analysis. Again, S_t represent the school statistics, Q_t the interviewed cross-sectional sample, and P_t the panel sample. In this table all five school types are reported, including the so called "Sonderschule" (SO), which is a special educational institution for pupils with learning difficulties. Due to the small number of "Sonderschule" involved and the small amount of pupils who took part in all the panel measurements, this type of schools has been excluded from the panel sample (P_t).

Table 3.6: School sample and population statistics for four time points (from 2002 to 2005)

		School type (%)					Total N
		HS	RS	GS	GY	SO	(100 %)
t_1	S_{t_1}	23,9	22,0	32,0	21,3	0,8	3 910
	Q_{t_1}	22,0	23,7	31,1	22,8	0,4	3 407
	$P_{t_{1,2,3,4}}$	17,8	24,7	33,6	23,9	—	1 715
t_2	S_{t_2}	27,5	22,7	30,4	18,7	0,7	3 763
	Q_{t_2}	24,6	23,6	31,4	20,1	0,3	3 390
	$P_{t_{1,2,3,4}}$	18,3	24,7	33,9	23,1	—	1 715
t_3	S_{t_3}	24,9	21,5	32,3	20,0	1,3	3 925
	Q_{t_3}	22,6	22,9	31,9	22,2	0,5	3 339
	$P_{t_{1,2,3,4}}$	18,4	25,4	33,8	22,4	—	1 715
t_4	S_{t_4}	22,5	22,0	33,2	22,1	0,2	3 543
	Q_{t_4}	21,9	22,4	33,0	22,5	0,1	3 243
	$P_{t_{1,2,3,4}}$	18,7	25,4	33,3	22,6	—	1 715

Over the four time points the majority of the population sample (S_t) attend a "Gesamtschule" (GS) (about 31%), whereas the less represented school type is the "Gymnasium" (GY) with about 20%. The picture changes when looking at the panel sample. In this case, although "Realschule" (RS) and "Gesamtschule" are representative of the school population, the "Hauptschule" (HS) is strongly underrepresented and the "Gymnasium" overrepresented. With regard to this, it can be concluded that the panel sample is biased for what concern those two kind of school types that highly correlate with substance use and deviant behaviours. In fact, the "Gymnasium" is considered the highest educational institution in Germany, where generally less delinquency and truancy can be found. On the contrary, the "Hauptschule" is the lowest institution in the educational system and generally characterized by higher level of delinquency and truancy (Reinecke, 2006). The latter could be also a cause for the higher attrition rates in this school, and subsequently for its lower representativeness.

3.3 Sampling and attrition effects on substance use

The aim of this section is to give a brief overview on the possible effects that attrition and panel construction might have on the behaviour of interest, and thus help the interpretation of the results.
The following tables report a comparison of the prevalence and frequencies of substance use between the panel sample (P_t) and the single cross-sectional samples (Q_t). The first table shows the results for alcohol consumption, whereas the second those for cannabis use.

Table 3.7: Alcohol use: panel and cross-sectional sample

	t1 (2002) 7^{th} Class	t2 (2003) 8^{th} Class	t3 (2004) 9^{th} Class	t4 (2005) 10^{th} Class	t5 (2006) 11^{th} Class
Life-time prev (Q_t)	16.9	44.5	58.2	63.9	70.2
Life-time prev (P_t)	15.2	38.8	52.9	63.5	70.6
Last-year prev (Q_t)	15.7	42.5	56.6	61.9	68.2
Last-year prev (P_t)	14.2	36.9	51.5	61.5	69.1
Freq. $\bar{x}$ (Q_t)	0.86	1.46	1.84	2.00	2.19
Freq. $\bar{x}$ (P_t)	0.30	0.61	0.90	1.17	1.31

All but the frequency values are given as percentage of users in the samples and include also the missing values. The frequencies of alcohol use measure whether the respondent has been drunk in the last twelve months, using a five-items Likert scale coded from 0 "never" to 4 "several times per week"[2].
The largest discrepancies are visible at the beginning of the study (especially the first two waves), where the panel sample (P_t) seems to underestimate both the last-year prevalence and the frequencies of alcohol use. In the successive waves, only the frequencies remain slightly underestimated, whereas no significant differences are observed for the other measures.

Table 3.8: Drug use: panel and cross-sectional sample

	t1 (2002) 7^{th} Class	t2 (2003) 8^{th} Class	t3 (2004) 9^{th} Class	t4 (2005) 10^{th} Class	t5 (2006) 11^{th} Class
Life-time prev (Q_t)	9	19.1	26.5	29.3	33.3
Life-time prev (P_t)	6.1	13	19.4	24.9	27.1
Last-year prev (Q_t)	8	16.6	23	22.7	21.6
Last-year prev (P_t)	5.4	12	17	19.1	17.3
Freq. $\bar{x}$ (Q_t)	13.4	25.8	42.7	43.4	53.3
Freq. $\bar{x}$ (P_t)	7.3	14.7	30.7	30.4	39.2

The percentages of subjects who reported using cannabis in the last 12 months are clearly underrepresented in the panel sample (P_t). The mean frequencies of use show also some discrepancies between the cross-sectional and the panel sample. The latter underreports the average frequency of cannabis use at all five time points.
In general, there is less bias for alcohol consumption than for illegal drugs when the panel sample is compared to the single cross-sectional samples, which in turn is the more representative information at disposal. For alcohol, in particular, the differences smooth out with the passing of time, whereas differences in drug use tend to escalate with age.

[2]The frequency of use is a five categories ordered variable, thus the mean frequencies represent means between 0 and 4.

3.4 Limitations and discussion

For the subsequent analysis of drug use behaviour the five waves panel sample (P_t) will be used. There are, however, some limitations that have been depicted above and that should be borne in mind when discussing and generalizing the results. First, due to the measurement design and procedures, there is a considerable panel attrition over the five time points; this results in the decreasing number of participants who were present at all measurements. Second, the impossibility of reaching the whole school population has caused representativeness bias for what concern the gender distribution and the attended school; female and vocational school attendees are overrepresented in the panel sample. Third, as an expected consequence of the above mentioned problems, there is a substantive difference in the outcome variables between cross-sectional and panel sample.

Although strategies to overcome panel attrition problems by mean of multiple imputation[3] and missing values estimation[4] exist (Collins, Schafer, & Kam, 2001; Schafer & Graham, 2002) and have been already tested with growth mixture models of criminal behaviour on data taken from this project (Mariotti & Reinecke, 2010), they will be not applied here for two reasons. First, Mariotti and Reinecke (2010) have shown that there are no substantial differences in the trajectories between the normal panel sample and the imputed one; only the frequency level results higher for the larger sample. Second, such methods are not yet easily applicable to categorical variables models, such as latent transition analysis, and for this reason, in order to use the same sample for both statistical analysis in this work, the original panel sample will be used. As a consequence, a generalisation and interpretation of the statistical results should be done with regard to these considerations.

[3]Multiple imputation, as proposed by Rubin (1987), has been implemented in many statistical software, for instance in NORM (see Schafer, 1997).

[4]A widely used estimation technique is the full information maximum likelihood (FIML), implemented in Mplus (Muthén & Muthén, 1998-2010).

Chapter 4

Descriptive statistics

4.1 Introduction

As outlined in the chapters above the aim of this study is to describe the longitudinal development of substance use across a specific span of time. The term substance use is used to refer to the consumption of both legal and illegal substances measured in the sample. That is, the variables of interest range from the frequency of "being drunk" in the last year, to the assumption of hard drugs such as heroin and cocaine; in between the whole range of illegal substances is investigated, including party drugs like ecstasy and LSD, and more common substances like hashish and marijuana. In the questionnaire used for the CriMoC project, the consumption of illicit drugs and alcohol has been measured by means of two main questions[1]. The most interesting items for the subsequent analysis are - among others - the frequencies of drug and alcohol consumption across five time points. Furthermore, information are also collected for the consumption of single types of drugs, the social context connected with the behavior (for example the use in the group), age of onset, life-time prevalence, and last-year prevalence of use.

The aim of this chapter is to give a general overview of the distribution of this phenomenon in the sample. In the following section the more important items for the subsequent longitudinal analysis will be described in more detail. Moreover, a bivariate analysis will be presented to describe the distribution of substance use between male and female and among different school types. Although the latter analyses will not be incorporated in the more advanced statistical analysis, their inclusion is deemed important in order to better describe the phenomenon of interest.

4.2 Drug use

The questions about illicit drug use[2] were all comprised within a single page in the questionnaire, and belonged to the core part of the latter concerned with the measurement of deviant behaviours. After a selective question about whether the subject has ever used illicit drug in his/her life, other information where gathered about the age of onset, the frequency and prevalence of use in the last twelve months since the last measurement, and the typologies of substance taken. These information are reported below.

[1]For more details see the translated excerpt of the questionnaire in the Appendix.

[2]This question does not include alcohol use, which is measured in a separate question.

Age of onset

The following table reports the average age of onset for the 5 time points. This variable refers to the use of all types of illicit drugs.

Table 4.1: Age of onset for drug use

	2002	2003	2004	2005	2006
Mean	12.20	12.93	13.61	14.19	14.68
s.d.	1.40	1.22	1.22	1.25	1.41
Mode	12	13	14	14	15
Minimum	14	15	17	18	19
Maximum	6	9	9	8	8

The increasing value is a consequence of the growing number of subjects that each year start consuming illicit substances. An approximate average age of onset can be calculated as the mean across the above reported values. This average age of onset for drug use is 13,5. Another way to summarize the data presented in the table is to take the last response as reference value for all five time points. In the ideal situation a subject, who started using drugs prior to the first measurement, should be able to report the same value of this variable at all five waves. In many cases, however, there are discrepancies in the reported age of onset; some respondents were not able to replicate the same response at the successive measurements. An explanation could be that with the passing of time some subjects were not able anymore to recollect facts that had happened many years before. Consequently this problem could also indicate a poor reliability of the given information. In any case, the utility and interpretability of this variable is strongly reduced.

Life-time prevalence of drug use

Table 4.2 reports the proportion of subjects in the sample that used drugs at least once in their life. This variable refers to the use of all types of illicit drugs.

Table 4.2: Life-time prevalence of drug use

	2002	2003	2004	2005	2006
%	6.1	12.9	19.4	24.9	27

At the first time point in 2002, when the subjects were on average 13 years old, only about 6% of the sample had already had experience with drugs. In the course of the study, across 5 waves, the proportion of subjects who admit having used drugs increases constantly up to about 27% at the last measurement point in 2006, when the subjects are about 17 years of age. It can be concluded, that by the end of adolescence, about one third of the interviewed youths have tried, at least once, an illicit substance.

Last year prevalence of drug use

Table 4.3 reports the proportion of subjects who admited having used illicit drugs in the last 12 months. This variable refers to the use of all types of illicit drugs.

Table 4.3: Last year prevalence of drug use

	2002	2003	2004	2005	2006
%	5.4	12	17	19.1	17.3

There is an increasing percentage of respondents who report using drugs more regularly over time. This pattern reaches a peak in 2005 at the age of 16 with 19% of the sample using prohibited substances and decreases thereafter.
Although the life-time prevalence increases constantly over the years, it is not the same for the last-year prevalence; the latter decreases at the last time point. These results suggest that although the number of those who have used at least once illicit substances increases, in many cases it is a mere experimental behavior, which is later abandoned.

Frequencies of drug use

Table 4.4 reports the frequencies of drug use for the five measurements. This items measure how often a subject consumed illicit substances in the last year.

Table 4.4: Frequencies of drug use

	2002	2003	2004	2005	2006
mean	.35	1.51	4.50	4.93	5.79
s.d.	2.65	12.40	26.67	30.98	32.63
skewness	12.20	15.44	9.15	9.57	7.87
kurtosis	189.48	276.20	98.07	102.94	71.30
max.	50	250	365	365	365
min.	0	0	0	0	0

The values' range increases constantly from a maximum of 50 times in a year to a maximum of once a day. The distribution of the data in all five measurements is highly left skewed, consequence of the large number of zeros among the respondents (i.e., those who did not consume). Similarly, the large kurtosis reflects the presence of possible "outliers", or people who reported a high frequency of use (see the maximum value: 365, once a day). Such a high consumption is, however, plausible, and these subjects should not be excluded from the analysis.
Although the proportion of subjects who use illicit drugs decreases in the last wave (see Table 4.3), the frequency of use increases constantly over time. This might well reflect the changing status of drug use among growing adolescents; whereas at the beginning of the

adolescence drug use is probably mainly an experimental incident (most of the subjects consumed only once, thus the low mean frequency), with growing age those who continue might do it more often (see the average use at age 17: nearly 6 times).

Typologies of drugs

Table 4.5 reports the percentages of subjects in the whole sample that used one of the mentioned illegal substances in the last twelve months. Being a separate question and allowing the respondent to give multiple answers, in many cases it is not possible to associate this variable to the others mentioned in the sections above. In other words, when a multiple answer is given (e.g., one person reports the use of marijuana and heroin/morphine), it is not possible to discern whether the frequencies and all other questions refer to one of the given substances.
There are seven different drug items, which are labelled as follows:

- t0295, Cannabis (Hashish/Marijuana)
- t0296, Heroin/Morphine
- t0297, Cocaine/Crack
- t0298, Speed
- t0299, Ecstasy/Designer Drugs
- t0300, LSD/Mushrooms
- t0301, other drugs

In the following table the prevalence of use for the single groups of drugs is reported for each time point.

Table 4.5: Prevalence of use of different drugs in percent (from 2002 to 2006)

%	t0295	t0296	t0297	t0298	t0299	t0300	t0301
2002	3.2	0.4	0.4	0.6	0.5	0.5	2.2
2003	10.2	1.2	1.6	1.7	2.3	1.6	3.5
2004	16.2	0.8	1.2	1.9	2.1	1.7	3.1
2005	18.9	0.8	1.6	2.6	2.5	1.8	2.4
2006	17.1	0.5	1.7	2.2	2.3	1.5	2.1

In general, over the whole time span the most consumed drug is cannabis and its derivates. Only a small portion of the sample reports the use of any other substance than marijuana. Worth to be noticed is the large portion of subjects who responded, especially at the beginning of the study, to the category "other drugs". The great variety of names used in everyday language to define a specific type of drug might have led to great confusion, especially among the younger consumers, who might have not found the corresponding name in the questionnaire.
Taking the year 2005 as an example, where the larger proportion of the sample used illicit substances, it can be noticed that nearly 19% reported cannabis consume. The second most used substances are, thereafter, party-drugs like speed, ecstasy, and designer drugs

with about 2,5% of consumers. All other substances do not go over 1%. The use of drugs with highly proved addiction potential (e.g. heroin, cocaine) is limited to less than 1% across all waves.
Finally, comparing the percentages for cannabis use with the "last year prevalence" it can be noticed how similar their values are. This is due, on the one hand, to the fact that most of the participants use cannabis, and, on the other hand, that a portion of the consumers can be actually defined as "poly consumers". That is, most of those reporting the use of other drugs than cannabis, are also cannabis users[3].

4.3 Alcohol use

The question about alcohol consumption contains less variables if compared to those about other deviant behaviors. However, apart from the kind of beverage used, all the information presented already for illicit drugs were also measured for alcohol. These are: age of onset, life time and last year prevalence, and the frequency of being drunk measured for the last twelve months as an ordinal-scale variable. It should be remembered that all the questions about alcohol refer to the condition of being drunk and thus involve the subjective perception of an abuse. Keeping this in mind, from now on, I will refer to this behavior as simply alcohol use.

Age of onset

Table 4.6 reports the average age at which the subjects got drunk for the first time, presented for the five time points.

Table 4.6: Age of onset of alcohol use

	2002	2003	2004	2005	2006
Mean	11.90	12.96	13.48	14.15	14.57
s.d.	1.90	1.16	1.39	1.44	1.53
Mode	12	13	14	14	15
Minimum	15	20	19	19	19
Maximum	2	7	7	8	7

The increasing mean age of onset is the consequence of the increasing number of respondents who got drunk over the five waves. The average age of onset across the five time points is approximately 13.4, which is very close to the 13,5 years reported for illicit drug use. However, as pointed out already in the section on illicit drug use, there were many discrepancies in the responses over time. Also in this case it seems that some subjects failed to recollect the exact year every time they are asked.

[3] The tables above are calculated as the percentage of responses to every single item, without taking into account the responses to the other items. Thus it is possible that many participants have responded affirmatively to more than a single item.

Life-time prevalence of alcohol use

Table 4.7 reports the proportion of subjects in the sample that have ever been drunk in their life.

Table 4.7: Life-time prevalence of alcohol use

	2002	2003	2004	2005	2006
%	22.7	39.1	53.2	64.2	71.4

The percentage of subjects who reported having been drunk at least once in their life increases dramatically across the measurements. Already in 2002, at the age of 13, more than 22% of the subjects had been drunk once. By the end of the covered time span, at the age of 17, nearly three quarter of the sample had used “disproportionately” alcohol.
The reported trend fulfills the expected development of a legal substance like alcohol. The abuse of alcoholic drinks becomes a normative experience in the course of adolescence. According to the picture above, the developmental pattern has not yet stabilized and is expected to increase in the following waves.

Last year prevalence of alcohol use

Table 4.8 reports the proportion of subjects who admit having been drunk in the last 12 months.

Table 4.8: Last year prevalence of alcohol use

	2002	2003	2004	2005	2006
%	21.6	37.9	52.6	63.7	71.1

The proportion of subjects who abused alcoholic drinks in the last twelve months increases substantially over time. At the last measurement point - when the pupils are on average 17 years old - 71% of the sample report having been drunk at least once in the last year.
Another interesting point is the comparison with the life-time prevalence presented in the section above. The percentages of heavy-alcohol users are nearly the same to those reported in the last-year prevalence table. This is possibly due to the fact that each year, the majority of those who report heavy drinking maintain the habit also in the subsequent waves. More than an experimental behavior - as could be argued for illicit drug use - getting drunk is a habit that once learned is not easily given up.

Frequencies of alcohol use

The frequencies of alcohol consumption are measured by means of a categorical variable with four response categories. To the question “how often did you get drunk?” the response possibilities were coded: 1 “once or twice a year”, 2 “once a month”, 3 “several

times per month", and 4 "several times per week". Finally, those who never got drunk were recoded as zero.
Table 4.9 reports the average score on the four categories of the alcohol variable, and excluded the zeros from the analysis (i.e., the means are calculated for the consumers only). Being the prevalence of those who get drunk large in the sample, the aim of the following table is to give a preciser picture of the average consumer.

Table 4.9: Frequency of alcohol use

	2002	2003	2004	2005	2006
Mean	1.38	1.60	1.72	1.83	1.84
s.d.	.70	.88	.91	.92	.93

The frequencies with which the subjects report having been drunk in the last twelve months show increasing mean values, which stabilizes themselves at the last time point. By that time, the average frequency settles around the value of 2, which means at least "once a month".
It can be concluded that by the end of adolescence heavy drinking is more than an episodic occurrence. Indeed, the average consumer reports getting drunk at least once or twice a month. Considering that the normal consume of alcohol has not been asked, the results prove that alcohol consumption is fairly widespread and a normative behavior among this population.
The distribution of the consumers across the four categories of the variable "alcohol" is presented in Table 4.10:

Table 4.10: Distribution of the variables of alcohol consumption (from 2002 to 2006)

		Freq.	%	Cum.
2002	Once or twice a year	159	71.95	71.95
	Once a month	42	19.00	90.95
	Several times per month	16	7.24	98.19
	Several times per week	4	1.81	100.00
	$\sum$	221	100.00	
2003	Once or twice a year	355	62.06	62.06
	Once a month	116	20.28	82.34
	Several times per month	74	12.94	95.28
	Several times per week	27	4.72	100.00
	$\sum$	572	100.00	
2004	Once or twice a year	441	55.13	55.13
	Once a month	176	22.00	77.13
	Several times per month	149	18.63	95.75
	Several times per week	34	4.25	100.00
	$\sum$	800	100.00	
2005	Once or twice a year	462	48.38	48.38
	Once a month	232	24.29	72.67
	Several times per month	220	23.04	95.71
	Several times per week	41	4.29	100.00
	$\sum$	955	100.00	
2006	Once or twice a year	517	48.18	48.18
	Once a month	249	23.21	71.39
	Several times per month	262	24.42	95.81
	Several times per week	45	4.19	100.00
	$\sum$	1,073	100.00	

The frequencies show a constant increase across the five time points; from 2002 where the largest category is "once or twice a year", to 2006 where about 25% of the consumers report having been drunk "several times per month". It is also interesting to notice that the category "several times per week" remains constant all the time with about 4%.

4.4 Substance use among specific groups: gender and educational level

In this section the gender of the participants and their educational level are taken into account. By means of bivariate crosstables gender and school differences among drug and alcohol consumers will be briefly explored.

4.4.1 Gender

The 1552 subjects in the panel sample are composed of 642 males (41.37%) and 910 females (58.63%). This distribution does not represent the male/female proportion in the city of Duisburg, as outlined already in Chapter 3, since females here are largely overrepresented.

Life-time prevalence

Table 4.11 reports the proportions of male and female respondents which have ever used drugs in their life up to the age of 17. The significance of the differences between genders is tested by means of a t-test.

Table 4.11: Life-time prevalence of drug use and t-test

%	2002	2003	2004	2005	2006
Male	7.6	16.5	22.4	29.9	30.9
Female	4.9	10.4	17.4	21.3	24.2
t-test P	.0297	.0005	.0144	.0001	.0037

There are substantial differences between gender all over the covered time span. Although at the beginning of the measurement both genders show similar prevalences, by the fifth time point 31% of the males compared to 24% of the female respondents reported having tried illicit drugs. These differences are also confirmed by the significant values of the single t-test for mean comparison carried out at each time point.
Differences between male and female respondents in alcohol consumption are presented in Table 4.12.

Table 4.12: Life-time prevalence of alcohol use and t-test

%	2002	2003	2004	2005	2006
Male	24.8	37.6	53.1	67.9	75.4
Female	21.4	40.1	53.2	61.6	68.6
t-test P	.2003	.3149	.9584	.0115	.0035

For what concern the abuse of alcohol, there are no remarkable differences between genders untill the last two waves; only from this point onwards the prevalence of males is significantly higher than those for females. This is also confirmed by the t-test: only the last two time points show significant differences between the two groups. However, considering the last measured time point, among the males 75% reported having been drunk at least once in their life; female respondents lay not too far from their male counterparts with 68%, even if this difference is statistically significant.

Frequencies

There are significant differences for what concern the frequencies of drug use. They are reported in the Table 4.13 together with the t-test.

Table 4.13: Frequency of drug use (by gender)

	2002	2003	2004	2005	2006
Male	.37	2.40	7.08	8.65	10.28
s.d.	2.64	16.44	35.01	42.41	46.27
Female	.34	.89	2.69	2.36	2.70
s.d.	2.65	8.43	18.51	19.09	17.40
t-test P	.8395	.0197	.0017	.0001	.0000

Whereas females show quite stable frequencies of consumption - especially after the second measurement point - with an average value of about twice a year, the frequencies for males increase constantly up to 10 times in the last 12 months. According to the t-test the differences between the two groups are all significant but for the first time point, where both male and female show a similar mean frequencies of consumption.
The frequencies for heavy drinking do not show particularly interesting differences, and are not reported here.

Concluding, there are overall substantial differences between the two groups, where males generally report a higher prevalence and frequency of illicit drug use than females. The picture for alcohol use is slightly different. The prevalence of use is high for both groups, although male respondents tend to be more involved in heavy drinking than female ones. For what concern the frequency of being drunk in the last 12 months, no substantial differences are found; here the values obtained in Section 4.3 are valid for both groups, suggesting that the average frequency settles around the value of 2, which means at least “once a month”.

4.4.2 Educational Level

The German educational system is composed of four main educational institutions: Gymnasium, Gesamtschule, Realschule, and Hauptschule. Only the “Gymnasium” (equivalent to the English grammar school) and part of the pupils in the “Gesamtschule” are later given access to university education, whereas all others are directed to a more professional-oriented education (i.e, “Berufskolleg”). Among the latter, the “Realschule” can be considered a medium level institution, whereas the “Haupschule” is the lower educational path in the German school system (with a subsequent high rate of unemployed among its former pupils).
Changes from one type of school to another are possible, but rather difficult and demanding. The “Gesamtschule” is an attempt to overcome such a problem, since it includes within one institution all three school typologies, and should encourage a better distribution of the pupils. Because of this characteristic, it is difficult to place the “Gesamtschule” on a continuum from lower to higher educational level together with the other schools. Remarkable is, that within a “Gesamtschule” there is much more social heterogeneity (with all its consequences) than within any other school-type.

The access to a specific school is regulated on the basis of the skills and notes achieved by the pupil in the primary school. Although the decision to which school a pupil will be assigned is mainly a task of the teachers, the parents are given the chance to influence such a decision. It is then obvious, that only engaged parents will be actively involved in shaping the future of their children. This system is widely criticised for enhancing and perpetuating social inequalities; the weaker part of the society - such as immigrant, unemployed, low-income workers and lower class families - in fact, is overrepresented in the lower institutions of the educational system (i.e. “Realschule” and “Hauptschule”).
The descriptive statistics for the educational level have to be distinguished in two different tables. The first table reports the sample distribution among the above mentioned four types of school in the town of Duisburg. The second table refers to the last measurement point in 2006 and distinguishes only between three groups: subjects still in school (i.e., in “Gymnasium” or “Gesamtschule”), those who now attend a professional training (“Berufskolleg”), and those who left completely the educational system.
This is necessary because after the 10th class pupils attending either “Realschule” or “Hauptschule” (and the corresponding classes in the “Gesamtschule”) obtain their grades and are confronted with different choices. “Realschule” pupils can move to a professional-training institution or, after additional exams, are given access to the last two years of the “Gymnasium”. “Hauptschule” pupils are given the same possibilities, but having a lower educational level than their colleagues in the “Realschule”, face more difficulties to gain admission to the “Gymnasium”. Thus, most of them move on to professional education.
Table 4.14 shows the pupils’ choices after the 10th class:

Table 4.14: Crosstab between school attended before and after the 10^{th} class

Up to 10^{th} class	After 10^{th} class			
	In school	Berufskol.	Not in sc.	$\sum$
Gymnasium	356	27	4	387
Gesamtschule	222	254	21	497
Realschule	135	212	14	361
Hauptschule	26	207	20	253
$\sum$	739	700	59	1,498

Most of the pupils that were in the “Gymnasium” remain in the same institution. After two more years they obtain the “A-level” and gain the right to pursue university education. On the contrary, most of the pupils in the “Hauptschule” move on to professional education. Really few succeed to gain access to the “Gymnasium”.
Table 4.15 reports the distribution across the four school types between time point one (2002) and five (2005), whereas Table 4.16 reports the new distribution after the 10th class (2006).

Table 4.15: School up to the 10^{th} class

	Freq.	%	Cum.
Gymnasium	392	25.2	25.2
Gesamtschule	517	33.3	58.5
Realschule	373	24.0	82.6
Hauptschule	270	17.4	100.0
$\sum$	1,552	100.0	

Table 4.16: School after the 10^{th} class

	Freq.	%	Cum.
In school	739	47.6	47.6
Berufskolleg	700	45.1	92.7
Not in school	59	3.8	96.5
Missing	54	3.4	100.0
$\sum$	1,552	100.0	

As already mentioned in Chapter 3, up to the 10^{th} class, the lower educational level ("Hauptschule") is underrepresented compared to the other institutions. For what concern the year after, the subjects are equally distributed between "in school" and "Berufskolleg". Only a small 3% of the pupils have left school.

Life-time prevalence

Table 4.17 and Table 4.18 report life-time prevalence of drug and heavy alcohol consumption.

Table 4.17: Life-time prevalence for drug use in percent

%	2002	2003	2004	2005	2006
Gymnasium	3.6	8.9	14.5	22.5	25.8
Gesamtschule	5.5	14.3	20.4	25.4	25.1
Realschule	8.9	11.6	19.6	22.8	28.4
Hauptschule	7	18	24.5	30.4	30.5

The most striking difference is the high prevalence value for the pupils attending "Haupschule". 30% of them, by the end of the covered time span, reported having tried illicit substances in their life. The other schools show smaller values around 22-25%, with the "Gymnasium" reporting the lowest prevalence rate. Illicit drug use seems to be a problem especially in the lower section of the educational system.

Table 4.18: Life-time prevalence for alcohol use

%	2002	2003	2004	2005	2006
Gymnasium	18.7	34.2	50.5	66.6	76
Gesamtschule	24.2	40.2	51.9	60.8	66.7
Realschule	23.6	41	57.3	67.9	76.1
Hauptschule	25	41.5	52.9	62.3	67.4

Heavy drinking shows a completely different trend. Although all schools report high prevalence rates, the highest values are measured in the middle-upper section of the German school system. In 2006, in fact, the higher prevalence are measured for the "Gymnasium" and the "Realschule" with about 76%. However, at the same time, the other two school types also show remarkable prevalence values of about 67%.

Frequencies

The frequencies of use for the different school types are presented only for the use of illicit drugs, since there are no remarkable differences for what concern heavy drinking.

Table 4.19: Frequency of drug use

	2002	2003	2004	2005	2006
Gymnasium	.17	.66	1.84	1.81	2.92
Gesamtschule	.46	1.33	5.07	6.12	6.56
Realschule	.33	1.52	4.32	3.68	5.62
Hauptschule	.46	3.15	7.66	9.45	8.86

Similar to the pattern outlined in the section above, pupils in the "Hauptschule" report not only the highest prevalence rate, but also higher frequencies than any other school type. Whereas in "Gymnasium" drug use seems to be more an experimental behavior with an average frequency of only two times in twelve months, the pupils in the other school types report a more frequent consumption. Pupils in the lower part of the educational system seem to be involved in a more systematic consumption, especially at time four (2005), exactly before leaving the school for a professional training.

For a more precise description of these phenomena, differences in the last measurement point should be compared with the new educational institution attended by the subjects

in that year.
Table 4.20 represents the life-time prevalence for drug use and heavy drinking in 2006.

Table 4.20: Life-time prevalence of drug and alcohol use after the 10^{th} class

%	Drug use	Alcohol use
In school	22.7	68.2
Berufskolleg	30	75
Not in school	40.7	69.5

The proportion of those who have used illicit drugs in their life is much bigger among the subjects who left school than among those who either stayed in school or went to a professional training. Furthermore, the latter show a higher prevalence compared to pupils in school.
The values for heavy drinking do not show comparable large differences as illicit drug use, but still highlight the higher prevalence for the subjects in professional training.
Table 4.21 shows differences in the frequency of drug use in 2006.

Table 4.21: Frequency of drug use after the 10^{th} class

	Mean
In school	2.78
Berufskolleg	7.79
Not in school	9.01

These patterns are similar to those seen before. Subjects still in school show a lower frequency compared to the other two categories, which suggests a more experimental behavior. The same cannot be said for the other two groups: frequency values between 7% and 9% suggest a slightly more established consumption habit.

4.5 Conclusions

Age of onset is an important issue, especially for what concern the definition of target populations for preventive interventions. At the first measurement point - when the subjects are approximately 13 years old - an average age of 12.2 is given for drug use, with a minimum value of 6. A similar picture is presented also for alcohol abuse, where a similar (11.9) average age of onset is reported, but with a smaller minimum value of 2[4] . Thus, for both illicit and licit substances, there is a general tendency to begin with their experimentation around the age of 12.

[4]The reliability of this value can be challenged, since the question asks about the first time being drunk.

Illegal drug use remains however a rather experimental behaviour. For instance, the last-year prevalences across the five time points report at first an increasing pattern which peak in 2005 with about 19% of subjects using these substances, and decrease thereafter to 17% of the sample. When the amount of subjects using illicit drug stabilizes, the frequencies of use increase across time: from less than once to about 6 times in twelve months. However, while interpreting these statistics it should be kept in mind that they refer mostly to the use of marijuana, rather than other illicit drugs. The distribution of these substances in the sample, in fact, shows that at each time point, no more than 1% of the subjects get in touch with other substances than marijuana. To this extent, illicit drug consumers in this sample can be easily described as mainly marijuana users.
For what concern alcohol abuse - since here it is asked about being drunk - the picture is slightly different. Although the age of onset seems similar to those for illicit drugs, the last-year prevalences show a different pattern. Here, there is a constant increase in the proportion of the sample who have been drunk at least once in the last twelve months. From 21% in 2002 to 71% at the last measurement. That is, across a five year span - involving great part of adolescence - nearly three quarter of the subjects have abused alcohol in the last year. Less striking is the picture for the frequencies of being drunk; here, from an average of once or twice a year in 2002, an increase to once a month in 2006 can be witnessed, which however remains a considerable change for the average age of the subjects (about 17 years old).

Another interesting picture can be obtained from the bivariate statistics. Although not exhaustive, the inclusion in the analysis of two group variables like gender and school has helped to gain a better understanding about the distribution of licit and illicit substances used in the sample.
The typical profile of an illicit drug user in this sample is male, attends a “Hauptschule”, and after the 10th class either leaves completely the educational system or joins a professional training (“Berufskolleg”). A bit different is the picture for heavy-drinking behaviors. There are still remarkable difference between female and male subjects, with the latter reporting higher level of consumption. For what concern the school types, differences are less evident, although they suggest a higher involvement in drinking for those attending the highest levels of the educational systems. The picture is, however, turned upside down after the 10th class. Here the subjects undertaking professional education are more involved in heavy drinking behaviors.

Chapter 5

Drug use trajectories: latent growth models and growth mixture models

In the last twenty years the increasing availability of longitudinal data has boosted the development of ad hoc techniques for the analysis of panel data. One of the most challenging research interest has been the measurement of the developmental patterns of particular behaviors over time. Within the framework of structural equation models, latent growth models (LGM) were firstly introduced by Meredith and Tisak (1990), and subsequently adapted to the need of the more general research community, becoming a widespread instrument in social research (see for different model applications Bollen & Curran, 2006; T. Duncan, Duncan, Strycker, Li, & Alpert, 2006). For example, adolescence is a particular dynamic phase in life where many behaviors undergo constant and rapid change; LGM allows the definition of both individual and aggregate developmental trajectories across time for any particular behavior of interest. LGM, in fact, define both intra-individual differences (i.e., a trajectory for each individual is estimated) and inter-individual difference (i.e., differences among individuals in the form of variance around the mean trajectory) in the developmental patterns. Furthermore, this modelling technique offers the possibility to study observed and unobserved heterogeneity in the sample. The former can be analysed by means of covariates that are used to predict the trajectories. The latter is modelled with finite mixture techniques, in particular by means of growth mixture models introduced by Muthén and Shedden (1999). More specifically, growth mixture models (GMM) assume that the sample does not belong to a single homogeneous population - as simple growth models do - but rather to a mixture of different groups. These groups (or classes) are not directly observed (i.e., are not directly measured as it would be for gender, educational level, neighbourhood, or other measured groups), but are implied in the distribution of the outcome variable. GMM, thus, allow the definition of this heterogeneity and have been widely applied in criminology over the last ten years (Reinecke, 2006; Kreuter & Muthén, 2008b, 2008a). GMM can be applied to a wide variety of behaviors, drug use included (see Li, Barrera, Hops, & Fisher, 2002; Wiesner et al., 2007, 2008).

In this chapter I will first shortly introduce latent growth models, growth mixture models and, a special case of the latter, latent class growth analysis. Finally the results of those models estimated for five wave panel data will be presented and discussed.

5.1 Latent growth models

5.1.1 Formal model

Latent growth models (LGM) are the first simple step in the study of the development of a particular outcome over time. These models are estimated within the more general statistical framework of structural equation models (SEM) (Bollen, 1989), which allow the simultaneous estimation of models with observed and latent variables, and also the inclusion of measurement error (Schumacker & Lomax, 2004). Since the main purpose of latent growth models is the definition of a mean trajectory that summarize the development of a particular behavior over time, a necessary condition is the availability of longitudinal panel data. In the case of drug use, for instance, the interest lies in the estimation of a developmental pattern that summarizes drug use behavior of the entire sample. The first step consists in the estimation of individual trajectories for each single subject. This is done by means of a simple equation of a line (simple regression equation), where the behavior of interest becomes a function of time:

$$y_t = \alpha + \lambda_t \beta + \epsilon_t \tag{5.1}$$

y_t is the measured frequency of drug use at each time point t, λ_t is the variable "time" (here the independent variable), α is the intercept and measures the level of drug use at time 1, and β is the slope, which measures the steepness of the line and thus the speed in the increase/decrease in consumption across time. Thus, if we assume that the relationship between drug use and time is linear, then we can easily estimate a line for each individual, that represents his/her individual development in consumption across the measured time points. Is the relationship not linear but rather curvilinear, a quadratic term can be included in the equation:

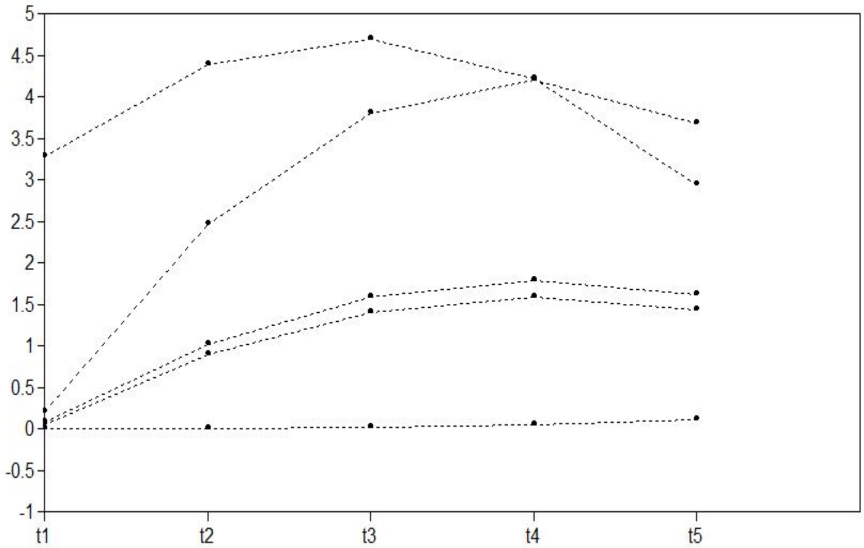
$$y_t = \alpha + \lambda_t \beta_1 + \lambda_t^2 \beta_2 + \epsilon_t \tag{5.2}$$

The new β_2 coefficient estimates the curvature of the trajectory, and the λ_t^2 is the square of the time variable. This formula represents the equation of a curve. The values for λ_t are used to specify the expected shape of the trajectory, and for this purpose are generally fixed as follow: for the intercept the factor loadings are all fixed at 1, so that the α represents for each individual the y value at the first time point; for the linear slope they are fixed to 0,1,2,3,4 to represent a linear development; finally, for the quadratic slope they are fixed to 0,1,4,9,16 to represent a curvilinear growth in the equation. In some cases, when a perfect linear or curvilinear development is not expected, some of this restrictions can be relaxed, and some of the λ_t can be freely estimated in the model (see Bollen & Curran, 2006). In sum, once a trajectory is estimated, the parameters of interest are:

- α (I) intercept: level of the outcome at time 1
- β_1 (S) linear slope: steepness of the development
- β_2 (Q) quadratic slope: rate of curvature

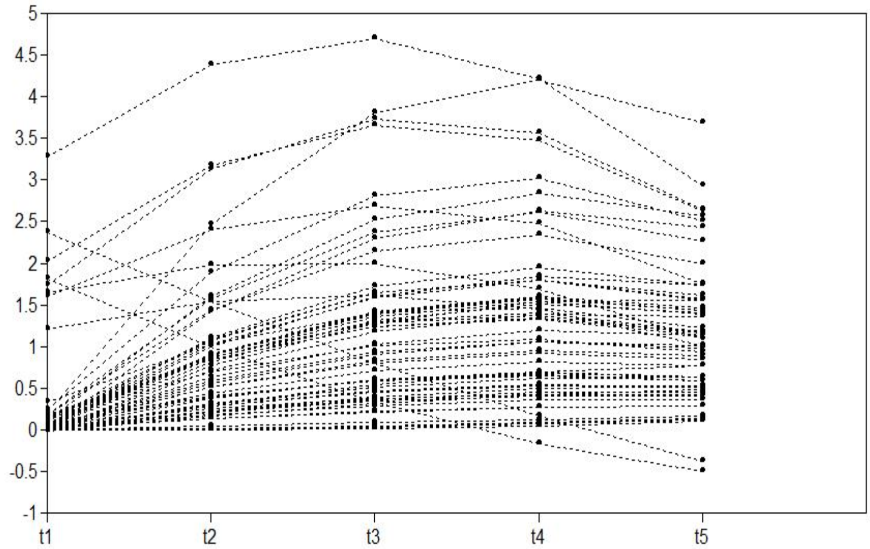
In the case of drug use, with 1552 individuals observed at five time points, 1552 trajectories can be estimated. Figure 5.1 reports the trajectories for five individuals taken at random.

Figure 5.1: Five random individual trajectories



On the x axis is reported the time (five time points), and the y axis represents the frequencies of the outcome variable. There is heterogeneity in the development of the five random subjects. For instance, the subject at the bottom of the figure do not report drug consumption across the whole time span. By contrast, the two individuals at the top, show respectively a bell shaped development that peaks at time four and decreases thereafter, and a fairly constant high level of use across the whole time span.
The same has been done for 200 random subjects in the sample in Figure 5.2.

Figure 5.2: 200 random individual trajectories



The picture above shows how LGM estimates individual developmental trajectories for each single subject in the sample; these trajectories are allowed to be different from each other on the estimated developmental parameters presented above. In case of a quadratic developmental process, individual trajectories can be different according to the intercept, slope and quadratic slope values. This can result, as shown in Figure 5.2, in large heterogeneity in the shape of the estimated individual curves. As a consequence, the interpretability of the results becomes quite difficult.
In a second step, the goal of latent growth models is to summarize intra-individual information about development, and to reproduce them mathematically. For this purpose a single mean trajectory can be estimated as the mean of the individual developmental parameters. It represents inter-individual differences in the development. In the case of a quadratic (curvilinear) development the measurement and structural equations are:

$$y_{it} = \alpha_i + \lambda_t \beta_{1i} + \lambda_t^2 \beta_{2i} + \epsilon_{it} \tag{5.3}$$

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i} \tag{5.4}$$

$$\beta_{1i} = \mu_{\beta 1} + \zeta_{\beta 1 i} \tag{5.5}$$

$$\beta_{2i} = \mu_{\beta 2} + \zeta_{\beta 2 i} \tag{5.6}$$

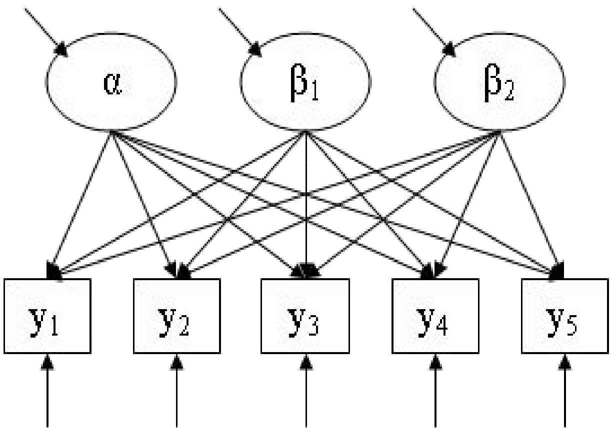
The first equation represents the measurement part of the model, and reports the intra-individual development of the outcome variable across time. The suffix i, in fact, points out that for each subject in the sample an individual trajectory is estimated based on the curvilinear equation presented above.
The other three equations represent the structural part of the SEM model and are used to estimate the average intercept and slopes of the mean sample trajectory. These latent variables consist of the mean values of the individual developmental parameters plus the residual (ζ). Since there are no covariates in the model, the latter value represents the

deviation of the latent variables from the sample means. These values can be used to calculate the variance/covariance matrix for the latent variables, which represent also the variance around the mean trajectory:

$$\Psi = \begin{pmatrix} \psi_{11} & & \\ \psi_{21} & \psi_{22} & \\ \psi_{31} & \psi_{32} & \psi_{33} \end{pmatrix} \tag{5.7}$$

Within the SEM framework, a latent growth model can be easily represented by a graphic. Those representations of models have become widely used within the SEM research field. An example is given here for a LGM in Figure 5.3:

Figure 5.3: Latent curve model



The coefficients in the oval boxes represent the latent variables (in this case latent factors); the boxes are the observed variables used to define the latent factors (e.g. drug use measured at five time points). The linear and quadratic development is captured by the factor loadings (λ_t and λ_t^2 in the equation, and the arrows in the graphic) that are fixed to represent a quadratic trajectory as specified above. Error terms for the observed outcomes and variance for the latent factor are estimated as well (small arrows pointing to the boxes in the figure), and, if needed, equality restrictions can also be applied on them (Bollen & Curran, 2006; T. Duncan et al., 2006).

5.1.2 Model-fit indices

The choice of the best LGM model follows the same criterias used for structural equation models (Bollen, 1989). The goodness of fit is calculated as the difference between the sample matrix S and the estimated matrix $\sum(\theta) : (S - \sum(\theta))$. For this purpose different estimation methods are at disposal and the preference for a specific one depends largely on the distribution and characteristics of the observed variables (Bollen, 1989). Commonly

used methods to define model fit in LGM are based on Maximum Likelihood estimation procedure (Eliason, 1993).
There are generally two situations in which model-fit indices are necessary. In the first case the researcher has already formulated a specific model and wants to test it for goodness of fit. In this situation model-fit indices are needed to determine whether the given model is acceptable or not. For this case, the most common are: the chi-square statistic, the RMSEA, and the CFI (see Bollen, 1989; Bollen & Curran, 2006). In the second situation, the researcher has formulated different model variations, whereas these variations are based on paramater restrictions. One needs statistics which can allow a comparison among similar nested or non-nested models. Here widely accepted methods are the likelihood-ratio difference test, the AIC, and the BIC. The latter two statistics can be directly compared among models without any further calculation.
For what concern the comparison of models, the more commonly used tests are those belonging to the information-based test family. Among these, there are the AIC (Akaike, 1973) and the BIC (Raftery, 1993). The AIC is calculated as:

$$AIC = -2ln(L) + 2p \tag{5.8}$$

The AIC considers the loglikelihood value and applies a penalty where p represents the number of estimated parameters. Here, parsimonious models with few parameters are preferred. The BIC uses a similar approach, with the main difference consisting in taking into account also the sample size n:

$$BIC = -2ln(L) + pln(n) \tag{5.9}$$

In both cases, when comparing nested models, the model with the smaller value on these statistics should be preferred to the models with larger values.
The chi-square test of model fit is based on the null hypothesis that the estimated and observed mean and covariance matrices are equal. This situation means that the estimated model perfectly reproduces the observed data and thus the reality. Thus, a significant test statistic suggests that the specified model does not perfectly match the mean and covariance structure of the observed data. In fact, the size of a chi-square value can be tested; being chi-square distributed all values can be tested for significance using a normal chi-square table and knowing the degree of freedom (Bollen & Curran, 2006).
Another largely used statistic test is the RMSEA (Root Mean Square Error of Approximation) (Steiger, 1990). The value of RMSEA shows how close the estimated and the observed covariance matrix are. It has a minimum of zero and no maximum, where zero represents perfect model fit. There are accepted guidelines for assessing the result of a RMSEA test: Browne and Cudeck (1993) suggest that values smaller than 0.05 indicate a very good model fit, whereas values larger than 0.10 indicate a poor fit.
The CFI is another widely used fit index. Its computation is based on the comparison between the estimated model and a baseline model, which is more restricted than the estimated one. The values of the CFI range between zero and one, where one represents a perfect fit. Also in this case, a general accepted rule of thumb suggests that values of CFI smaller than 0.90 represent poor model fit (Bollen & Curran, 2006).
In the results section model-fit indices for the best fitting model will be presented alongside the estimated results.

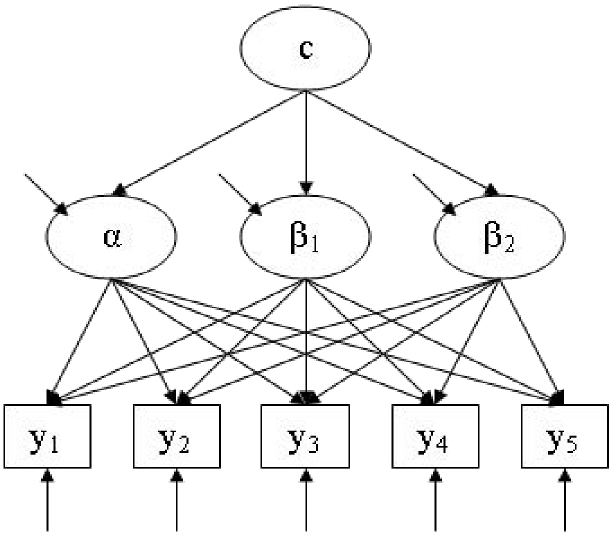
5.2 Growth mixture models

Growth mixture models assume that the sample does not belong to a single homogeneous population, but rather to a mixture of different groups (Muthén & Shedden, 1999). In some cases, a single trajectory well represents the development of the behavior of interest, and it can be used for further more complex analysis where, for instance, covariates are included in the model (see Muthén, 2004). In other situations, however, the researcher might suspect the existence of groups of subjects that share a particular development worth to be represented separately. In fact, either theoretical and statistical assumptions might indicate the necessity of more than a single trajectory in order to represent the given behavior in the sample. An important distinction for the statistical analysis of group differences in developmental processes is between observed and unobserved heterogeneity, i.e. the fact whether the source of these differences is known. Observed heterogeneity uses known and measured information to divide the sample in specific groups and then estimate single trajectory for each of them. This is the case when the researcher suspects that particular characteristics, for instance gender, ethnic, and psychological differences, might influence the development of the behavior under study for those people belonging to each category of the observed independent variable. A straightforward example is the assumption that important differences in the development of drug use behavior can be observed between male and female, suggesting thus the necessity of estimating two independent trajectories, one for each group. In unobserved heterogeneity these groups (or classes) are not directly observed (i.e., are not directly measured as it would be for gender), but are implied in the statistical distribution of the outcome variable. Groups with different trajectories are then statistically inferred from the distribution of the dependent variable, and these models are generally known as mixture models. Mixture techniques applied to latent growth models are known as growth mixture models (GMM), although similar techniques are also widely used (see for instance factor mixture analysis, FMA, for an overview see Muthén, 2001).

5.2.1 General model

GMM modeling techniques account for the unobserved heterogeneity in the sample by means of subgroups (or classes). Each group is allowed to have its own trajectory (independently estimated growth parameters), and each individual is probabilistically assigned to a particular group. For each estimated trajectory a completely different equation can be specified, allowing each group to have its own singular trajectory. This is the result of the combination of both continuous and categorical latent variables within the SEM framework, which is also the basis for both LGM and GMM model construction. This idea can be better understood by introducing a categorical latent variable C to the above shown graphical description of a simple LGM for a curvilinear development assuming five time points.

Figure 5.4: Growth mixture model



The new latent variable C is used to probabilistically group all individuals in K classes using the same methodological technique applied to latent class analysis (LCA) (see McCutcheon, 1987).
The equation for the estimation of a GMM remains similar to that of the latent growth model.

$$y_{itk} = \alpha_{ik} + \lambda_{tk}\beta_{1ik} + \lambda_{tk}^2\beta_{2ik} + \epsilon_{itk} \tag{5.10}$$

$$\alpha_{ik} = \mu_{\alpha k} + \zeta_{\alpha ik} \tag{5.11}$$

$$\beta_{1ik} = \mu_{\beta 1k} + \zeta_{\beta 1ik} \tag{5.12}$$

$$\beta_{2ik} = \mu_{\beta 2k} + \zeta_{\beta 2ik} \tag{5.13}$$

where the new suffix k is introduced for all parameters to underline the fact that unique trajectories are estimated for each of the K subgroups (classes) of the latent variable C.
Model parameters are estimated by means of the EM-algorithm (Dempster, Laird, & Rubin, 1977). The estimation procedure follows an iterative process to maximize the likelihood function. With different starting values for the model parameters, different iterative attempts are made to obtain the best value for the loglikelihood function (Muthén & Shedden, 1999). The procedure is repeated until the difference between the last and the second last generated covariance matrix are not significantly different and thus the parameter estimates converge. In Mplus version 5, the software used for this analysis, an integration method is used for the estimation with the EM-algorithm: in the estimation process different cluster of starting values for the model parameters are evaluated in order to maximize the likelihood function. The best set of starting values is then used for the estimation process (Muthén & Muthén, 1998-2010).

5.2.2 Special models: latent class growth ananlysis

A special case of GMM is the so called latent class growth analysis (LCGA), which was first developed by Nagin and Land (1993) as a semi-parametric group-based approach[1] (Nagin, 1999), and later included by Muthén within the more general framework of general growth mixture models (Muthén & Shedden, 1999; Muthén, 2004). LCGA can generally be considered a sub-model of the more general mixture models presented above, in which no variance is estimated around the random parameters. In other words, no variance is estimated for the group-specific intercepts, slopes and random slopes, and, as a conseguence, the assumption is made that all individuals belonging to a particular class share exactly the same trajectory. The new equations are a restricted version of Equations 5.10 to 5.13 for growth mixture models:

$$y_{itk} = \alpha_{ik} + \lambda_{tk}\beta_{1ik} + \lambda_{tk}^2\beta_{2ik} + \epsilon_{itk} \tag{5.14}$$

$$\alpha_{ik} = \mu_{\alpha k} \tag{5.15}$$

$$\beta_{1ik} = \mu_{\beta 1k} \tag{5.16}$$

$$\beta_{2ik} = \mu_{\beta 2k} \tag{5.17}$$

There are no changes at the individual level, where individual trajectories are estimated. The key difference, however, is at the aggregate level. Although different trajectories are allowed for each group of the categorical latent class K, no variance is allowed for each group specific random effect, so that each person in the group shares the same random parameters. This is specified in the equation by the absence of the residual term ζ for the single mean random parameters.
There are advantages and disadvantages in using this particular analysis technique compared to more complicated GMM models. The advantages can be summarized in two main points (see Muthén, 2004):

- Compared to a simple LGM the estimation of a categorical latent variable still allows the researcher to identify possible unobserved heterogeneity in the sample, represented in this case by different groups. Furthermore, in comparison to the GMM, the complexity of the model is strongly reduced by not allowing the random effects.
- Secondly, being LCGA computationally less demanding than GMM, it can be used as a first step to identify, for instance, the possible number of classes needed, and the general developmental patterns of each single group.

There are however shortcomings that should be considered when estimating such models. Although the discussion on the validity of LCGA compared to GMM is not yet finished (Bauer & Curran, 2003; Muthén, 2004), as well as for what concern the more general group-based trajectory research (Nagin & Tremblay, 2005), many researchers agree on a major problem. In particular, Muthén (2001, 2004) highlights the risk that LCGA classes do not really represent substantive significant groups (i.e., real groups of people observable in the population), but merely statistical artefacts which are estimated to represent the implicit variance of each estimated latent class. In other words, the

[1]From now on I will use only the term LCGA to refer both to the semi-parametric group-based approach from Nagin (1999), and the further develoment introduced by Muthén (2004).

simpler model achieved by not allowing random effects might result in an overestimation of classes, which in reality do not exist and simply represent the constrained variance of substantive classes.
Another problem arises in case of covariates; these can be regressed only on the categorical class variable and not on the single growth parameters. In the latter case, the explanatory power of covariates is reduced since it not possible to test their influence on the single growth parameters. This is reduced to the simple difference among classes.
In any case, the utility of LCGA should not be underestimated; here it will be used as an explorative step toward the estimation of the more complex GMM.

5.2.3 Model-fit indices

Similar to the measures presented for the LGM, also for the GMM there are many indices that can be used to asses model fit. The model-fit indices presented for the LGM can also be used to test GMM. However, being GMM a mixture of categorical and continuous variables, new indices have been introduced to test this typology of models. As mentioned above, the major research question concerns the number of classes that should be estimated. Beside the substantive interpretation of the classes, which is left to the researcher's theoretical expectations, over the last fifteen years many statistical measures have been developed to accomplish this task. Thus, beside the BIC and AIC, specific tests have been developed to assess the correct number of classes: the LMR-LRT (Lo, Mendell, & Rubin, 2001), the BLRT (McLachlan & Peel, 2000), the Skew and Kurtosis test (cited in Muthén, 2003, p. 8), and the Analysis of the Residuals (Wang, Brown, & Bandeen-Roche, 2005; Muthén & Asparouhov, 2009).
Model fit indices can be roughly divided into three groups: (a) information-based criteria, (b) nested model likelihood ratio tests, and (c) goodness of fit measures (Tofighi & Enders, 2008).
Among the (a) information-based indices there are the BIC and AIC families, which have been already discussed in Section 5.1.2. However, it has been shown (Tofighi & Enders, 2008) that the BIC is consistent, i.e. it tends to choose the correct model more often as sample size increases. The adjusted BIC has been introduced to reduce the penalty for a large samples and it is thus preferred with large sample size (Sclove, 1987; Muthén & Muthén, 1998-2010). In its equation (see Equation 5.9) the n is substituted by the equation $n = (n+2)/24$, which was found to have superior performances in model comparison. The penalty term $pln(n)$, which is not present in the AIC, reduces the bias when a new class is estimated. With every additional class the value of the AIC goes down; with the penalty term this problem is avoided and the BIC can be used as a good fit estimate for latent class analysis. The penalty term includes the number of parameters, and favours models with less parameters. It failed too, however, to recognize homogeneity in a non-normal distributed population (see Bauer & Curran, 2003, p. 349). When two competing model specifications estimated on the same data set yield the same loglikelihood, the BIC favours parsimony by choosing the model specification with fewest parameters (Brame, Nagin, & Wasserman, 2006, p. 39).
The (b) nested-model family of tests is based on the difference in loglikelihood between two nested models. Nested models are models "that differ by a set of parameter restrictions" (Tofighi & Enders, 2008, p. 320). This difference is expressed by the formula:

$$LR = -2[ln(L)_{restricted} - ln(L)_{full}] \tag{5.18}$$

where the restricted model is the one with one less class (fewer parameters), and the full the one with one more class. Under certain condition the LR is chi-square distributed, however, this is not the case in GMM. To overcome this shortcoming Lo et al. (2001) have derived an approximated distribution of the LR in mixture condition which resulted in

the Lo-Mendel-Rubin likelihood ratio test (LMR-LRT), and the subsequently adjusted version (supposedly more accurate, even if Tofighi and Enders (2008) did not find any difference). The LMR-LRT provides a standard of comparison to find the appropriate number of classes to be included in the model. It uses the normal likelihood ratio for testing the $k-1$ model against the k model. The p value represents the probability that the $H0$ is accepted, namely, that the model with $k-1$ classes is to be accepted. A low p value indicates that the model with $k-1$ classes has to be rejected. A resulting p value greater than 0,05 indicates that the $H0$ model ($K-1$ Classes) cannot be rejected. When comparing two models the adjusted LMR-LRT should be preferred to the normal LMR-LRT test for deciding how many classes better represent the data.
A significance test can also be carried out using a bootstrapping procedure. This is known as bootstraped likelihood ratio test (BLRT). A series of bootstrap samples are generated using the loglikelihood of the $k-1$ model. For each new sample a LR_b[2] is calculated and an empirical distribution of their values is generated. The subsequent p value is calculated as follow: the original LR is compared with the distribution of LR_b, and the proportion LR_b larger than the original value is calculated. When the $k-1$ model is incorrect, then the LR should be larger compared to the LR_b, and the resulting probability will be small. Thus, small p values reflect a correctly specified k model (Tofighi & Enders, 2008, p. 321). Bootstrapped likelihood ratio test (McLachlan & Peel, 2000) is used in mixture models to compare the $k+1$ model with the k one. A low p value indicates that the model with one less class has to be rejected in favour of the estimated one. In recent articles on GMM, LCA and np-GMM this test has been preferred to the LMR-LRT (see Kreuter & Muthén, 2008b, 2008a; Muthén & Muthén, 1998-2010). The BLRT is, however, computational demanding, and it is suggested to run it after having already estimated the model (this is the case for complex GMM; the second run is facilitated by means of the starting values of the original model). The validity of this new test was also confirmed in a simulation study by Nylund, Muthén, Nishina, Bellmore, and Graham (2006).
Goodness of Fit Tests (c) are not intended for comparing nested models, but rather for model-based assessment of model fit. A first measure is entropy (E_k); it represents the quality of the classification, and it ranges from 0 to 1, where values close to 1 indicate a good classification of the data by means of the latent classes. The entropy however is by definition a function of the number of classes. If one were to fit a model with as many classes as there are observations, entropy would necessary be 1 (Kreuter & Muthén, 2008b). Another tests, recently implemented in Mplus (see Muthén, 2003), is known as Multivariate Skewness and Kurtosis Tests (MST and MKT). The latter can be considered, to some extent, as the result of an ongoing discussion on the capability to distinguish between true substantive mixtures and statistical artefacts (see Bauer & Curran, 2003). The test compares the estimated multivariate skewness and kurtosis with the same sample measures. The sampling distribution of the test is generated over a number of replications in data generated from the estimated mixture model. Being the statistical distribution of the test complex (unknown) when more than one class is estimated, this is generated by means of 200 Monte Carlo replications. A large probability value indicates a good model fit (small values mean a discrepancy between the Monte Carlo-estimated values and the observed ones). The basic principle of the SKT lies in the fact that Bauer and Curran (2003) argued that non-normally distributed data have a high probability to be represented by a mixture. This new test, takes the original degree of non-normality in the data (skewness and kurtosis) and compares these values with the skewness and kurtosis present in the estimated model. If the level of non-normality in the estimated model is respected (i.e. similar to the original data) than the model is confirmed, and the mixture distribution can be accepted (if any). If the values are not replicated correctly, than the

[2]the LR_b is calculated as the likelihood ratio between the k and $k-1$ class models for each new boostraped sample

mixture might only represent the non-normality in the sample (Bauer & Curran, 2003, p. 385). Further simulations (see Muthén & Asparouhov, 2009) have found that the SKT is reliable with non-normal data, but failed to detect an homogenous population when this has a mild non-normality (e.g. skewness/kurtosis of 0.1/0.5 (Muthén, 2003, p. 11)).
The last proposed test is the Analysis of the Residuals (Wang et al., 2005; Muthén & Asparouhov, 2009). It considers the number of residuals that are significant, and thus show misfit, at a 5% level for the 10 most frequent response patterns across time. The smaller the number of significant residuals across models with different class number, the better the model fit, i.e. a better model should show a reduction in the number of significant residuals.

The abundance of such tests has however its pitfalls. Its number, in fact, is not synonymous with more certainty; on the contrary, the fact that researchers are still looking for better measures to assess model-fit implies that those now available are not yet satisfactory. This idea suggests that a model should not be evaluated merely on the basis of such statistics, but that the researchers own substantive interpretation of the models still plays an important role. For the purpose of simplicity, not all these tests will be applied in the next section. Only the more common and established ones will be used: entropy E_k, adjusted BIC and LMR-LRT.

5.3 Results

In this final section the results for three typologies of models presented above will be shown. Altough in many cases, on the basis of theoretical and substantive reasoning, a LGM analysis might be the target of the quantitative researcher (see S. Duncan et al., 1996; S. Duncan, Duncan, Biglan, & Ary, 1998; Hussong, Curran, Moffit, Caspi, & Carrig, 2004), in many other situations this modeling strategy is just the first step toward more complex models (Muthén, 2004). In estimating GMM, in fact, a stepwise procedure is used to get to the final results. LGM and LCGA are used as explorative models to gain information about both the form of the development and the existence of different curves, before a more complex GMM analysis is carried out.
In the following sections a similar stepwise procedure will be used for the purpose of estimating specific drug-use related developmental trajectories using GMM. In the first section different LGM model specifications will be tested to decide whether a linear or a curvilinear development better represents the data. In the second section, LCGA will determine first whether more than one trajectory is needed, and second how many of them are necessary. In the last section LCGA models will be expanded to allow variance for each specific curve.
All the above mentioned models will be estimated using the self-reported frequencies of drug use. Before proceding to the estimation of the models, some important issues should be considered.
First, although the object of this work is marijuana use, for the purpose of the empirical analysis all the illicit drugs measured in the questionnaire will be used. This is for two reasons. On the one hand, descriptive statistics in Chapter 4 have shown that marijuana is the most used substance in this sample; other illicit drugs were never used by more than 1% of the subjects, and when used, they were also taken in combination with other substances, above all with marijuana. On the other hand, the few number of users relative to the sample size at each time point, made it desiderable to have the largest amount of information about drug use for the purpose of estimating complex statistical models. Thus, considering these two issues, I decided to include all available information about substance use. This decision was also supported by the knowledge that most poli-consumers were also marijuana users, and that was not possible to discern which

substance was predominant in their consumption habits[3]. Thus, although I might talk mainly of marijuana use in the interpretation of the latent models results, these will also include some minor information about other types of illicit drugs.
Second, due to the large number of non-users in the sample, the relatively small number of drug users, and the presence of some outlying values, the count values of the frequency of drug use were strongly skewed and zero-inflated. An important condition for the estimation of reliable maximum likelihood parameters is a multivariate normal distribution for the outcome variables (Eliason, 1993); this is however not the case for the frequencies of drug use in the CRiMoC sample. The problem of non-normality was evident in the estimation procedure of simple latent growth models, where convergence problems and poor model results were the visible consequences. Also the estimation under the assumption of a zero-inflated Poisson distribution (see Roeder, Lynch, & Nagin, 1999) was not sufficient to account for the strong skewness of the observed outcome. To overcome this problem the observed frequencies were logged using the natural logarithm (ln). This transformation is largely used in the criminological literature when highly skewed data, such as delinquency (Bollen & Curran, 2006) and drug use (Krohn et al., 1996) are used in the analysis; by means of logging the observed count data their distribution is "normalized" and also the influence of outliers is reduced[4]. The logged frequencies were then used as the observed outcomes of all growth models presented in this study. When interpreting the results, it should be kept in mind that the value on the y-axes does not represent count frequencies, but their logarithmic transformation. For the purpose of interpretation, the exponential (e^{ln}) of a logged value will give back the frequency value. Table 5.1 and 5.2 report descriptive statistics for logged and non-logged frequencies of drug use at each time point.

Table 5.1: Descriptive statistics for the frequencies of drug use

Variable	Mean	s.d.	Skewness	Kurtosis
Freq. (t_1)	.35	2.65	12.20	189.48
Freq. (t_2)	1.51	12.40	15.44	276.20
Freq. (t_3)	4.50	26.67	9.15	98.07
Freq. (t_4)	4.93	30.98	9.57	102.94
Freq. (t_5)	5.79	32.63	7.87	71.30

[3]In the questionnaire, the frequencies of drug use were not asked for each specific substance, but in general. Thus, when more than one drug was taken, it was not possible to know the relative frequencies for each substance.

[4]The natural logarithm does not create a linear transformation. The closer the values to 1, the larger is their logarithmic value. In this way, smaller frequency values gain more importance compared to large outlying values once transformed.

Table 5.2: Descriptive statistics for the logged frequencies of drug use

Variable	Mean	s.d.	Skewness	Kurtosis
ln freq. (t_1)	.08	.41	5.78	38.78
ln freq. (t_2)	.19	.67	4.18	22.52
ln freq. (t_3)	.34	.97	3.28	13.88
ln freq. (t_4)	.35	.98	3.32	14.43
ln freq. (t_5)	.35	1.03	3.40	14.57

The statistics above clearly show the effects of the logarithmic transformation on the outcome variable in two ways. First, the natural logarithm reduces the range of the observed values. Furthermore, a particularity of the ln transformation is that it minimizes differences at the high end of the value scale compared to the differences at the low end. In other words, the influence of outlying values on mean and covariance statistics is strongly reduced compared to smaller count values. Second, the large skew and kurtosis measured in the original data at each time point are strongly reduced; the logged variables are "normalized" and should better perform under the assumption of multivariate normality. The logarithmic transformation of the observed outcomes also has an important effect on the correlation matrix. Another important condition when estimating LGM is that the correlations in the correlation matrix respect the time sequence of the observed variables. The matrices in Table 5.3 and 5.4 report the correlations among time points for both normal and logged frequencies of drug use.

Table 5.3: Correlation matrix of the frequencies of drug use

	Freq. (t_1)	Freq. (t_2)	Freq. (t_3)	Freq. (t_4)	Freq. (t_5)
Freq. (t_1)	1.000				
Freq. (t_2)	0.512	1.000			
Freq. (t_3)	0.335	0.622	1.000		
Freq. (t_4)	0.418	0.537	0.594	1.000	
Freq. (t_5)	0.192	0.357	0.430	0.424	1.000

The correlations in this matrix do not always respect the time sequence as required by LGM. The correlation between t_3 and t_1 is smaller than the one between t_4 and t_1. It is in fact expected that adjacent time points correlate stronger with each other than not adjacent time points. If this condition is not respected estimation problems could arise.

Table 5.4: Correlation matrix of the logged frequencies of drug use

	ln freq. (t_1)	ln freq. (t_2)	ln freq. (t_3)	ln freq. (t_4)	ln freq. (t_5)
ln freq. (t_1)	1.000				
ln freq. (t_2)	0.532	1.000			
ln freq. (t_3)	0.367	0.621	1.000		
ln freq. (t_4)	0.277	0.414	0.591	1.000	
ln freq. (t_5)	0.161	0.331	0.458	0.493	1.000

However, the new correlation matrix calculated with the logged frequencies shows a better picture; here the time sequence in the correlation values is fully respected. It is possible, that beside correcting to a certain degree the non-normality as shown above, the logarithmic transformation of the original variables has also reduced the influence of outliers and thus provided a reasonable correlation matrix.
In any case, using the natural logarithm of the outcome count variables has helped correcting two major problems: the strong non-normality and the presence of outliers in the observed data; these, however, have reduced the interpretability of the results. With these two issues in mind, the following sections will present the results of the anticipated growth models.

5.3.1 Results for LGM

After looking at the distribution of the mean frequencies of drug use in the sample (see Chapter 4), it is clear that the aggregate development of such behavior follows a curvilinear trajectory. Although aggregate measures of cross-sectional data do not always correspond to individual longitudinal data, this is a clue that a curvilinear term could be necessary in the LGM equation. In order to test this supposition, I compare three main modeling options with different restrictions on the random effects: (a) a LGM with only intercept, (b) a LGM with intercept and slope, and (c) a LGM with also a curvilinear slope in its equation. The first model assumes only a constant starting value and neither linear nor curvilinear development; the trajectory is thus a straight horizontal line with an estimated intercept (mean value at time point 1). The second model includes a slope term in the equation, thus allowing for variability in the steepness of the estimated line; here the behavior can be represented by an increasing or decreasing line with a specific intercept. The last model, although less parsimonious, introduces a quadratic term. The estimated developmental trajectory is now allowed to assume a curvilinear form and thus has developmental changes over time. All the above mentioned models are nested within each other. They differ only in the applied restrictions on some model parameters[5]. Table 5.5 sums up the goodness of fit of the models and lays the basis for a comparison.

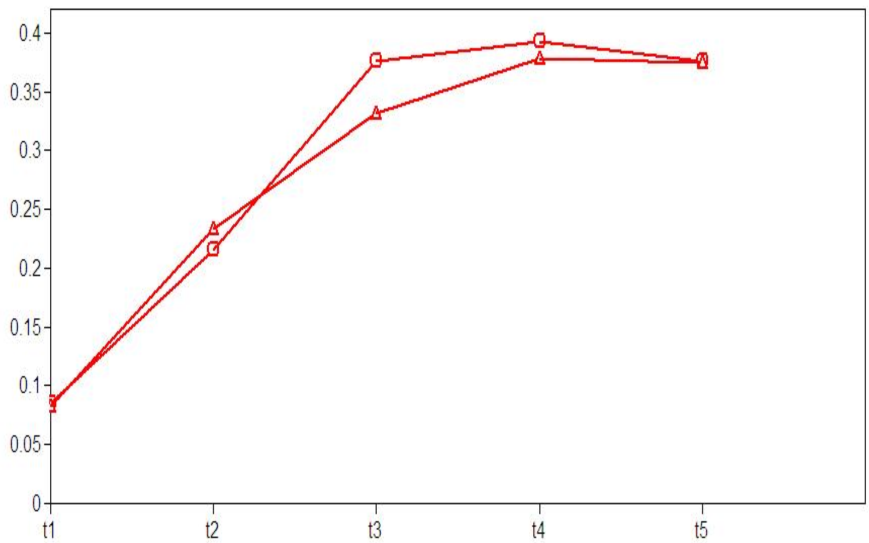
[5]In model (a), for instance, the linear and the quadratic slopes are fixed at zero. Similarly, in model (b), only the quadratic term is fixed at zero.

Table 5.5: LGM models comparison

Random eff.	Est. par.	Loglikelihood	CFI	Adj. BIC	RMSEA
I	7	1318.16 (0.000)	0.313	16797.42	0.254
IS	10	366.34 (0.000)	0.812	15858.11	0.152
ISQ	16	10.64 (0.030)	0.997	15527.43	0.033

As outlined above there are two main general aspects to consider when analyzing model fit; there are in fact measures that can be used to determine the model-fit of a specific model, and those that can be used to compare nested models with each other. In the first case, looking at first at the loglikelihood statistics, it can be noticed that its value sharply decreases as more growth parameters are added. Similarly, the CFI gets closer to the value of 1 as a curvilinear model is specified. The value of the RMSEA shows similar patterns, and only in the quadratic model it shows an acceptable value smaller than 0.05. Thus, by looking at every single model, the specification of a quadratic slope seems to improve the model-fit statistics to an acceptable level. A similar trend can be observed when comparing the models against each other. The BIC shows its smaller value for the quadratic solution, suggesting again that this is the best choice among the three.
Thus, as anticipated by the aggregate mean values, a curvilinear trajectory seems to better represent the average longitudinal development of drug use in our sample.

Figure 5.5: Latent growth model for drug use



The development[6] presented in Picture 5.5 shows how drug use consumption among youths in Duisburg increases constantly at the first three time points and stabilizes at

[6]The development of marijuana use shown in Picture 5.5 is represented by both the observed (circle) and the estimated (triangle) trajectories. The same will be done for all

the last two. At the last measurement point the frequency of drug use seems to slowly decrease, suggesting that substance use at this age either stabilizes or starts to decrease at the end of adolescence. The interpretation of the actual frequencies reported on the y-axis is not straightforward. As anticipated before, by using the natural logarithmus of the observed frequencies strongly increases the malleability of the data at the cost of direct interpretability of the results. Although the focus of this analysis should remain on the development itself and less on the simple frequencies, the logarithmized values on the y-axis can again be transformed into frequencies by simply calculating the exponential of the logged frequencies. The intercept, which represents the mean starting point of the individual trajectories, has a value of 0.083, which corresponds approximately to 1. This means that on average at time point one the sampled youths have used at least once marijuana in the last twelve months. Similarly, at time point four, when the subjects are 16 years old and the consumption of illicit substances reach a peak, the average logged value is about 0.4, i.e., the reported use increases to 1.5 times. Furthermore, all three developmental parameters show a significant variance (0.142 for the intercept, 0.261 for the slope, and 0.009 for the quadratic term), suggesting important heterogeneity within the sample concerning the developmental trajectory. The overall picture for this first analysis shows a general reduced use of illicit drugs in the sample. This behavior remains constant across the observed time span, although a small increase can be observed especially in the first three years. This is confirmed by the results of the descriptive statistics; the number of drug users in our sample is fairly small (see Section 4.2) and among these, only few seem to report heavy use or abuse of any sort. The majority of the sample can be described as either abstainers or simply experimental/occasional marijuana users. However, the presence of significant variability for all three developmental parameters also suggests that some subjects deviate from this developmental pattern. Descriptive statistics have also revealed that "heavy users" exist in the sample. The simplified representation of the whole sample by a single curve might ignore these subjects who are of great sociological interest. Can a single trajectory represent all, or do some specific groups of users exist which share a different development? This question can be answered by means of mixture models.

5.3.2 Results for LCGA

The need for a curvilinear development has been confirmed in the last section by means of LGM. This assumption will be now used in LCGA analysis, where unobserved heterogenity in the distribution of the observed outcomes will be searched for.

As a first step, models with increasing number of classes are estimated and compared with each other by means of model-fit indices. All the estimated curves have a curvilinear function with respectively intercept, slope and quadratic terms. As already specified no variance is estimated for these parameters. In Table 5.6 the estimated models are reported; for comparison purposes, the first model presented is the quadratic LGM estimated in the section above. This model has only one trajectory and thus no LMRT and entropy E_k is reported.

the pictures in this chapter.

Table 5.6: LCGA models comparison

Classes	Est. Par.	E_k	Adj. BIC	LMRT-LRT (P)
-	16	-	15527.43	-
2	12	0.999	14421.46	2893.60 (0.029)
3	16	0.992	12555.06	1821.10(0.019)
4	20	0.993	11582.98	956.22 (0.478)
5	24	0.992	10368.67	1190.47 (0.513)

(In brackets are reported the significance values for the LMR-LRT).

The adjusted BIC can be used for comparison purposes; the smaller the BIC value the better the model fits the data. However, this is not always the case. There are some instances where the BIC decreases by every new added class, even if the interpretability of the new added classes could be questionable. We can however notice, that the larger drop in BIC occurs when three classes are estimated; here the BIC difference from the two classes model is twice bigger than any other comparison in the table, which could be a first hint of the goodness of the three-classes model. Another largely used model-fit indice is the LMR-LRT test, which tests whether the new estimated class is statistically necessary or redundant. A significant LMRT value suggests that the new estimated class is not statistically redundant. According to the results of this test in Table 5.6 the estimation of a third class is still held necessary, whereas a fourth class is deemed redundant (the LMRT value is not significant at the 5% level); this is also the case when a fifth class is introduced in the model. Thus, based on merely statistical evidence a three class model can be considered the best solution so far.

Beside the above mentioned model-fit tests, the entropy value uses the posterior class membership probabilities to sum up how well the estimated model assigns each subject to a given class. The model estimates for each person the probability to belong to a class; then, the subject is assigned to the class where it has the highest probability to belong to. A good model is one where probability values close to one are assigned to each individual. The E_k for a three class solution is close to one, and suggests that the average individual probablity to be assigned to a specific class is close to one.

Furthermore, posterior class membership probabilities can be used for comparisons among models with different specifications. Table 5.7 reports a cross classification between the two and three class solutions. In this way it is possible to see how class composition changes when a new class is added. The values represent the stability and change between the solutions. The values on the diagonal represent subjects that remain in the same class across the two solutions. Off-diagonal values, on the contrary, represent subjects that are assigned to a different class.

Table 5.7: Class comparison between the two- and three-class LCGA models

Class	1	2	3	$\sum$
1	1413	85	0	1498
2	0	5	48	53
$\sum$	1413	90	48	1551

(Class interpretation: 1=low use; 2=adolescence limited; 3=desisters).

Before the comparison all classes have been matched with the 3-class solution in order to make the interpretability of the table easier. Thus, class 1 represents the low-use group, class 2 the adolescence limited, and class 3 the desister group. The results from the table above suggest that the old second class lend near all its members to the desister class in the 3-class model. The old first class do not loose any considerable number of subjects, the few who move built the adoloscence limited group in the new model. Thus, adding a new class to the old 2-class model seems to fill the gap between the older two classes and generate a new group with a quite specific substantive meaning. This new group shows a well known trajectory which increases during adolescence and decrease thereafter. Beside the results of the model-fit tests, a third class seems to bring new important information in the model. Similarly, a table can be produced for the comparison between the three- and the four-class models.

Table 5.8: Class comparison between the three- and four-class LCGA models

Class	1	2	3	4	$\sum$
1	1404	4	5	0	1413
2	0	87	1	2	90
3	0	0	31	17	48
$\sum$	1404	91	37	19	1551

(Class interpretation: 1=low use; 2=adolescence limited; 3=desisters; 4=new class).

The picture obtained from the table above is quite reassuring. In fact, it seems to suggest that a fourth class is not necessary, confirming thus the results of the model-fit indices. Looking at the values along the diagonal it can be noticed that the low-use and the adolescence limited classes are very stable across the two solutions. They loose only a few portion of members. In fact, the new fourth class seems to be the result of the split of the old third one in two groups. Beside that this new class is both very small and shares a very similar trajectory with class 3 (compare figure with Figure 5.7), suggesting that this new trajectory might be more a mere representation of the variance on the intercept of the desister class than a real class on its own. This table confirms the reliability of the first two classes, and suggests that there is no need for a forth one, since the desister class already well represents that specific pattern of development. The three-class model remains, so far, the best representation of the observed data.

The next step in exploring the substantive meaning of a mixture model consists in the comparison of the estimated classes with the cross-sectional means of the observed variables. This method, however, should be taken with a pinch of salt. There are important statistical and substantial differences between the two measures compared in the table; on the one hand are reported trajectories estimated by means of individual-longitudinal data, and on the other hand are presented cross-sectional mean values. Thus, one should not be surprised if differences are found. However, similarity in the patterns could support the substantive validity of the estimated results. On the other hand, by means of logging the observed frequencies the influence of outliers and large values have been reduced. However, when comparing the classes that have been estimated with logged frequencies with the original frequencies, outliers and large values regain their original influence on the calculation of the means. The mathematical meaning and the problems of such a comparison will not be discussed here any further. The following table has in fact the simple purpose of giving a general picture of the possible frequency distribution of the found classes. Table 5.9 shows the results for the three-class model.

Table 5.9: Posterior class probabilities and observed frequencies of drug use in the sample

Class	n.	$\overline{x}t_1$	$\overline{x}t_2$	$\overline{x}t_3$	$\overline{x}t_4$	$\overline{x}t_5$
$Cl.1$ low use	1413	0.02	0.18	0.39	1.74	2.59
$Cl.2$ adolescence lim.	90	0.15	15.96	58.42	51.38	54.24
$Cl.3$ desisters	48	11.00	19.68	38.14	30.25	19.84
Sample $\overline{x}$	1551	0.36	1.52	4.51	4.94	5.79

The low-user class seems to well represent the observed mean frequencies of drug use measured at each time point. The trend respects the pattern of the estimated curve where a small and slow increase in consumption is observed across time. This use does not go as further as twice in the last twelve months (only at the last measurement point it is slightly larger than 2), confirming a low and experimental use. A similar picture is presented for the adolescence-limited group. Here, the observed value match the expected development, even if at the last measurement point a small increase is witnessed. This should be, however, interpreted not as an upturn of the group development, but rather as a stabilization as depicted in the estimated curve. The development of this class, in fact, can be rightly defined as adolescence limited, since it starts from nearly no consumption at the beginning of the measurement (at age 12-13 the participants can be considered at the beginning of adolescence), reaches a peak around age 15, and then slowly decreases thereafter.

The last class, the desisters, shows a not perfect match with the observed means. Even if, as stated above, a perfect match should not be expected due to the different nature of the values compared (on the one side estimated longitudinal individual values, and on the other side cross-sectional aggregate means), similar patterns might confirm the validity of the estimated curves. Thus, for the case of the desister group, instead of a decreasing pattern a curvilinear development of the observed means is reported. This group is, however, very small in number and thus greater variation is expected within it than for the other two classes. In fact, as seen above, the estimation of a fourth class causes the splits of the desister group, suggesting the presence of different curves within it.

As a final step, the four- and three-class models can now be graphically compared.

Figure 5.6: LCGA model for drug use, three classes

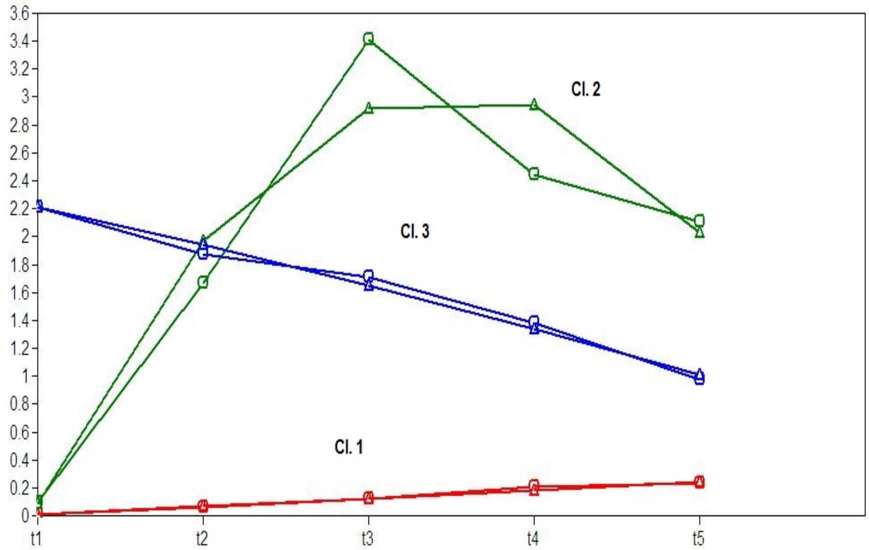
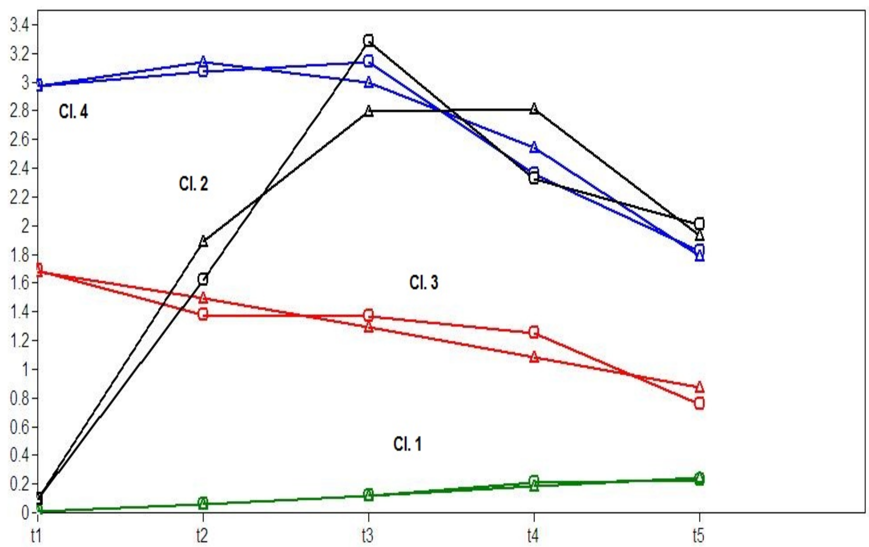


Figure 5.7: LCGA model for drug use, four classes



As outlined above the larger difference between the two solutions consists in the split of the desister class and in the subsequent estimation of a new fourth one, which shares a very similar developmental pattern with its original "mother-class", and differ from it for developing at a lower frequency level. Since no variance was estimated for the growth parameters, this result seems to point out that the last fourth class is a mere representation of the variance within the decreaser group. Thus, the LCGA analysis suggests that three classes are the best representation of the observed data. Suspecting, however, that some variability in the classes exists (especially in the desister class), which is not captured by the LCGA estimation. This hypothesis can be further explored by means of GMM.

5.3.3 Results for GMM

GMM analysis, if compared to LCGA, can be considered a less restrictive approach to the estimation of developmental curves. This is due to the fact that the more general GMM allow to estimate class-specific variance for the random terms. Thus, each subject assigned to a class is allowed to deviate from its trajectory, and the total amount of deviation within each group is measured by the variance on the intercept, slope and quadratic term. The amount of new parameters that can be estimated depends on both the researcher's substantive interests and the necessity to estimate as parsimonious models as possible. In this way a full unrestricted model can be estimated where group-specific variance for all the three random terms is calculated, so that each class has its own three singular variance values; it is also possible to opt for a less complicated and more parsimonious solution where the random effect variance is set equal for all the estimated classes. Similarly, specific random effect variance can be fixed at zero and models can be tested where, for instance, only the variance for the intercept is computed. However, good practice has shown that, especially with small classes, estimating all the possible variances in a single model can lead to convergence problems. Thus, the estimation procedure and the choice of the best model will follow some particular steps with regard to the variance for the random terms. Keeping in mind that the LCGA confirmed the validity of a quadratic model as the best representation of the observed data, I will calculate GMM quadratic models with increasing number of classes and different specifications for the variances. First, a model with variance on the intercept only, then a model with variance on the slope only, and finally a model with variance on both terms. The variances, in all three cases, are held equal across classes. Further specifications, such as class-specific variance and classes with different trajectories were also tested but not included in the analysis due to computational problems or bad model fit compared to the models proposed here. In a second step the different model specifications will be compared against each other using first model-fit indices and subsequently substantive observation of the results. In the comparison process the best LCGA model will also be included, with the purpose of testing whether the estimation of variance is necessary or not.

The following table reports the model-fit indices for both LCGA and GMM model with different restrictions on the variance of the random effects. For a better comparison the models are arranged in groups with the same number of classes. Each group will contain a LCGA model, and three GMM: one with intercept variance, one with slope variance, and one with both. The variance for the random quadratic term is fixed at zero since small in size compared to the variance for the other two factors (see the results for the LGM), and of less substantive interest.

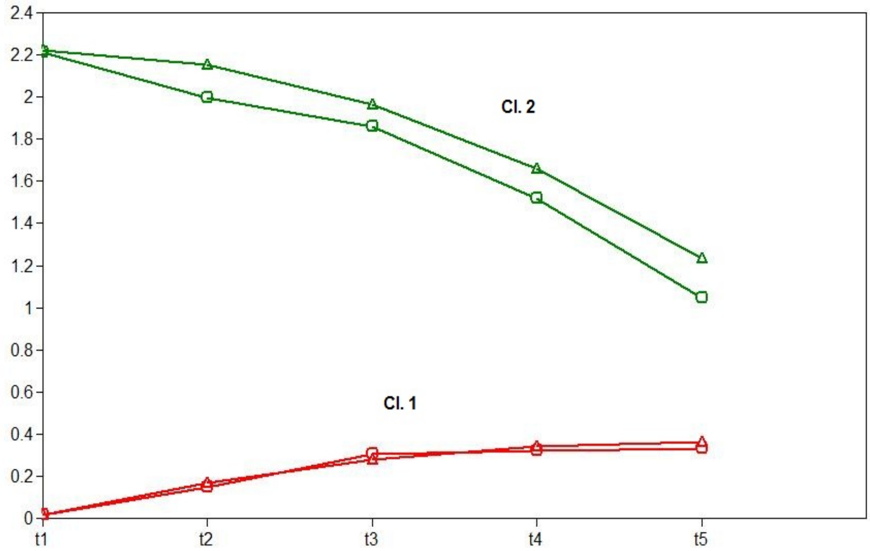
Table 5.10: GMM model comparison

Model	Cl.	Var. on:	Est. par.	E_k	Adj. BIC	LMR-LRT (P)
LCGA	2	-	12	0.999	14421.46	2893.60(0.029)
GMM	2	IS	15	0.999	13353.84	2404.88(0.033)
GMM	2	I	13	0.999	14267.19	2156.62(0.043)
GMM	2	S	13	0.999	13474.87	2817.96(0.028)
LCGA	3	-	16	0.992	12555.06	1821.10(0.019)
GMM	3	IS	19	0.988	12195.01	1136.82(0.235)
GMM	3	I	17	0.992	12373.79	1847.21(0.019)
GMM	3	S	17	0.991	12262.30	1188.79(0.099)
LCGA	4	-	20	0.993	11582.98	956.22(0.478)
GMM	4	IS	23	N.C.	-	-
GMM	4	I	21	N.C.	-	-

(In brackets are reported the significance values of the LMR-LRT. N.C. refers to the fact that the model did not converge).

First, the two-class models will be discussed. In general, by estimating the variance of the random effects and independently of the number of variances estimated, I achieved a better model-fit than with the LCGA according to the adjusted BIC. The latter, in fact, prefers a model where the variance is calculated for both the random intercept and the slope. The LMR-LRT too suggests that a two-class solution is to be preferred to the single-class model. For all models the p-values of the LMR-LRT are significant at the 0.05 level. The two estimated trajectories for the two-class solution are shown in Figure 5.8.

Figure 5.8: GMM model for drug use, two classes



The majority of the subjects (97%) is assigned to the first class, whose trajectory shows a slow increasing pattern which tends to stabilize at the last two measurement points. The remaining 3% are assigned to the second group, whose development is represented by a decreasing trajectory that, although it starts with a relatively high rate of drug use - if compared to the other class - tends to recede thereafter. In both cases the variances for the random terms are significant and similar in size (see Table 5.11):

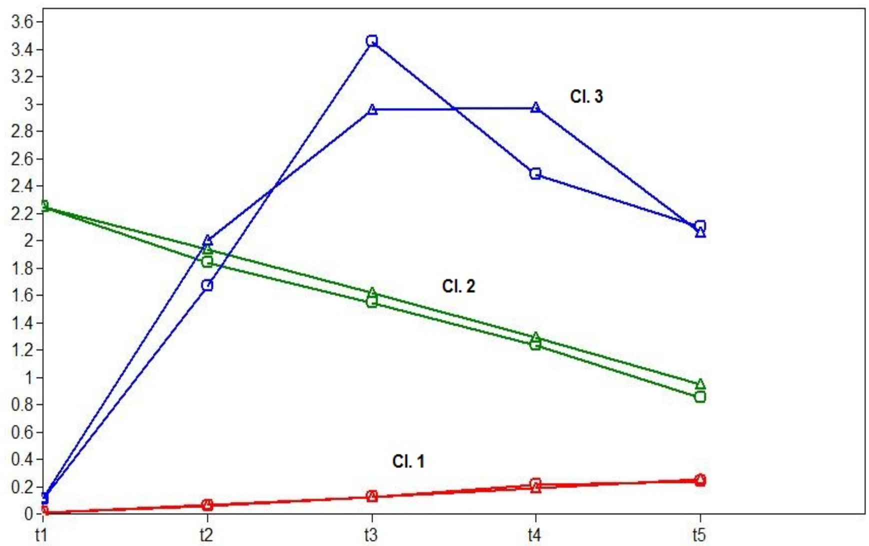
Table 5.11: GMM, two-class model; Variances for the random terms

Parameter	Estimates	S.E.	Est./S.E.
I	0.023	0.006	3.834
S	0.049	0.006	7.987

Since the LCGA prefers a three-class solution, in a second step a third class for all models is calculated and the results compared in Table 5.10. The adjusted BIC suggests that the estimation of variance is needed to better represent the observed data; all GMM models report a smaller BIC than the LCGA. Even in this case, the smaller BIC value is obtained from the model with variance on both random intercept and slope. However, the picture changes when looking at the LMR-LRT. Here the latter mentioned model is clearly not significant, suggesting that a third class might be superfluous. The same can be said for the model with variance on the slope. Only for the GMM with intercept variance and the LCGA the new third class seems to bring new information to the results. For what concern the estimation of a four-class GMM some estimation problems arise, even after increasing the number of starts and iterations in the estimation process. However, as Muthén (2004) suggests, GMM compared to LCGA should generally produce a lower

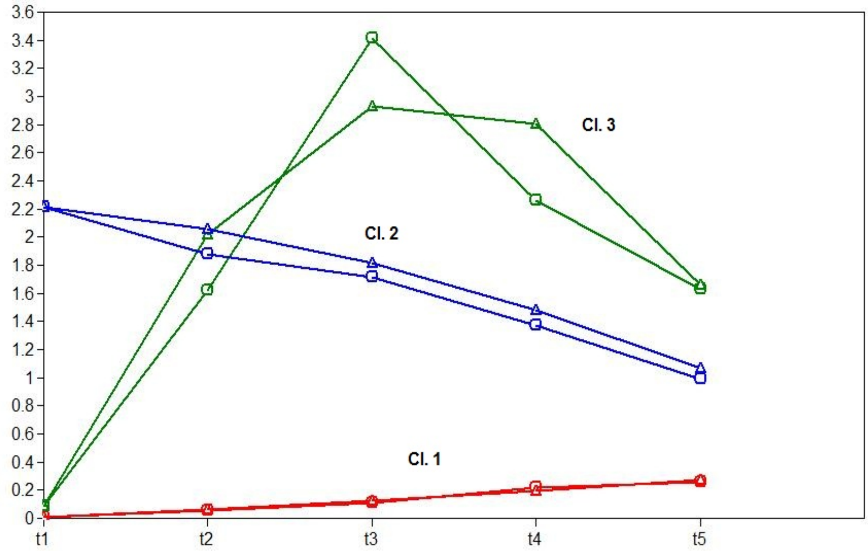
number of classes. In LCGA, in fact, due to the absence of variance within the groups, more trajectories might be estimated to compensate actual variation in the sample. Thus, it is not surprising that a GMM with more than three classes shows either estimation problems or unfitting results.
According to the model-fit indices and their interpretation, there are two models that compete as the best solution. On the one hand, the model with variance on both the slope and the intercept could be chosen because of the lower BIC values; however it shows a non-significant LMR-LRT. On the other hand, the model with variance on the intercept only (even if it scores slightly higher on the BIC) has a good significant LRM-LRT p value. The estimated trajectories for the two models are presented in Figure 5.9 and 5.10.

Figure 5.9: GMM model for drug use, three classes, random intercept



The intercept-only model estimated three classes of individuals with specific trajectories. The first class, which represents the norm in the sample with 91% of the subjects (n=1,412), shows a slightly increasing pattern of development across time, which however never reaches concerning values. A second smaller class (n=46, 3% of the sample) is characterized by a decreasing pattern of involvement with drugs, which is higher at the beginning of the measurement, and tends to decrease thereafter. Finally, a last third class, which also includes only 6% (n=93) of the surveyed subjects, shows an interesting bell-shaped trajectory, that starts from very low level of drug use at the beginning, increases steadily over the next two time points, stabilizes at time point four, and decreases thereafter. The variance on the random intercept has a significant value of 0.022, suggesting the necessity of its estimation.

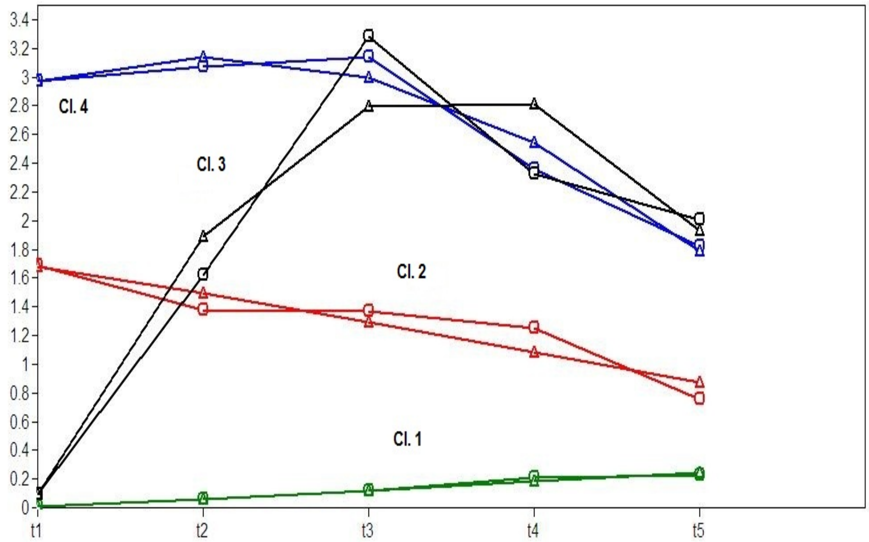
Figure 5.10: GMM model for drug use, three classes, random intercept and slope



The depicted trajectories are very similar to the previous model and can be interpreted similarly. The few slight differences lay in the number of subjects assigned to each class. The models show high similarities both for what concern the trajectories and the estimated variances. In this case also, both variances are significant with a value of 0.026 for the intercept and 0.021 for the slope. The graphical representation suggests, however, that in the intercept-only model the estimated trajectories better match the observed ones, suggesting thus a more precise reproduction of the observed data. Further investigations are, however, needed.

A model with a fourth class was only possible using a LCGA model where no variance at all was estimated for the random terms. A picture of the found trajectories is presented again below, for the purpose of comparison.

Figure 5.11: LCGA model for drug use, four classes



Being a LCGA model there is no estimated variance for the random terms. These trajectories respect the already found patterns of development; however, it seems that the group of subjects desisting from taking drug in the sample have been now divided in two similar groups, where the only visible difference is in the starting frequency of use at beginning of the measurement. The other two classes maintain the same developmental pattern as before.
The next step in the comparison between these models consists in the analysis of the posterior probabilities calculated for each subject, which are used to assign each individual to one or the other class. In other words, I compare the membership in each class across the different models to see if they are able to assign the subjects to the same trajectory. First of all, an interesting comparison is that between the two-class model and the newly presented three-class one. This comparison makes it possible to note, substantively, whether a third class was really necessary or not. Table 5.12 shows the crosstabulation between the best two-class model (the one with variance on both intercept and slope) and the three-class model with estimated variance on the random intercept only.

Table 5.12: Class comparison between the two- and three-class GMM models

Class	1	2	3	$\sum$
1	1,412	0	89	1,501
2	0	46	4	50
$\sum$	1,412	46	93	1,551

(Class interpretation: 1=low use; 2=desisters; 3=adololescence limited).

The estimation of a new class helps the model to better classify the subjects in the first class of the two-class model. As noted before, this group included the vast majority of the sample (97%) to the point that a second group did not bring much more information than a general LGM. The newly estimated class in the three-class model instead, brings new interesting information with it. The old desister group remains basically the same, losing only four members in the new solution, whereas the new third class is the result of the split of the original first group, from where it takes all its members (plus the four mentioned before). The advantage of this new group is straightforward, since, although being still small in number, it permits to isolate a new different, and also interesting, trajectory with its own original pattern of development. After having confirmed the necessity of a third class, both statistically and substantively, the following chart compares the results for the two models with three classes and thus test the stability of their results.

Table 5.13: Class comparison between the three-class GMM models

Class	1_{is}	2_{is}	3_{is}	$\sum$
1_i	1,400	0	12	1,412
2_i	0	46	0	46
3_i	5	2	86	93
$\sum$	1,405	48	98	1,551

(Class interpretation: 1=low use; 2=desisters; 3=adolescence limited).

High values on the diagonal suggest good stability between the two models. Subjects, in fact, tend to be ordered in the same groups even when different restrictions are applied to the model (in this case the estimation of the variance for the random slope). All in all, only 19 subjects move to another class when the model specifications are changed, confirming the good stability of the results.
In Table 5.14 the three-class GMM with random intercept is at last compared with the four-class LCGA model (a four-class GMM could not be calculated due to estimation problems). The classes are matched to represent the similar group in the two solutions.

Table 5.14: Class comparison between the three-class GMM and four-class LCGA models

Class	1	2	3	4	$\sum$
1	1,402	5	0	5	1,412
2	0	29	17	0	46
3	2	3	2	86	93
$\sum$	1,404	37	19	91	1,551

(Class interpretation: 1=low use; 2=desisters; 3=adolescence limited; 4=fourth class).

The results, again, confirm the validity of a three-class solution against a four-class one. In fact, the newly estimated group does not bring any particular new information

in the model, but rather only contributes to the split of the already small group of the desisters. Furthermore, observing also the trajectories in the picture reported above, the similar shape between the two new resulting groups can be clearly seen. It can be argued that, being this a LCGA model with no allowed variance for the random terms, the two new classes are the mere representation of the variation within the desister group found in the three-class model. The analysis of these tables has further confirmed the validity of a three-class model, similarly to what was found in Section 5.3.2.
Due to high similarities between the two three-class solutions, the intercept-only model is chosen to represent the development of drug use behavior in the sample. Besides being more parsimonious than the model with variance on both intercept and slope, its estimated trajectories show a better match with the observed data. Furthermore, for the purpose of this research, there is no substantive and theoretical need for variance on the random slope, since the main purpose remains the precise description of the developmental trajectories in the observed sample.
Besides the simple developmental trajectory of each single group, another important aspect is concerned with the level of drug use consumption reported across time. This is however not possible if looking at the estimated trajectories directly. They are in fact estimated by means of the logged frequencies of the indicators variable, thus the values reported in Figure 5.9 do not represent real frequencies but logged frequencies. A possible solution could be to match the estimated posterior class membership with the original frequencies of drug use at each time point and see if the observed values correspond to the developmental trajectories. However, as described in the LCGA section, these data should be interpreted with care for two reasons: first, results of a longitudinal model are compared with cross-sectional aggregate data; second, the trajectories were estimated with logged frequency values and are now compared using the original count variables. With this in mind, Table 5.15 reports the time-specific mean values of marijuana use for each latent class.

Table 5.15: Posterior class probabilities and observed frequencies of drug use in the sample

Class	n.	$\overline{x}t_1$	$\overline{x}t_2$	$\overline{x}t_3$	$\overline{x}t_4$	$\overline{x}t_5$
$C1$ low use	1412	.01	.17	.38	1.96	2.77
$C2$ desisters	46	11.33	20.14	33.02	28.5	16.90
$C3$ adolescence lim.	93	.2	15.55	60.86	48.94	52.96
Sample $\overline{x}$	1551	0.36	1.52	4.51	4.94	5.79

Comparing Figure 5.9 with the table above it is possible to approximately check the validity of the estimated trajectories, with the limitations discussed above. The frequencies for the low-use class follows a slow increasing pattern that remains at low levels of consumption all across the measured time span. This is confirmed by the trajectory of the class and also supports the already mentioned idea that the members of this group are not only non users, but also experimental consumers; this is made clear by the increasing frequencies which reach a mean value of nearly three times in the last 12 month in 2006. The mean frequencies for the class of high-level desisters do not perfectly match the estimated curve as in the first case. Here, in fact, a desisting process is only visible from the third time point onwards. A better picture is instead given by the adolescence-limited group. Their measured frequencies approximately match a bell-shaped curve as depicted in Figure 5.9. Here also, from a mean value of nearly zero (0.2 times) they reach a peak of 60 times in the last twelve months in 2004, and then slowly desist to a level at about 50 times in the last two measured years. More in general, it can be stated that the observed frequencies match the estimated classes very well for the larger group of low users and for the adolescence limited, and slightly worse for the desister class. Keeping in mind the possible pitfalls involved in such a transformation, the interpretation of the observed frequencies suggests that the smaller class of desisters could be a statistical representation of a more heterogeneous group of subjects characterized by unusual developments and high level of consumption.

5.4 Conclusion

The number of subjects using illicit drugs is small compared to the large sample size. Nevertheless, some of those using such substances also reported high frequency of use (see Chapter 4). Furthermore, the aggregate values suggest that this behavior does not remain constant across the covered time span, but rather increases at the beginning and tends to recede at the last measurement point. This fluctuation in the aggregate level of the frequency and prevalence of drug use was a good premise for further investigations using longitudinal analysis techniques such as GMM. In a first step LGM analysis was carried out, which suggested that a curvilinear development better represented the aggregate development of drug use behaviors in the sample. The found trajectory showed an increasing pattern across the first three time points which then stabilized at the remaining two measurement points. Furthermore, variability was found in all three estimated random effects, which suggested that this variability could be further investigated by means of GMM. According to the model-fit indices and substantive interpretation of the graphical results, three classes were deemed necessary to represent the sample development in drug consumption. In fact, compared to the two-class model, the newly estimated third group isolated a specific pattern of development otherwise hidden within the low-user class. A further fourth class, which could only be estimated by a LCGA model, was clearly a consequence of the restricted zero variance on the random terms, and thus superfluous. The results of the GMM showed high stability across different model specification, especially those concerning the variance of the random terms of each single trajectory. For this reason the model with variance for the random intercept was preferred because of its parsimony and a slightly better reproduction of the observed values. According to this results, the development of drug use in the sample can be represented by a large low-user class (91%), a class of adolescence-limited consumers (6%), and a smaller desister class (3%).
The low-user class is characterized by being the more representative group in the sampled population, and thus arguably the most common marijuana use developmental pattern during adolescence among youths in Duisburg. Although a considerable amount of subjects in this group has never used drugs in the analyzed five years period, some of them have reported experimental and sporadic use. The average amount of times that members of this group used drugs in the last 12 months never goes over the three times a year, although the estimated trajectory shows a constant increase across the measured time span. This result is also supported by recent studies on trajectories of drug use. Although some studies report separate trajectories for low users and abstainers (Ellickson et al., 2004; Schulenberg et al., 2005; Tucker et al., 2005), many other also included abstainers and experimental users into a single class (Brown et al., 2004; Jackson et al., 2008; Brook et al., 2011). The results in this work support the idea that marijuana use is a common experience among the general school population, a phenomenon which tends to increase over time in late adolescence and that involves a large proportion of the youth population.

Similarly, also the amount of abstainers remains large, even if hidden within the variance of the low-user trajectory.
The adolescence-limited class is the second largest group in the sample and is represented by a well-known bell-shaped pattern of development. For these youths, drug use behavior is clearly limited to the adolescence period, although by the end of the measured time span they do not yet completely desist from use. Their pattern of development clearly begins at the age of 13, increases rapidly in the next two years to an approximate average level of 20 times a year, and decreases at a slower pace thereafter. In terms of frequencies they reach the highest point at age 15, and although they clearly diminish the average use, by the age of 17 they still remain the group with the highest frequency of use. If compared to recent literature on the subjects, Flory et al. (2004) and J. Guo et al. (2002) also found a similar trajectory with a similar age-development. However, compared to other studies (Jackson et al., 2008; Brook et al., 2011), the adolescence-limited group found here seems to desist earlier than expected. In any case, the adolescence-limited class supports the reassuring perspective that high frequencies of marijuana, and drug use in general, in the sample are a temporary phenomenon, limited to a specific and short phase in life.
The last group is also the smallest in the sample and includes those subjects who reported a decreasing use of drug over the five year period. Their trajectory clearly differentiate itself from the other two for an earlier start and a consequent slow decreasing trend. At the first time point, at the age of 13, they already report fairly high frequencies of drug use (approximately an average of 10 time a year), which, although they tend to decrease in the following years, by the age of 17 they still maintain a level which can be defined as “occasional consumers”. A similar pattern has also been found in many of the studies cited in Table 2.1. Ellickson et al. (2004) and Tucker et al. (2005), for instance, also found a group of subjects who reported high frequencies of marijuana use prior to the age of 13 and decreased thereafter, still remaining occasional users by the age of 23. Also Windle and Wiesner (2004), analyzing a shorter period of time, found a small group of adolescents with already high frequencies of marijuana use at the age of 15, and a decreasing pattern thereafter. However, in the remaining studies, a decreasing trajectory was associated with an adolescence limited development of marijuana use. In this study, by the age of 17 they are still involved in marijuana consumption and it cannot yet be stated, whether this pattern is limited to adolescence only. In any case, this group retains its importance, especially because it enables the identification of an early-starter group that by the time of late adolescence is still involved in drug consumption.

It can be concluded that the resulting trajectories have found empirical and substantive support also in the principal current studies. The general trend that can be identified is one of a general reduction in the frequencies of use with the approach of late adolescence. Although the low-user group is still characterized by an increasing pattern, those who during adolescence were characterized by elevated marijuana consumption are characterized by a clear declining trend. Whether or not this trend will continue over the next years, can only be answered by means of the introduction in the analysis of successive panel waves.

Chapter 6

Latent transition analysis

6.1 Stage development of drug use: LTA

The idea behind latent transition analysis (LTA) was first applied to drug use by Kandel (1975), who by means of a Guttmann[1] scale tested for the first time the gateway hypothesis of drug involvement. The results confirmed the existence of gateway drugs that facilitate the subsequent consumption of other, more dangerous substances. She found that tobacco and alcohol are gateway drugs to hard liquors, which subsequently increase the chance to use cannabis, which in turn act as a gateway for harder substances. She also pointed out that being in an earlier stage is necessary, but not sufficient, for advancing to the next, this process being not a simple causal relationship among drugs, but rather the simultaneous action of individual and social factors (Kandel, 1975; Kandel & Faust, 1975). The development of longitudinal techniques and the availability of panel data have recently allowed a more precise empirical test of the gateway hypothesis. Collins and colleagues (see Graham et al., 1991; Collins & Wugalter, 1992), for instance, have been quite active in the field over the last fifteen years; they developed a particular technique called LTA, which is a special case of LCA[2] applied to longitudinal data. This technique has been extensively used to test the existence of sequential stages in the development of drug consumption (see also Graham et al., 1991; Collins, Graham, Rousculp, & Hansen, 1997; Collins & Flaherty, 2002).

In this chapter I will first introduce the concept of LTA, its methods and some special features that can be applied to drug use behaviors. Thereafter I will present the results of a LTA applied to five waves of the German study CriMoC (Boers et al., 2010).

6.2 LTA - General model

In the previous chapter growth mixture models (GMM) have been used to measure the quantitative development of the frequencies of drug use across time. Although a lot has been learned by means of GMM, these models do not provide much information about qualitative change between qualitatively different stages (which are represented by categorical latent variables). In fact, a growth model cannot be used for the analysis of categorical observed variables, which are widely used to define qualitative states.

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[1]This method stems from the psychological research and was used with cross sectional data. LTA, developed later, is particularly suited for panel data and adds thus more reliability to the results.

[2]LCA - Latent Class Analysis (see McCutcheon, 1987).

Latent transition analysis (LTA) is a special case of latent class analysis (LCA) that enables the researcher to specify a number of discrete stages using categorical variables, and to calculate the transition probabilities between them. The main purpose of LTA is to statistically describe movement across discrete latent stages.
Mathematically speaking a LTA is based on the combination of two independent models: a Markov chain and a LCA.
In the simplest case, where there is a single observed categorical variable measured four times, in a Markov chain (see Blalock, 1970) the probability P of being in a particular state over four time points can be expressed as follow[3]:

$$P_{ijkl} = \delta_i^1 \tau_{j|i}^{21} \tau_{k|j}^{32} \tau_{l|k}^{43} \tag{6.1}$$

where i, j, k, l are the categories of a single categorical variable measured at four time points (response category $i = 1 \dots n$ at time 1, response category $j = 1 \dots n$ at time 2, etc...), the τ's represent the time specific transition probabilities to move from one category to another across time (for four time points there are obviously three transition probabilities), and the δ_i^1 parameter represents the observed proportion of individuals in each category of the observed outcome at time point 1.
However, a simple Markov chain gives us information about movements across discrete stages, but being an observed model does not allow for measurement error; this is, in turn, an important feature when modelling in social science. Furthermore, Markov models cannot be used when the variable of interest is not directly measured but it is captured by means of observed indicators. Latent class analysis can be used to overcome this shortcomings (see Lazarsfeld & Henry, 1968). LCA assumes that an individual belongs to one exclusive class, i.e. the classes are mutually exclusive. “Latent classes are, in essence, categorical factors arising from the pattern of response frequencies to categorical items”, where the response frequencies (i.e. the cross-table of the response patterns) play a similar role to that of the correlation matrix in factor analysis (D. Kaplan, 2008, p. 459). LCA assumes that the association between the observed variables is totally explained by the latent variable. According to this definition, also known as local independence, the number of classes of the latent variable should be larger than 2, whereas a single latent class would mean total independence among the observed items (McCutcheon, 1987). An LCA for four items can be represented as follows:

$$P_{ijkl} = \sum_{a=1}^{A} \delta_a \rho_{i|a} \rho_{j|a} \rho_{k|a} \rho_{l|a} \tag{6.2}$$

The conditional probabilities ρ are analogue to factor loadings in factor analysis and estimate the probability of a particular response $i = 1 \dots n$ on a manifest item given membership in the latent class $a = 1 \dots A$. The parameter δ represents the proportion of individuals in latent class a.
LCA can be employed to represent class membership at a specific point in time, but in its simple form cannot be used to test changes in latent class composition across time. However, this limitation can be overcome when combining it with a Markov chain into a single model. In this way it is possible to calculate transitions across different latent classes estimated at different points in time; this model is known as latent transition analysis (LTA). In fact, LTA shares the properties of the transition probabilities of a Markov model applied to latent classes, allowing for measurement error in the estimation of the unobserved classes. Expanding the two examples presented above and joining them into a single model - in the case of two items with categories i and j measured at two time points - the probability of having a given combination of responses on the observed items will be:

[3] For the equations in this chapter the notation of Collins and Wugalter (1992) is used.

$$P_{iji'j'} = \sum_{a=1}^{A} \sum_{b=1}^{B} \delta_a^1 \rho_{i|a}^1 \rho_{j|a}^1 \tau_{b|a}^{21} \rho_{i'|a}^2 \rho_{j'|a}^2 \tag{6.3}$$

where P represents the expected probabilities of the multivariate contingency table, i.e. all the possible response patterns generated by the combination of the observed items. The parameters are the same as for the above mentioned two models. The most interesting parameters are obviously the transition probabilities τ (in this case only one because of only two time points), and the δ, which represents the estimated proportion of individuals in each category of latent class a at time point 1. For what concerns the second time point the values for δ are not directly estimated but can be derived from δ for time 1, and are presented in the results[4]. Finally, the ρ parameters represent the measurement part of the model which map the observed items onto the latent classes. In LTA different restrictions can be applied to these parameters according to the researcher's interest. The most important restrictions are generally applied to the ρ parameters in order to assure the stability of the latent classes at each time point. In fact, although not always necessary, achieving the same number of latent classes with the same substantial meaning is a necessary condition for the interpretation of the transition probability and the results; this can be done using either an explorative or a confirmatory procedure. In the first case, for instance, the analyses carried out by D. Kaplan (2008), Nylund et al. (2006) and Nylund (2007) involved the use of a LCA to map the indicators on the categories of the latent variables. That means, the ρ values are freely estimated by means of a LCA, and then used as starting values for the ρ's in the LTA. On the other hand, in the LTA specified by Collins and Wugalter (1992) and Graham et al. (1991) the ρ's were modelled by means of specific starting values, chosen to correctly map the observed indicator onto the latent statuses, and thus assure the stability of the latent model across the time points. In this confirmatory approach the developmental position of each latent status (in the stages sequence) is defined by means of the probability to endorse a specific value of the observed indicator; the ρ's are not freely estimated, but rather are fixed by the researcher in order to match the wanted developmental process (see Table 6.3 in the result section). The decision of the number and type of constrained ρ's is left to the researcher and can be used to decide the best fitting model. In fact, models with different restrictions on the ρ's are nested, and nested models can be compared with each other to find the more parsimonious ones.
The results of a LTA are interpretated by means of the transition matrix, which contains all the transition probabilities between time point 1 (on the left side) and time point 2 (above, on the upper side of the matrix).

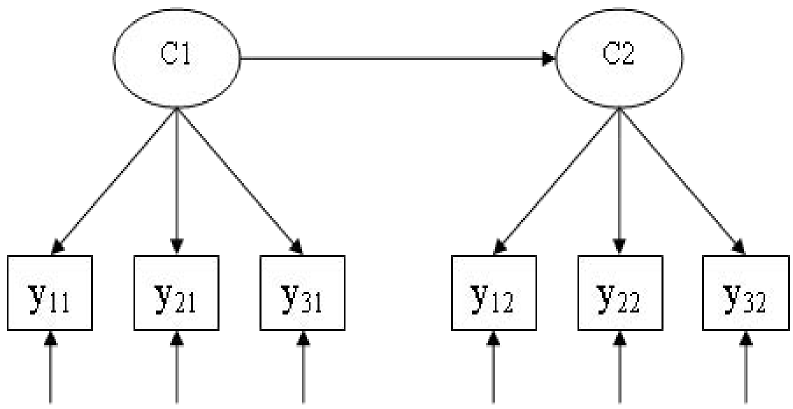
$$\begin{bmatrix} \tau_{1|1} & \tau_{2|1} & \tau_{3|1} & \tau_{4|1} \\ \tau_{1|2} & \tau_{2|2} & \tau_{3|2} & \tau_{4|2} \\ \tau_{1|3} & \tau_{2|3} & \tau_{3|3} & \tau_{4|3} \\ \tau_{1|4} & \tau_{2|4} & \tau_{3|4} & \tau_{4|4} \end{bmatrix} \tag{6.4}$$

The τ parameters on the diagonal represent the probabilities of staying in a given latent status between time 1 and time 2 (i.e., those subjects that do not change their behavior over time). The τ's in the upper corner represent the probabilities of moving upwards across stages (i.e., the percentage of subjects that between time 1 and 2 move

[4]The software Mplus (Muthén & Muthén, 1998-2010) reports the values for δ at each time point in the output. These values can also be calculated by: $\delta_a^1 * T$, where T is the transition probabilities matrix and δ_a^1 is the value at time point 1 (see Reinecke, 1999).

to another, higher status). The τ's in the lower corner, on the other hand, represent the percentage of individuals who move back from one latent status to a previous one. All these transition probabilities can be restricted to one, to zero, or to other values according to theoretically specified needs.[5] For the interpretation of the matrix it should be remembered that $\sum \tau_{b|a,g} = 1$: all the lines of the transition matrix sum up to one.
Similarly to the models presented in the previous section, a LTA can be graphically represented using the general notation of a structural equation model as specified by Muthén and Muthén (1998-2010):

Figure 6.1: Diagram for LTA model with three items and two time points



In this example there are three observed dichotomous indicators y_{it} measured at two time points. Each of the groups of indicators are used to generate a categorical latent variable c_t by means of a latent class analysis. The transition between the different categories of the two latent classes - here depicted by a straight line - are estimated by means of a Markov process. Measurement error is also considered for the observed items as shown by the small arrows pointing to the items' boxes.
For what concern the estimation of the model, all the parameters presented in Equation 6.3 are estimated by ML. However, being the observed variables not continuously distributed, the ML values cannot be obtained by means of the general ML procedure. As for GMM, where the mixture is captured by a categorical latent variable, the Expectation Maximisation (EM) algorithm is used (Dempster et al., 1977). The estimation procedure follows an iterative process to maximize the likelihood function. With different starting values for the model parameters, different iterative attempts are made to obtain the best value in the loglilkelihood function (Muthén & Shedden, 1999). The procedure is repeated until the differences between the last and the second last generated covariance matrix are not significant and thus the parameter estimates converge. The resulting estimates are used for the model parameters.

[5]For instance, in a developmental process where no withdraw is possible, all the τ's in the lower corner of the matrix are fixed to zero (see Collins & Wugalter, 1992).

Finally, missing values can also be included in the analysis when full information maximum likelihood estimation is used (Schafer & Graham, 2002). This procedure is implemented in Mplus (Muthén & Muthén, 1998-2010) and can be applied to LTA when missings are present on the dependent variables in the model (which is always the case when analysing models without explanatory independent variables). Only the subjects with missing information on all the observed outcomes are excluded from the analysis.

6.3 Model-fit indices

When LTA models are tested, data are treated like a large contingency table, with cells corresponding to different response patterns; the more the variables and their categories, the larger is the table. A simple example are two dichotomous variables: there are 4 possible response patterns 00, 01, 10, 11. When measuring the same variables in a longitudinal context at two time points, then the possible responses, and as a consequence the table's cells, increase to 16 (4x4). This means: 0000, 0001, . . . to 1111. The assessment of model fit is done by comparing the predicted with the observed response patterns table and by measuring the discrepancies between them. A model, in fact, predicts the number of subjects which give a particular response, and then compares it with the real observed data. If the discrepancies are small, the model reproduces the data well and the goodness-of-fit statistic is small. In the case of LTA the G-square (Read & Cressie, 1988) statistic is widely use. Being the G-square approximately chi-square distributed, a significance test can be carried out under this assumption, with degrees of freedom equal to the number of response patterns minus one (see Graham et al., 1991). Once estimated, the larger the value of the G-square, the greater the evidence against the $H0$ hypothesis of independence and thus the lower the model fit (Agresti, 2002, p. 24). Furthermore, Agresti (2002) suggests that when the independence hypothesis holds the Pearson chi-square and the G-square tend to assume similar values, becoming asymptotically equivalent. Is this not the case, they both grow proportionally to n and do not take similar values. The software Mplus (Muthén & Muthén, 1998-2010) reports in the output both the G-square and the Pearson chi-square. However, the above mentioned chi-square tests must be interpreted with caution. The frequency-table chi-square statistics, in fact, are not recommended when large number of sparse cells are present in the data, since possibly biased; this condition is often the case in LTA (McLachlan & Peel, 2000; Nylund, 2007). Although useful for a general overview of the goodness of the model, other approaches to model-fit should be considered. For instance, another possible way to measure model fit in LTA is the analysis of the residuals, more specifically the bivariate residuals and the response pattern standardized residuals. The first refer to the standardized Pearson residual. A residual larger than 2 in absolute value indicates that the given cell shows a greater discrepancy than expected if the variables were independent (Agresti, 2002, p. 81). The latter are calculated as the difference between the observed and the estimated response pattern frequencies. If the residual in absolute value is larger than 1.96 it is considered significant at the 5% level and thus adds up to other larger ones to determine poor model fit. In both cases, the model with lower amount of significant residuals should be preferred (Nylund, 2007, p. 59). Another possibility to assess model fit is the AIC and BIC for nested models (Collins & Wugalter, 1992). Nested models, which differ only in the restrictions applied to specific parameters, can be compared by means of BIC and AIC, where the model with the smaller values is preferred. Keeping this in mind, and also considering the great amount of possible model restrictions applicable to a LTA model, a stepwise process can be used to asses model fit and to define the more parsimonious model. However, due to a lack in consensus in the research community on the best model-fit indices for LTA, a suggested good way to define the goodness of a chosen model is a stepwise procedure in which the researcher carefully analyses descriptive statistics, parameter restrictions (especially the number of ρ's and τ's), and other possible model specifications (e. g. second order models, developmental reversal, mixture models, etc.) (Nylund, 2007). Furthermore, model fit can be also assessed through the analysis of the ρ estimated probabilities. These reflect how well the latent statuses predict the real distribution of the sample. Values close to 0 and 1 represent good estimation, whereas values close to 0,5 represent poor capability of reproducing the true values. Last but not least, the substantive interpretability of the results is also a determinant issue for assessing the goodness of the model.

6.4 Special models: LTMA - Latent mixture transition analysis

A limitation of a general LTA is that it considers the sample arising from a single population that can be easily represented by a single Markov model (i.e., a single developmental process). However, in reality this is not always the case. It is possible, in fact, that the population is comprised of a finite number of unobserved mixture of subpopulations characterized by different Markov chains. This means that a single transition matrix does not properly represent the whole sample, but the subjects should be better divided into groups with their own specific transition structure. Similar to the GMM seen in the previous chapter, unobserved heterogeneity is introduced into the model, in which latent classes are estimated with their independent LTA process. Failing to account for this heterogeneity might lead to biased transition matrix. A mixture latent Markov model, which assumes a mixture distribution, can be used to overcome this restriction.

$$P_{ijkl} = \sum_{s=1}^{S}\sum_{a=1}^{A}\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{d=1}^{D} \pi_s \delta^1_{a|s} \rho^1_{i|as} \tau^{21}_{b|as} \rho^2_{j|bs} \tau^{32}_{c|bs} \rho^3_{k|cs} \tau^{43}_{d|cs} \rho^4_{l|ds} \tag{6.5}$$

where π are the proportion of observations in one of the estimated Markov chains. The other parameters are the same as before, with the only difference that they are freely estimated for each chain $s = 1 \dots S$. General and group specific restrictions on the model are also possible. Thus, mixed Markov latent class models describe the change among discrete measures across time in terms of several Markov chains, each one of those can show different developmental features over time (see Van de Pol & Langeheine, 1989).

A special case of LMTA is the mover-stayer model, which is another way to model heterogeneity in developmental processes. It uses a second order latent class variable that classifies individuals as "movers" (those who change status at any point during the process) and "stayers" (those who remain in the same status across the whole span of the study) (Van de Pol & Langeheine, 1989, 1990). By estimating transition probabilities for movers only, the transition probabilities describe more accurately the movement among the given statuses, since they do not include those who remain in the same status all the time (Nylund et al., 2006, p. 16). For the movers, the transition matrix can be specified as in the sections above, including all possible different restrictions and model specifications according to particular theoretical interests. The stayers' matrix, on the contrary, assumes no movement across time, and this is reflected in its transition matrix below:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6.6}$$

The restrictions imposed on the matrix apply to those subjects who have a probability of one to stay in the same status over time (here the ones on the diagonal), and consequently no probability at all of moving across statuses (the zeros in the upper and lower corners of the matrix). Although this matrix represents a possible and widely used pattern of restrictions applied on the transition matrix, also different restrictions can be applied to each Markov chain, and especially on the "stayer" one. For instance, another interesting definition of the "stayer", especially when dealing with substance use, is the following: a "stayer" is a subject who remains in the first category all over the considered time span. This means, "stayers" are only those subjects that are abstainers all across the covered time span. In this way, the estimation of the "movers" will not be inflated by the large amount of "zeros" in the response patterns. The new matrix for the "stayers" is reported below:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{6.7}$$

They are now characterized by a probability of one to stay in the "abstainers" category, and no probability at all to move (or stay) in any other stage.
Also in the case of LTMA models, the goodness of fit is assessed by means of likelihood-ratio statistics and information criteria (BIC, AIC) for model comparison (see D. Kaplan, 2008). All these particular models can be applied to test the gateway theory of drug use.

6.5 Results

The above mentioned models have been applied to the study of drug use behaviors using data from the longitudinal study Crime in the Modern City (CRIMOC), a representative school sample of the German town of Duisburg (Boers et al., 2010). Latent transition analysis will be used to test transition among stages in substance consumption using three observed dichotomous variables. These are:

1. alcohol consumption: "have you ever been drunk in the last 12 months?" (yes/no)
2. marihuana use: "have you ever used marihuana in the last 12 months?" (yes/no)
3. harder drugs use: "have you ever used any other drug[6] in the last 12 months?" (yes/no)

The model is a cumulative stage sequential process of development, which starts with no use of any substance, moves to alcohol abuse, then to alcohol plus marijuana, and finally to alcohol plus marijuana plus harder drugs. All the items refer to the use during the last twelve months. The process is cumulative since it is assumed that the experimentation with a new substance does not imply the dismissal of the previously consumed one, as proposed by the gateway hypothesis (Kandel, 2002). In other words, marijuana users continue to abuse alcoholic drinks, and harder drugs consumers continue to drink and use marijuana.
Table 6.1 reports year-specific percentages of marijuana users that also abused alcohol, and the other way round.

[6] Any of the other drugs mentioned in the questionnaire: heroin and morphine, cocaine and crack, speed, design-drugs and ecstasy, LSD and mushrooms

Table 6.1: Pairwise proportions comparison between alcohol and marijuana users

	2002	2003	2004	2005	2006
(a)	88%	91%	96%	97%	97%
(b)	14%	24%	29%	29%	23%

Row (a) presents the amount of alcohol users within the marijuana users. The cumulative process suggested by the gateway hypothesis is overall confirmed; on average more than 90% of those who used marijuana in the last twelve months consumed also alcoholic drinks until being drunk. Row (b) reports the inverce process. In this case only a very small amount of alcohol users also used marijunana within the last twelve months. Thus, in accordance with the gateway hypothesis, it can be stated that nearly all marijuana users are also alcohol consumers, but not the other way round. A LTA model where alcohol acts as a gateway substance for marijuana is thus plausible.
Table 6.2 reports year-specific percentages of hard drug users that also used marijuana, and the other way round.

Table 6.2: Pairwise proportions comparison between marijuana and hard drug users

	2002	2003	2004	2005	2006
(a)	34%	60%	79%	86%	95%
(b)	32%	29%	24%	19%	21%

Row (a) reports the percentage of hard drug users that also used marijuana. In 2002, at the first time point, only a small amount of hard drug users also used marijuana in the previous twelve months. The proportions change from year to year. A year later 60% of hard drug users also consumed cannabis, and the trend increases over time to reach 95% at the last measurement point. Looking at the inverse relationship in row (b), constanly only a small percent of marijuana users consumed other drugs. Again, apart form the first measurement point, where the relationship is not the one expected by the gateway theory, all other years respect the cumulative stage sequential pattern of development; similar to the previous table it can also be stated that the majority of hard drug users are also marijuana consumers.

The four stages of the LTA are modeled as latent variables (i.e., four stages of development). These latent statuses result from the combination of the different response patterns of the three measured dichotomous items about drug use. The four latent statuses are defined as such by means of constraints on the ρ parameters in the equation for the LTA, and represent the measurement part of the model. They are restricted according to the following table (for example the probability to respond “yes”):

Table 6.3: Restrictions on the ρ parameters

	Answer "yes" to item:		
Latent status	Alcohol	Marijuana	Hard drugs
No use	low prob.	low prob.	low prob.
Alcohol only	high prob.	low prob.	low prob.
Marijuana+A	high prob.	high prob.	low prob.
Hard drugs+A+M	high prob.	high prob.	high prob.

The ρ's are restricted to be equal across time. This allows the necessary stability required for a stage-sequential model where a key role is played by the latent classes. The stability of their substantive meaning is a necessary condition for the interpretability of the results (see Collins & Wugalter, 1992). After comparing different model solutions and considering also the value of parsimony in model estimation, a model with two estimated ρ's has been chosen and these values were fixed to be equal across time. Once the latent statuses are defined, the transition matrix can be computed. Since adolescence is a period of great and rapid change in the development of a youth, all the possible transitions between stages are estimated, even those in the lower corner of the matrix which represent the probabilities of giving up a previously acquired behavior.

6.5.1 Results for the five wave model

Based on the restricted model and the latent statuses presented in the section above, a latent transition analysis has been carried out for the whole time span. Using five waves from the longitudinal panel study CRIMOC, the transition probabilities between each time point have been estimated. The time span ranges from 2002 to 2006, and single models are calculated for each transition. A single model including simultaneously all transitions had to be discharged because of computational problems. Instead, models with only one transition pattern are mathematically less demanding and produce very similar results[7]. The following models are considered here: M1 for the transitions between 2002 (t1) and 2003 (t2); M2 for the transitions between 2003 (t2) and 2004 (t3); M3 for the transitions between 2004 (t3) and 2005 (t4); M4 for the transitions between 2005 (t4) and 2006 (t5).

Before the single models are presented, the process that has led to the best model fit should be explained a little further. This process has been done independently for each of the above mentioned models (i.e., M1, M2, M3, and M4). The choice of the best fitting model was not only determined by model fit indices, but also by comparing models with different restrictions on the ρ and τ parameters, and the substantive interpretation of the resulting matrices. The first two issues will be discussed here, whereas the interpretation of the transition matrices will be presented in more detail in the results. Especially by means of restriction on the τ matrix many different model alternatives were tested using different software programs (Mplus and WinLTA). By means of modifying the τ matrix it was in fact possible to specify different developmental processes. Among these, for instance, it was possible to test a cumulative process were only forward movement to

[7]For instance, a single model comprising transitions from 2002 to 2004 showed very similar transition matrices to single estimated 2002-2003 and 2003-2004 models.

a successive status was allowed (see for instance Graham et al., 1991). Another model alternative was also tested where marijuana was considered a gateway drug for itself (and thus its consumption considered alone and not together with alcohol). Also second-order transitions were tested were the influence of belonging to a latent status at time t on being in another latent status at time $t + 2$ were calculated. Variations of all these modelling processes were also tested. However, computational problems (unachieved convergence), bad model fit, and poor interpretability of the results have led to the choice of a full unrestricted model on the τ matrix with four latent statuses as specified already in detail above. This will be the starting point for further model fit analysis and model comparisons.

A similar process was used for each model. I moved from a general model with many parameters and few restrictions to a more parsimonious model, and compared the resulting model fit indices as specified below.

1. In a completely unrestricted model (in this case with four latent statuses) there are twelve ρ parameters which need to be estimated. However, in order to help the model to converge and to keep it as parsimonious as possible, Collins and Wugalter (1992) suggest to restrict the number of estimated ρ's by fixing some of them to be equal to each other. Here, where only two time points are used, in order to obtain an identified model, only two ρ's are estimated (estimating more than two results in a non-identified model).

2. Another important restriction can also be applied to the τ parameters in the transition matrix. Expecting that also developmental reversal are possible, a first unrestricted base model is estimated. On its basis, in case some transition probabilities τ result in small estimates, they will be restricted to zero. This model is then tested against the basic one.

3. Finally, for all models an analysis of the model fit indices will be taken into account in order to determine their validity. This will include: overall goodness of fit of the model estimation process (i.e., no convergence and identification problems), and comparison of BIC and adj. BIC for nested models.

In the following table each model will be separately presented. However, all model shares a similar baseline conditions. The basic model has two estimated ρ parameters and no restriction on the transition probabilities, so that all transitions are estimated. According to each model result, if necessary, restrictions on some parameters will be applied to achieve a more parsimonious model and a better model fit. Finally, model fit indices will be also used to test against each other different model solutions. In particular, the BIC and adjusted BIC will be used for model selection; the Pearson chi-square, due to its unreliability in case of sparce cells, will not be mentioned in the results.

Table 6.4: Model-fit indices for the model M1 to M4

		Est. Par.	Loglikelihood	BIC	Adj. BIC
M1	baseline	17	-2313.067	4736.344	4688.693
	3 τ fixed	13	-2313.067	4721.650	4680.352
M2	baseline	17	-3055.275	6235.455	6181.450
	2 τ fixed	15	-3057.728	6225.665	6178.013
M3	baseline	17	-3176.076	6477.055	6423.050
	2 τ fixed	15	-3178.314	6466.837	6419.186
M4	baseline	17	-3108.378	6341.660	6287.655
	1 τ fixed	16	-3109.544	6336.645	6285.816

In model M1, after testing a model with full unrestricted τ matrix, three estimated transition probabilities result equal to zero. In order to improve model fit, they are fixed to zero in the successive model. The result is a more parsimonious model which shows also a slight improvement in model fit indices such as BIC and adjusted BIC. The resulting estimated parameters are interpretable and the specified model structure makes sense according to the gateway theory. Thus, although the improvements from the baseline model are not striking, the second model is chosen as the best resulting solution for the time span between 2002 and 2003.
The results of the unrestricted model in M2 suggest the possibility of fixing two transition probabilities to zero, since their value is very small. The resulting model estimates less parameters and shows a slightly better model fit. The interpretation of the transition matrix, apart from the two values fixed to zero, does not show differences important of notice. Thus, due to the better fit obtained, the second model is chosen.
The baseline model in M3 reports some estimation problems although the high number of starting values chosen for its estimation. Furthermore, the resulting transition matrix suggests that two τ's could be restricted to zero due to their estimated small value (in one case the estimated parameter is zero). The new model shows some improvements compared to the baseline one. First, the model estimation process is smooth and shows no estimation problems; second, model fit parameters show a better model fit; third, the applied constrains on the transition matrix have been proven to be useful also in the previous two models. Due to these considerations, the latter model is chosen.
At the last two time points the baseline model can also be ameliorated by means of some restrictions. Fixing a single transition probability to zero further improves the goodness of the model. More restrictions are not needed.

Although in some cases estimation problems arose in form of non-positive matrix and singularity of the information matrix, they were overcome by fixing some transition probabilities to zero. In the end, all the chosen models did not report any estimation problems. The BIC and adjusted BIC indices were used as primarily means to define the best model, since chi-square tests were not considered reliable measures for model comparisons due to sparce cells in the observed data. In fact, beside a large proportion of non-user and of subjects reporting use of alcohol, the other two statuses included a small number of people relative to the size of the sample. This problem should not be underestimated in LTA, since sparse cell can cause both estimation difficulties and poor reliability of chi-square tests (McLachlan & Peel, 2000; Nylund, 2007).

However, the goodness of a model can only be declared after its results have been substantively interpreted. Therefore, the subjects distribution on the latent status and the transition matrices for all chosen models will be presented and discussed in more detail below.

A first interesting insight in the drug use habits of the sample are the δ's, the time specific latent status probabilities. They represent the proportion of subjects in each latent status at each time point. The values in the table below are taken from the single models and report the percentage of subjects in each latent status. They should not yet be interpreted as a longitudinal analysis, but rather as a cross-sectional representation of the estimated sample distribution across the various models.

Table 6.5: Sample distribution across the latent statuses

δ (%)	2002	2003	2004	2005	2006
(1) No use	81	60	46	35	28
(2) Alcohol only	15	28	38	46	55
(3) Marijuana+A	2	7	12	15	13
(4) Hard drugs+A+M	2	4	4	4	4

As expected, some general trends can be seen. For instance, the proportion of non-users decreases dramatically across time; from 81% in 2002 to 28% in four years. Simultaneously, the amount of subjects that have been at least once drunk increases constantly to 55% at the last measurement. Marijuana users also increase during the first three measurement points, and then stabilizes to 13% in 2006. Harder drug users, instead, are fewer and remain a small group across time. In general, it can be stated, that during adolescence the amount of youths that do not use any substance at all decreases dramatically, whereas the large majority of them experience the use (or better abuse at least once in a year) of alcohol. Marijuana remains the most used illicit drug, whereas the use of more dangerous drugs involves only a constant small portion of the sample.

Surely the most important results are the estimated transition matrices. With five waves four transition matrices are obtained and can be interpreted. Below the single matrices are reported, and for each a short presentation of the obtained probabilities. Thereafter, an overview will be given of the general trend across all time points. For the interpretation of the results it should be kept in mind that the values on the diagonal represent the probability of remaining in a particular latent status at a given time point; the values above the diagonal represent the probabilities of advancing to a successive latent status, whereas the lower part of the matrix represents the probability of receding to a previous status. Probabilities of zero are parameters that have been fixed to that value according to model specific needs. More generally, it can be distinguished between stable and unstable latent statuses. The former refer to high values in the transition probabilities on the diagonal, which represent statuses that remain stable across time, i.e., subjects tend to remain in that particular status across time. The latter, on the contrary, represents statuses that show more transitions across stages between the two time points considered. In this case, people tend to assume that status once and leave it the year after. Both situations are clearly visible in the tables below.

Table 6.6: Latent transitions between 2002 and 2003

2002/2003	(1)	(2)	(3)	(4)
(1)No use	**.748**	.217	.025	.011
(2)Alcohol only	.000	**.744**	.149	.107
(3)Marijuana+A	.000	.000	**.833**	.167
(4)Hard drugs+A+M	.000	.065	.348	**.586**

Between the 7th and 8th class, when the pupils are on average 13 and 14 years old respectively, the picture presented in the table is quite stable. The values on the diagonal are fairly high and suggest stability among non-user and user of other substances. Only hard drug users report a smaller value, which indicates a tendency for many to have experimented with these substances in 2003 and given up their use in 2004. Besides that, the values in the upper part of the table represent expected developmental pattern, as suggested by the gateway theory. In fact, in all cases but hard drugs, those who move to a successive stage move to the next one in the sequence. Thus, for instance, 21% of the non-user in 2003 (and the 86% of all non-user that move) become alcohol user in 2004, whereas only a very small 3% of them skip this stage and consume illicit drugs as well. The picture for alcohol user is slightly different. 14% of those who move from this status go on to try marijuana, and 10% skip this stage to try also harder drugs. For all stages but harder drugs there are no significant development reversals. For the latter, however, 34% of the user in 2003 move back to the previous stage in 2004. Only 6% abandon also the use of marijuana and move directly to alcohol use status. It seems that the stage theory is valid also for reversal developments.

Table 6.7: Latent transitions between 2003 and 2004

2003/2004	(1)	(2)	(3)	(4)
(1)No use	**.715**	.251	.026	.009
(2)Alcohol only	.035	**.755**	.178	.033
(3)Marijuana+A	.000	.224	**.624**	.152
(4)Hard drugs+A+M	.000	.233	.270	**.497**

One year after, between the 8th and 9th class, a general tendency to less stability - expressed by the values on the diagonal - can be noticed. A slightly larger amount of both non-user and alcohol-user in 2003 tend to move to the successive status in 2004. In fact, although in both cases about 70% of the subjects remain in the same status, 25% of the non-users start using alcohol and 18% of the former alcohol users try also marijuana. Only about 3% do not follow the expected pattern of development and skip one stage. In 2003 the picture for illicit drug users is different. A large number of marijuana users do not remain in the same status in 2004; interesting to notice is that although 15% move to the next stage and start using harder drugs, many of them (22%) move back to alcohol use. Similarly, more than half of the hard drug users in 2003 leave that status to become marijuana consumers (27%), or even give up completely the use of illicit substances (23%). All in all, there is a general tendency toward an increase in instability for the statuses concerned with illicit substances, although the number of people who remain consumers is still important (>50% in both cases).

Table 6.8: Latent transitions between 2004 and 2005

2004/2005	(1)	(2)	(3)	(4)
(1)No use	**.695**	.267	.026	.012
(2)Alcohol only	.070	**.777**	.134	.019
(3)Marijuana+A	.000	.316	**.601**	.084
(4)Hard drugs+A+M	.000	.221	.394	**.385**

The third transition is concerned with youths moving from the 8th to the 9th class. They are about 15/16 years of age and in the middle of adolescence. The tendency observed in the previous transition matrix is also confirmed at this point in time. The amount of non-users decreases whereas alcohol use becomes a stable pattern of behaviour. This confirms the fact that alcohol abuse is becoming a normative behaviour in the sample and at this particular age; 78% of those who got drunk in 2004 keep this behaviour the next year. Illicit drug use increases its tendency to become a more experimental and temporary behaviour. This time only 60% remain marijuana users, whereas only 38% stay in the hard drugs status. Even stronger than before is now the tendency to move backward in the developmental pattern. In fact, this time, 32% of the marijuana users in 2004 go back to the previous stage (against only 8% who move forward). Hard drug users show a similar picture, although marked by a stronger dismissal process.

Table 6.9: Latent transitions between 2005 and 2006

2005/2006	(1)	(2)	(3)	(4)
(1)No use	**.675**	.303	.016	.005
(2)Alcohol only	.072	**.802**	.105	.021
(3)Marijuana+A	.000	.455	**.477**	.068
(4)Hard drugs+A+M	.101	.347	.191	**.361**

The last transitions concern the time between the 9th and 10th class. The youths are now about 17 years of age and some of them have already left school for vocational training (as outlined already in Section 4.4.2). In fact, about 47% are still in school, 45% in vocational training, and 4% are not attending any of them (taken from Table 4.16). Again, the general picture is confirmed and the tendency outlined before strengthened. The non-user group, although still consistent, is less stable than the previous time point. The alcohol abuse status, with a value of 80% on the diagonal, is the most stable group. On the contrary, illicit drugs statuses have become less and less stable across time. Now more than 50% for marijuana and 65% for hard drugs move to another status in 2006, whereas the vast majority of them goes back to a previous status. A particularity of this model is that it was not necessary to fix to zero the transition from hard drug use to non-use. In fact, about 10% of the hard drug users in 2005 give up completely the use of any substance in 2006.

Concluding, there are some general issues that have emerged and should be considered more in detail.
First, apart from the first transition matrix between 2002 and 2003, which show some anomalies compared to the others[8], it can be stated that the developmental pattern proposed by the gateway theory is confirmed. In fact, for all substances considered here, those subjects who move from one status to another move to a successive one without skipping any developmental stage. Furthermore, developmental reversals are also observed especially for illicit drugs. The necessity of estimating the τ's in the lower part of the transition matrix is confirmed.
Second, the abuse of alcohol tends to become a normative habit in the social life of youths. The stability of this pattern of behaviour increases with age and tends to remain a gateway substance which is yet rarely abandoned. In fact, very few give up this habit in the observed time span (no more than 7% go back to non-user status), whereas the vast majority of those who move on proceed to experiment with illicit substances, especially marijuana.
Third, the picture for illicit substances is slightly different from those of alcohol. Consumer behaviour over adolescence tends to be unstable, especially with the process of maturation toward adulthood. Within a time span of five years less and less subjects remain marijuana consumer longer than one year. Furthermore, the majority of those who give up this habit, instead of moving forward to the next stage, recede to alcohol use. This process is even stronger for hard drug users. Across all measurement points the percentage of those who remain in the status decreases to 36%. The movers, instead, generally go back to the previous stage or even give up completely the use of illicit substances. This is the reason why the term "experimental use" has been used to describe illicit drugs consumers in this sample. It seems, in fact, that the most common pattern of consumption of these substances is limited in time (the reason of so many "movers") and involves a return to a previous stage.

It can be concluded that the gateway theory of drug use, as proposed by Kandel (1975) and empirically explored and expanded by Collins and Wugalter (1992), holds, and that alcohol abuse, besides being a normative behaviour during adolescence, is also a gateway substance for later involvement in illicit drug use.

6.5.2 Results for the "mover-stayer" model

As stated already above, there are different applications of a mover-stayer model in a LTA. In this study, the idea behind such a model was the possibility to divide those who stay non-users all the time from the rest of the subjects, allowing thus a better and unbiased

[8]This might be due to the fact that at the beginning of the study very few pupils reported illicit drug use. This resulted in very sparse contingency table and problems in model estimation (as shown by the poor model fit especially for the first matrix). Furthermore, there were many substance users in t1 that were not able to define the type of drug they had used (they ticked the category "other drugs"). These subjects were included in the "hard drugs" status, although it could be that they experimented with drugs similar to marijuana and hashish, but were not able to recognize them under such names (it should be kept in mind the many unconventional names that can be attributed to the same substance, especially among youths and users).

estimation of the transition probabilities for the "movers".
There were, however, some problems to overcome before choosing the best model structure. First, a model with more than two time points is needed in order to achieve model identification. Second, being a mixture model, its estimation is more complex than a simple LTA as performed before; the presence of sparse cells might be more troublesome than in a simple model. Third, as a consequence a mover-stayer model is also more computationally demanding, so that by increasing the number of time points, also the processing time and the possibility of estimation problems increases.
In order to explore this issues different model specifications were tested. A five waves model was soon discharged as it failed to converge due to the long computational time. Then, different three wave models were computed and analysed. Only the model from t3 to t5 (2004 to 2006) produced satisfactory results, whereas all models including the first two waves always reported convergence problems, mostly probably due to the large number of sparse cells for the illicit drugs statuses. Thus, only the above mentioned model was further analysed, especially with the intent to test its results against the simple models calculated in the section above.

The transitions are calculated over a period of three years. The youths are aged between 15 to 17 on average, and the measurements refer to the year between 2004 and 2006. The sample size is 1552.
First, a baseline model was tested with no restrictions on the transition probabilities. Althought general good model fit indices were obtained, the transition matrices suggested the possibility to fix a parameter to zero. This was done and the resulting model compared with the baseline one. The results are reported in Table 6.10.

Table 6.10: Model-fit indices for the "mover-stayer" models

Model	Est. Par.	Loglikelihood	BIC	Adj. BIC
Baseline	30	-4458.67	9137.77	9042.46
2 τ fixed	28	-4459.79	9125.32	9036.37

By constraining a transition probability to zero, the overall model fit increases, although not impressively. However, being the constrained model also parsimonious, the latter has been chosen as the final model for the substantive analysis.

A first interesting insight in the results can be obtained from the estimated δ values. They report the proportion of subjects present in each status at each time point. The first table reports the values for the group of the "movers", the second for the "stayers".

Table 6.11: Sample distribution across the latent statuses; "movers"

δ (%)	2004	2005	2006
(1) No use	33	27	22
(2) Alcohol only	46	50	59
(3) Marijuana+A	15	18	15
(4) Hard drugs+A+M	6	5	4

Table 6.12: Sample distribution probabilities across the latent statuses; "stayers"

δ	2004	2005	2006
(1) No use	1	1	1
(2) Alcohol only	0	0	0
(3) Marijuana+A	0	0	0
(4) Hard drugs+A+M	0	0	0

The table for the "stayers" is clear: their probability is fixed at one to stay in the non-user class across all time points. Having included this second chain in the model, the results for the "movers" are not inflated with those subjects who do nothing across time, and thus more precise in depitching those who consume substances across that time span. The δ's for the "movers" can be summarized as follow:

- The proportion of non-users decrease constantly over time.
- The percentage of alcohol consumers increase constantly over time, suggesting the increasing importance of alcohol use among youths.
- The percentage of marijuana users reaches a peak at the age of 16 and decreases thereafter. This is in line with the general trend outlined by the latent curve model and the descriptive statistics.
- Hard drugs use remains constant, and involves only a small 4% of the subjects. This reflects the fact that most people in this sample consume marijuana.

The values presented in Table 6.11 differ slightly from the same parameters obtained from the simple models and presented in Table 6.5. The δ values here tend to be larger (exept for the non-users) than the previously estimated ones. It is possible, that the discrepancies between the two tables are due to the fact that in the mover-stayer model, the results for the movers are not inflated from the "zeros" and thus report larger values; here it seems to be the case. Furthermore, these discrepancies tend to decrease with the passing of time. This could be the result of the decreasing number of abstainers and the increasing number of users in the sample. Consequently, the last measured time point is less "zero inflated" than the previous time points, and thus less differences are observed between the two models.

The second step consists in the analysis of the transition matrices for the "movers" (the one for the "stayers" is constrained to have a probability of one to be an abstainers). With three time points there are two transition matrices, one between 2004 and 2005, and another one between 2005 and 2006.

Table 6.13: Latent transitions between 2004 and 2005

2004/2005	(1)	(2)	(3)	(4)
(1) No use	**.690**	.267	.027	.015
(2) Alcohol only	.075	**.773**	.133	.019
(3) Marijuana+A	.000	.305	**.613**	.082
(4) Hard drugs+A+M	.035	.196	.383	**.386**

The transition probabilities printed in bold on the diagonal represent the percentage of individuals that did not change status between 2004 and 2005. On average 60-70% of non-users, alcohol users and marijuana users neither step forward to a more dangerous substance, nor give up the consumption of the used one. A good 30% of the non-users move; nearly the majority of them experiment with alcohol, and only a small 3% either move directly to marijuana or to harder drugs. A similar pattern can be seen for alcohol consumers. This group of individuals seems to be the most stable one, with 77% of its members remaining alcohol users. From the small fraction of people who move, 13% move forward and try marijuana and about 7% give up the use and move to the non-user category. For what concern marijuana use, this status shows a quite stable pattern, with more than 60% of its members remaining consumers. Interesting, however, are the probabilities off the diagonal; the majority of the "movers", in this status, does not move on to harder drugs (only 8%), but rather go back to alcohol use, suggesting that marijuana consume in 2005 is for many a temporary, experimental experience. As expected, the most unstable status is harder drugs one. Here, among the few[9] who reported the use of these substances, only 39% remain, whereas 38% reduce their use to marijuana only, and nearly 20% give up completely the use of drugs.

Table 6.14: Latent transitions between 2005 and 2006

2005/2006	(1)	(2)	(3)	(4)
(1) No use	**.676**	.302	.016	.006
(2) Alcohol only	.068	**.810**	.101	.021
(3) Marijuana+A	.000	.446	**.491**	.063
(4) Hard drugs+A+M	.092	.356	.179	**.373**

The interpretation of the results for the transition from 2005 to 2006 can be interpreted similarly as the previous table. To be noticed are the different percentages on the main diagonal. The pattern here is different from the one in Table 6.13. The proportion of non-users remains the same, although a little smaller. Almost the complete majority of those who move, experiments with alcohol. The alcohol-users status becomes even more stable than before. Those who in 2005 got drunk for the first time, tend either to keep

[9]Please refer to Table 6.11 for the δ values, which report the proportion of subjects in each status for each year.

getting drunk in 2006 or to experiment with marijuana too. Across these two time points nearly all the alcohol users remain alcohol users, and only 10% start using cannabis. In opposition to the results of the previous transition matrix, the marijuana latent status becomes highly unstable. This reflects the general trend in the sample which reports a reduction in drug consumption. Now, only 50% stay, whereas the other half of the marijuana users instead of moving forward to harder drugs gives up completely the use of illegal substances and goes back to alcohol use. For what concerns hard drugs users, the trend is similar to the previous transition matrix, with the only difference that those who move jump directly to the alcohol-only status instead of retreating to the closer marijuana status.

The two resulting matrices of the mover-stayer model do not differ consistently from the corresponding ones estimated in the previous section. Thus, especially for what concerns the validity of the models, it can be argued that a more complicated mixture model which isolates the non-users from the developmental process do not add much more information if compared to the computation problems involved in it. The simple models remain a valid instrument for the analysis of the sample at hand. Furthermore, the results of the mixture models confirm the validity of the previously calculated models, adding thus strength at the interpretation given to the results and to the difficulties to interpret measures of model fit.

6.6 Conclusions

Concluding, LTA analysis applies well to adolescence, a phase in the life where a lot of change is expected. Licit and illicit substance experimentation in adolescence is a recurrent feature of the youths' developmental process, and a lot of change is expected concerning their use habits. Latent transition analysis, as an instrument to test the gateway hypothesis of substance use (Collins, 2002; Kandel & Jessor, 2002), allows to test both the existence of a specific stage sequential development among different types of substances, and the rates of transition among them. In accordance with recent studies[10] that tested the gateway hypothesis using LTA, similar results have also been found.
Firstly, although the lack of information about some possible initial gateway substances, such as simple alcohol and tobacco use, the entry substance found here in the data is alcohol abuse (experiencing drunkenness). In most of the studies rewieved in Chapter 2, drinking untill drunk was always the gateway substance to the use of marijuana (Graham et al., 1991; Lanza & Collins, 2002; Maldonado-Molina & Lanza, 2010). A further confirmation of the validity of this model is also the fact that alcohol abuse in the CriMoC sample was measured as being drunk at least once in the last year; this variable corresponds to a broad definition of drunkenness, which varies from once a year to every week, and thus suggests that marijuana use is preceded by both light and intense abuse of alcoholic beverages. The next stage found in the sequence is marijuana use followed by other illicit substances. Also this pattern can be found in nearly any study that has tested the gateway hypothesis. This confirms once more the fact that marijuana is, at the moment and in most western cultures, the gateway drug to more dangerous substances.
Secondly, the models tested here also confirm the association among developmental stages. Besides attesting the existence of a particular sequence, these models also show that the majority of the subjects who move across stages, move stepwise accordingly with the theory. In all situations, nearly all of those who move do it by moving to the next adjacent step in the sequence, without skipping any single stage. These findings also confirm the association between stages, so that being in a previous status is a necessary condition to move to a successive one (Kandel, 1975). Thirdly, the stability of the proposed mod-

[10]For an overwiev see Table 2.2 in Chapter 2.

els was also confirmed over time. The four developmental stages were reproduced at all four transition points (i.e., for all four models tested), suggesting that this pattern of development in the use of legal and illegal substance remains stable all across adolescence. However, the amount of change in the transition processes was not the same at every time point. Substance use is in fact age-specific and particular substances are used mainly at particular points in life. This is the case especially for the age of onset; the four transition matrices show that alcohol abuse starts early in adolescence and stabilizes at high prevalence rates with the passing of time. Somehow different is the case for illicit drugs. Experimentation starts later and their use remains unstable across time; it seems that subjects experiment with illicit substance for a shorth period of time and then desist.
Finally, the estimated models also confirmed the assumption that backward movement is possible and expected. This is in fact the case especially for illicit substances; in late adolescence an increasing number of subjects experiment with them and then recede to the use of legal substances, which in turn tend to remain a constant habit once aquired. A very few percentage of subjects, in fact, move back from alcohol abuse to non use.
Concluding, the time span analyzed suggests an on-going variability in use patterns for these substances; this is shown by the values on the diagonal of the transition matrices. Although alcohol consumption is becoming a stable and normative behavior among youths, the same cannot be stated for the other substances. Furthermore, the δ values suggest that the number of pupils getting drunk is increasing, whereas the marijuana and harder drugs users are slowly decreasing. However, the high instability of this two latter behaviors suggest an experimental consumption rather than a more systematic and problematic use. In other words, the proportion of alcohol users is constantly increasing and this behavior is systematically becoming part of the youths' behavioral repertory. Illicit drug use, on the other hand, after having reached a peak between the age of 15 and 16, starts to decrease and rather than as a systematic and problematic consumption, it seems to resemble a more generalized occasional and experimental use.

Chapter 7

Summary and discussion

In this chapter the results of the models presented above will be discussed with respect to the formulated hypothesis. Furthermore, the validity and usefulness of this work will be critically assessed and suggestions for future research will be given.

7.1 Summary and results

The purpose of this work was to test particular hypothesis concerning the epidemiology of substance use among adolescents within the framework of an integrated life-course approach to drug use. The life-course perspective tries to explain the development of substance use by means of trajectories across an individual's life. Trajectories, defined as the long term developmental path of a particular behavior over time, are characterized in the short term by transitions and turning points, namely particular events in the individual's life that might determine the onset, a change, continuity, and also the end of a trajectory (Elder, 1985). Adolescence, as a time of great physical and psychical change, is a key life-phase where new behaviors are learned and internalized (Coleman & Hendry, 1999); this is also the case for substance use. It is in fact well known that most of the illicit and licit substances are first experimented during adolescence (Kandel, 1980). It is also well known that during adolescence both prevalence and frequency of substance use increase, new substances are tried, and with the process of entering adult life most of the users desist (Kandel & Logan, 1984). The life-course approach provides the researcher with the instrument to measure and describe this development; especially during adolescence, trajectories can be estimated to determine age of onset, distinct trajectories groups, frequency development, and desistance. Furthermore, also concepts like escalation and experimentation with different typologies of substance can be understand as a developmental process. In fact, the use of different substances is strongly age-related; legal substances are generally used first, followed by marijuana and harder drugs, where the first two stages are more likely to occur during early and late adolescence (Kandel, 1975).

Accordingly, an empirical approach to the study of drug use should take into account developmental processes; it should use longitudinal data to measure all different aspects highlighted by the life-course approach and the sequential stages of involvement in drug use.

For this work longitudinal panel data collected by the CRiMoC study on juvenile delinquency in the German town of Duisburg (Boers et al., 2010) were used. Developmental trajectories of marijuana use were estimated over a five year period using latent growth models (Bollen & Curran, 2006) and growth mixture model (Muthén, 2004). Stage se-

quential development across different substances during the same span of time were tested using latent transition analysis (Graham et al., 1991).
According to the proposition of an integrated life-course approach and the results of recent empirical studies proposed in Chapter 2, four main hypothesis were defined and tested in the empirical analysis. These hypothesis will be individually discussed below.

H1) *By means of latent growth models I expect to find clues of a bell-shaped trajectory in the individual development of marijuana use across adolescence. This, in fact, should show an increasing frequency pattern that tends to stabilize at the end of adolescence (i.e., by the last measurement point, at the age of 17, I expect a still increasing trajectory or a stabilizing one).*
The results of the latent growth model presented in Chapter 5 support only in part the hypothesized developmental pattern. When estimating a single average curve for the whole sample the best fit is obtained for a model that specify a negative bell-shaped curvilinear trajectory. So far, the hypothesized average trajectory is confirmed by the data. However, having used logarithmized frequencies for the outcome variable a straightforward interpretation of the amount of change in the trajectory is not possible. Only through the exponential of the logarithmized values it is possible to go back to the original count data. In this way the level of change showed by the trajectory can be more intuitively interpreted. The intercept term, i.e. the average frequency level at the first time point differs from zero, suggesting that the age of onset for marijuana use in the sample is located before the average age of 13 (the mean age at the first time point). From an approximated mean frequency of once a year at the first measurement point, the trajectory shows a constant increase over the next three years reaching a peak frequency level of nearly twice a year at time point four. At the last measurement point the curve decreases slightly, suggesting either a stabilizing or desisting rate of marijuana use.
Thus, although a statistically significant bell-shaped development is found, the amount of change observed in the five years time is very small: the average level of use starts from a frequency of once a year and grows to an average level smaller than twice a year. Although the trend confirms the hypothesis, marijuana use among pupils in Duisburg is more an experimental and occasional behavior rather than an established consume pattern with a well recognizable development over time. The average youth attending school in Duisburg can be thus described as a non user or simply experimental marijuana consumer. Furthermore, it can also be argued that age of onset is placed a little earlier than the age of 14, as sometimes suggested in the literature (Hser et al., 2007). In fact, at the age of 13 the average frequency of marijuana use is already different from zero; this result is also confirmed by the descriptive statistics of Chapter 4.

H2) *By means of growth mixture models I expect to estimate different developmental trajectories of drug use. They should resemble four different typologies of development across adolescence: non-users/low users, chronic users, late-onset users, and an adolescence-limited group.*
Growth mixture models (Muthén, 2004) allow the estimation of different trajectories, assuming that the sample is characterized by heterogeneity with respect to the development of the behavior of interest. The best fitting model estimated three different classes: the majority of the sample (91%) belongs to the class of low users, which resemble the average development estimated by the simple latent growth models. They show a trajectory that starts at zero at the first time point and constantly increases thereafter to an average frequency less than twice a year. This group well represents the general trend in the large sample, and can be described as including those subjects who either never used marijuana or tried it once a year. The second larger class (6%) is represented by the adolescence limited. Their development is very representative of the bell-shaped curve already found in the literature (Brook et al., 2011, see). Their development starts from no use at the age of 13 and increases sharply thereafter until the age of 15. By this time they use on average

33 times marijuana in a year. After this point, their frequency starts to decrease, and by the time they are 17, their annual average frequency of marijuana sinks to 6 times. The last class, the decresers, account only for the 3% of the sample. It shows a development that constantly decreases across the five measurement points, although at a very slow rate. They are early starters, since already by the age of 13 they report high frequency rates. After five years, although at a slightly lower frequency, they are still engaged in marijuana use.
Out of the four expected classes (see Brook et al., 2011), only three are found in the Duisburg sample. The hypothesis of a large, non-user and experimental-user class is largely confirmed. This pattern well represents the average use of marijuana in the schools of Duisburg. The adolescence-limited class confirms only in part the hypothesis; the curve found in this study is limited to a very short period of time compared to what is postulated in the literature; in other studies the adolescent-limited curve is in fact expected to cover a wider time span, with an increasing trend throughout adolescence, and desistance later in young adulthood. The last class, the desisters, can be in part compared to what in the literature has been defined as early onset/chronic users. Although to a lesser extent, the desisters found in this study show an early onset, but also a visible continuity in their consume pattern. No clues however, have been found of a late-onset group. This might be due to the fact that later onsetters have been found to start by the end of adolescence, and the time span covered in this study ends by that time; they might be not yet observable.

H3) *By means of latent transition analysis a cumulative model should be specified in which the following sequence is tested: use and abuse of licit substances precede marijuana use, which in turn is followed by hard drug use. I also expect that subjects will not skip stages but move always to the next in the sequence in a sequential fashion.*
Latent transition analysis (Graham et al., 1991) clearly shows that all over the five years the above hypothesized sequence is a valid representation of the sample approach to different substances. The role of alcohol abuse as a gateway substance for marijuana is confirmed. In fact, only a neglectable proportion of subjects skip marijuana and engage directly with other illicit substances. Similarly marijuana is confirmed to be a gateway substance for all other illicit drugs. The specified model was a cumulative stage sequential process, which assumed that the use of a new substance later in the sequence did not mean the dismissal of the previously used one. Accordingly, marijuana users continue to abuse alcohol, and harder drug users also continue to use alcohol and marijuana. The prevalence of subjects in each specific status at each time point confirms the expected trend as well. Whereas the number of youth abstainers decrease dramatically from 80% to 28% in five years, in contrast, the proportion of alcohol users increases exponentially form 15% to 55%. Marijuana use grows less dramatically and shows a more constant pattern across time: by the age of 17, 13% belong to the alcohol and marijuana user latent status. Hard drug use remains instead a rare event in the Duisburg school population. The proportion of subjects in this group remains a constant 4% all over adolescence.
Thus, the hypothesized sequence has been largely found, even if the reduced amount of information (i.e. no information on tabacco and simple alcohol use, for instance) has not made it possible to test for more specific stages, as suggested in the literature (Kandel, 2002).

H4) *LTA model should also include the possibility of backward movements in the stage sequential process. I also expect that not all subjects will move forward, but that many would remain in a given stage across time, and some would also recede to a previous one.*
Early tests of the gateway hypothesis using latent transition analysis (Collins, 2002; Graham et al., 1991) did not allow for backwards transitions from a later stage to a previous one. More recent studies, however, have shown that also developmental reversals are possible (Collins & Flaherty, 2002). This should be expected in a developmental phase of life such as adolescence, where experimentation is a key feature of drug consumption, and it

is not expected that the substances considered might generate an addiction of any sort. In the present study backward development has been observed, especially for what concerns illegal substances (both marijuana and other drugs). This last process confirms the experimental approach to illicit drugs of the sample, as already evidenced in the trajectory analysis. High instability in the latent statuses and backward developments confirm the hypothesis that during adolescence many subjects try illicit substances once, and desist thereafter. Alcohol abuse, on the contrary, is a well-established behavior, that once acquired is seldom given up; this is confirmed by the lesser backward transitions measured from this status to non-use. It can be concluded, that the hypothesized sequential process has been confirmed in all its part for the Duisburg sample.
The overall results found in this work can now be summarized.

Marijuana use remains the most widespread illegal substance among school children and youths in Duisburg. However, the amount of use and its development over time should not be of great concern; on average, when used at all, marijuana consumption remains rather a simple experimental than an established pattern of behavior. This is also confirmed when heterogeneous groups are searched for in the sample. Three main trajectories of marijuana use were estimated, that depict the more representative drug use careers in this sample. More than 90% of the interviewed subjects report a pattern of marijuana use similar to those described above. The remaining 10% engaged in more substantial consumption over time. Both the adolescence limited and desister groups during the five years' time engage in more regular use of marijuana, that ranges from 3 to 33 times in a year. This suggests, that despite the overall trend, a minority of youths is involved in a more serious drug related behavior. However, both trajectories tend to recede with the passing of time; although their members are still active users at the last measurement point, the developmental trend of both trajectories decrease constantly.

Marijuana is not only the most common illegal substance, but also acts as a gateway drug for other illicit substances. Its role in the sequence is clear: only a neglectable proportion of subjects progress from alcohol directly to harder drug use, even if the consumption of these substances is largely of a merely experimental form. To play a gateway role does not imply a not-going-back process. Also marijuana use is by large of an experimental fashion. Across the years, the latent transition analysis shows how more than 20% of marijuana users go back directly to alcohol abuse without either stepping forward or remaining in the same status. Alcohol abuse, on the contrary, besides being a gateway substance for marijuana, reports a far more higher stability across adolescence. Most of the youths that start abusing alcohol in fact, remain in this status all across the measured time span. Only a small proportion move forward to the next stage, and on average less than 7% go back to a non-user condition.

The overall picture that is inferred from these results is that, although the short period of time covered, adolescence is characterized by many changes in substance use related behaviors. According to the life-course perspective and the criminal career approach three distinct trajectories have been described. Furthermore, stages in drug use involvement were identified, all characterized by many transitions between them. Marijuana, as well as legal substances like alcohol, seem to undergo important and fast development in a relatively short amount of time.

7.2 Limitations and future research

There are some limitations to this study that need to be mentioned.
The first is strictly related to the CRiMoC study, from which the data have been taken. The CRiMoC study was not originally conceived for drug use research only, but rather to investigate a large spectrum of deviant behavior and possible personal, social, and structural covariates. For this reason, the amount and the type of information related to

substance use were limited. A major difficulty was the impossibility to clearly distinguish among the frequencies of use of different illicit drugs; the drug use frequency question in fact was not directly related to a specific type of substance but to the general question about substance use[1]. Thus, in the case of multiple use it was not possible to discern to which drug the given frequency value was referred. Important information for the gateway hypothesis were also missing. There were no questions concerned with cigarettes smoking and simple alcohol consumption, which according to the gateway hypothesis represent the first stage in substance use. Future research interested in testing these hypothesis on a German sample should provide more precise information about the single illicit drugs, and also about the more common consume behaviors of legal substances, in order to allow both a more precise test of the hypothesis, and also more reliable results for cross-national comparisons.

Furthermore, the CRiMoC study does not use a stratified sample, but a general population sample, representative of the school population as outlined in Chapter 3. For this reason, the number of substance users, especially illegal drugs, where small compared to the number of non-users. This drawback is also related to the issue of representativeness of the panel sample used for this empirical analysis. The panel sample includes only those individuals who participated to all of the first five waves of CRiMoC (n=1,552), causing it to deviate from the more representative cross-sectional samples in two major ways: first the panel data underrepresents male children from lower-class backgrounds (fewer children from "Hauptschule" are included); second, there are significant differences in marijuana use between cross-sectional and panel data. The latter, in fact, seems to underestimate the real frequency of use (A. Sutherland & Mariotti, 2011). Thus, although Mariotti and Reinecke (2010) showed that bias should only be expected for the frequency but not for the shape of the trajectories, these issues should be considered when interpreting the results: the marijuana and illegal drug users in the CRiMoC panel should not be representative of the real population.

Future research using the CRiMoC data could try to overcome these problems in many ways. For instance, using multiple imputation techniques, missing values could be estimated and thus more information included in the analysis; Mariotti and Reinecke (2010) were able to include all subjects that participated at least twice to the study, increasing significantly the panel sample size. Furthermore, this approach allowed to include into the panel sample also those youths that dropped out of school at some point or were absent at the time of the measurement, and that might be also particularly at risk of substance use.

However, research on more dangerous illicit drugs should focus on more stratified samples, aiming at those subpopulations outside the school that are more likely at risk. Marijuana use, on the contrary, is also a school phenomenon, more widespread than other illicit substances. An imputed panel sample from the CRiMoC study could provide a good picture of its spread in the youth population especially in its early and experimental phases; for more acute cannabis consumption, new studies should look somewhere else outside the school environment.

A second important limitation of this work, especially when dealing with developmental issues, is of course the time span covered. I was able to cover only a short period of time compared to what is expected to be the developmental phase of marijuana use in the general population. Thus, this work is limited to the early phase, from the beginning of, to late adolescence (or early young adulthood), and it fails to measure important processes that are expected later in time, such as the peak in the frequency and prevalence and the period of desistance. This is also a limitation for the growth models; more time points can bring new important information in the models and also permit the estimation of new trajectories (Muthén, 2004). Future research should include new measurement points to

[1]See the excerpt of the questionnaire in the Appendix A.3.

cover a longer period of time and thus to allow new possible developmental processes to be revealed. It can be expected that some of the smaller classes in the growth mixture analysis might disappear, and new patterns might emerge.

Another important limitation consists also in the interpretation of the latent transition analysis and growth mixture models. The models presented in this work are simple descriptive models not concerned with the search for the causes of the development they represent. In the case of latent transition analysis this should be kept in mind; in her formulation of the gateway hypothesis Kandel (Kandel & Jessor, 2002) warns the reader about the dangers involved in causal interpretation of the stage sequential process. Latent transition analysis confirms the gateway hypothesis inasmuch as a gateway substance is a necessary but not sufficient condition to move to the next substance in the sequence (Kandel, 1975); other factors might be at work in determining that particular sequence. Primary socialization actors, such as family, peers and school, and other psychological factors are also important variables which have been found to be strongly associated with substance use (Hawkins et al., 1992). The family, for instance, which is the main socialization actor in early childhood, might be responsible for transmitting behavioral models associated with legal substances, which in turn are also the first to be used by youths. Later, during adolescence, peers are responsible for transmitting role models associated to the local youth culture, and thus also the substances associated with it; therefore, "the universality of the gateway theory might [. . .] be limited to the extent that cultures differ across locations and evolve over time" (Golub & Johnson, 2002, p. 6). Future research on the gateway hypothesis should focus not only on the sequence itself, but also on all possible risk and preventive factors that might influence the probability to move from one stage to the next one. Covariates, in fact, can be included in a LTA model to test their influences on the transition probabilities.

To a similar extent also growth models are limited. According to the life-course perspective trajectories do not develop isolated but interact with each other, with the personal psychological traits, and with the social environment around the individual. A next step in the analysis of trajectories of marijuana use should be the search for explanatory factors. For instance, all the trajectories' parameters can be associated with covariates and tested separately: in this way it is possible to explain the onset frequency level, the speed of growth or decline of a trajectory, and the shape of its curve. Also other concomitant developmental processes can be tested, and allow for even more dynamic relationships among behaviors. For instance, it is possible to test whether the parameters associated to the development of alcohol use influence similar parameters of marijuana use (see T. Duncan et al., 1997; Bentler et al., 2002). Developmental outcomes can also be introduced into the models; for instance, each trajectory can be tested for its influences on events later in life, such as employment, partnerships, and health problems (see Brook et al., 2011).

In any case, the introduction of new variables into the growth model, similarly to the introduction of new time points, will certainly bring new information that might help defining new trajectories and explaining already known ones (Muthén, 2004).

Future research could also attempt to integrate the two statistical methods applied in this study. For instance, different stage sequential models could be tested for each single trajectory, and thus provide group specific information of how particular developmental patterns of marijuana use are related to qualitative transitions among different substances. Multiple group comparisons in latent transition analysis could be carried out using the posterior probabilities of being in a given mixture class. It is in fact possible that groups like adolescence limited and desisters might show more stable patterns of progression through the different developmental stages.

7.3 Conclusion

This work has been able to describe important developmental patterns of legal and illegal substance use in a school sample in Duisburg, Germany. Marijuana use during adolescence has been the main focus of this empirical study. According to the hypothesis some known patterns of consumption have been found: marijuana use between 13 and 17 years old pupils remain an experimental behavior, that is practiced on average less than twice a year. However, two small groups of youths deviate from this pattern: the adolescence limited, who engage in increasingly high levels of marijuana use in middle adolescence, and decrease thereafter; and the desisters, who by the age of 13 report already an important level of consumption, and slowly decrease, maintaining a moderate frequency of use even at the last measurement point.

The gateway hypothesis was also supported by the CRiMoC data. Marijuana use was confirmed a gateway drug for other illicit substance. Similarly, alcohol abuse acts as gateway substance for marijuana. In accordance with the growth models, cannabis and other illicit drugs are used sporadically; the vast majority of the interviewed illegal drug users are occasional consumers. Different is the picture for alcohol abuse: drinking until getting drunk is a recurrent and widespread age-specific behavior, that with moderate frequency characterizes this particular developmental phase. However, the limitations presented above should be kept in mind.

Trajectories in life are strongly interconnected with each other. Transitions and turning points also play a determinant role in shaping each trajectory. This work applied to the same sample two approaches to the study of drug use that have been developed and tested separately over the last twenty years, and limited to the US American and English speaking contexts[2]. Quantitative and qualitative epidemiological analysis of marijuana use can be used together within an integrated framework of analysis to achieve a better understanding of the developmental processes at work. Growth models are valuable instruments to test the existence of trajectories, whereas latent transition analysis allows to define important transitions within the trajectory of interest. The epidemiological character of this work is its greatest limitation. CRiMoC data provide valuable information that have not yet been tested and included in these models. However, a first step has been achieved: the description of the phenomenon. A second step stands ahead: the explanation of what have been described by means of relevant influencing factors.

[2]To my knowledge, few studies have applied GMM to substance use in Germany (Wiesner et al., 2007, 2008), whereas no study has explicitly dealt with marijuana in large school samples. No study has been yet published in Germany that applies latent transition analysis to test the development of substance use in a large school sample.

Bibliography

Adler, I., & Kandel, D. (1981). Cross-cultural perspectives on developmental stages in adolescent drug use. *Journal of Studies on Alcohol*, *42*, 701-715.

Agresti, A. (2002). *Categorical data analysis.* New York: Wiley.

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B. Petrov & F. Csaki (Eds.), *Proceedings of the 2nd international symposium on information theory* (p. 267-281). Budapest: Akademiai Kiado.

Akers, R. (1998). *Social learning and social structure: A general theory of crime and deviance.* Northeastern University Press.

Akers, R., & Cochran, J. (1985). Adolescent marijuana use: A test of three theories of deviant behavior. *Deviant Behavior*, *6*, 323-346.

Akers, R., & Lee, G. (1996). A longitudinal test of social learning theory: Adolescent smoking. *Journal of Drug Issues*, *26*, 317-343.

Allison, K., Edward, A., & Donna, M. (1997). Life strain, coping, and ubstance use among high school students. *Addiction Research*, *5*, 251-272.

Bandura, A. (1973). *Aggression. A social learning analysis.* Englewood Cliffs, NJ: Prentice-H.

Bauer, D., & Curran, P. (2003). Distributional assumptions of growth mixture models: Implication for overextraction of latent trajectory classes. *Psychological Methods*, *8 (3)*, 338-363.

Bentler, P., Newcomb, M., & Zimmerman, M. (2002). Cigarette use and drug use progression. Growth trajectory and lagged effect hypothesis. In D. Kandel (Ed.), *Stages and pathways of drug involvement* (p. 223-253). Cambridge University Press.

Bentrup, C. (2007). *Methodendokumentation der kriminologischen Schülerbefragung in Duisburg 2006. Schriftenreihe Kriminalität in der modernen Stadt Methoden* (Vol. 12). Münster, Bielefeld.

Blalock, H. (1964). *Causal inferences in non experimental research.* Chapel Hill: University of North Carolina Press.

Blalock, H. (1970). Estimating measurement error using multiple indicators and several points in time. *American Sociological Review*, *35*, 101-111.

Blum, K., Noble, E., & Sheridan, P. (1990). Allelic association of human dopamine D2 receptor gene in alcoholism. *Journal of the American Medical Association*, *263*, 2055-2059.

Blumstein, A., & Cohen, J. (1987). Characterizing criminal careers. *Science*, *237*(4818), 985-991.

Blumstein, A., Cohen, J., & Farrington, D. (1988). Criminal career research: Its value for criminology. *Criminology*, *26*, 1-35.

Blumstein, A., Cohen, J., Roth, J., & Visher, C. (1986). *Criminal careers and "career criminals". Report of the panel on research on criminal careers, National Research Council* (Vol. 1). Washington, D.C.: National Academy Press.

Boers, K., & Reinecke, J. (2007). *Delinquenz im Jugendalter. Erkenntnisse einer Muensteraner Laengsschnittstudie.* Muenster: Waxmann.

Boers, K., Reinecke, J., Mariotti, L., & Seddig, D. (2010). Explaining the development of adolescent violent delinquency. *European Journal of Criminology*, *7*, 499-520.

Boers, K., Reinecke, J., Motzke, K., & Wittenberg, J. (2002). Wertorientierungen, Freizeitstile und Jugenddelinquenz. *Neue Kriminalpolitik*, *14*, 141-146.

Bollen, K. (1989). *Structural equations with latent variables.* New York: Wiley.

Bollen, K., & Curran, J. (2006). *Latent curve models: A structural equation perspective.* New York: Wiley.

Brame, R., Nagin, D., & Wasserman, L. (2006). Exploring some analytical characteristics of finite mixture models. *Journal of Quantitative Criminology*, *22*, 31-59.

Brook, J., Balka, E., & Whiteman, M. (1999). The risk for late adolescence of early adolescent marijuana use. *American Journal of Public Health*, *89*, 1549-54.

Brook, J., Brook, D., Gordon, A., Whiteman, M., & Cohen, P. (1990). The psychosocial etiology of adolescent drug use: A family interactional approach. *Genetic, Social, and General Psychology Monographs*, *116*(2), whole.

Brook, J., Cohen, P., & Brook, D. (1998). Longitudinal study of co-occurring psychiatric disorders and substance use. *Journal of the American Academy of Child and Adolescent Psychiatry*, *78*, 463-474.

Brook, J., Lee, J., Brown, E., Finch, S., & Brook, D. (2011). Developmental trajectories of marijuana use from adolescence to adulthood: Personality and social role outcomes. *Psychological Reports*, *108*(2), 339-357.

Brown, T., Flory, K., Lynam, D., Leukefeld, C., & Clayton, R. (2004). Comparing the developmental trajectories of marijuana use of African American and Caucasian adolescents: Patterns, antecedents, and consequences. *Experimental and Clinical Psychopharmacology*, *12*(1), 47-

56.

Browne, M., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. Bollen & J. Long (Eds.), *Testing structural equation models.* Newbury Park, CA: Sage.

Brunswick, A., & Messeri, P. (1986). Drugs, lifestyle, and health: A longitudinal study of urban black youth. *American Journal of Publich Health*, *76*, 52-57.

Bukstein, O. (1995). *Adolescent substance abuse. Assessment, prevention, and treatment.* John Wiley and Sons.

Bundeszentrale für gesundheitliche Aufklärung. (2010). *Die Drogenaffinität Jugendlicher in der Bundesrepublik Deutschland 2008* (Tech. Rep.). Köln: Bundeszentrale für gesundheitliche Aufklärung.

Bundeszentrale für gesundheitliche Aufklärung. (2011a). *Der Alcoholkonsum Jugendlicher und junger Erwachsener in Deutschland 2010. Ergebnisse einer aktuellen Repräsentativbefragung und Trends* (Tech. Rep.). Köln: Bundeszentrale für gesundheitliche Aufklärung.

Bundeszentrale für gesundheitliche Aufklärung. (2011b). *Der Cannabiskonsum Jugendlicher und junger Erwachsener in Deutschland 2010. Ergebnisse einer aktuellen Repräsentativbefragung und Trends* (Tech. Rep.). Köln: Bundeszentrale für gesundheitliche Aufklärung.

Bundeszentrale für gesundheitliche Aufklärung. (2011c). *Der Tabakkonsum Jugendlicher und junger Erwachsener in Deutschland 2010. Ergebnisse einer aktuellen Repräsentativbefragung und Trends* (Tech. Rep.). Köln: Bundeszentrale für gesundheitliche Aufklärung.

Cadoret, R., & Gath, A. (1978). Inheritance of alcoholism in adoptees. *British Journal of Addiction*, *132*, 252-258.

Coleman, J., & Hendry, B. (1999). *The nature of adolescence* (3rd ed.). London: Routledge.

Collins, L. (2002). Using latent transition analysis to examine the gateway hypothesis. In D. Kandel (Ed.), *Stages and pathways of drug involvement* (p. 254-269). Cambridge: Cambridge University Press.

Collins, L., & Flaherty, B. (2002). Latent class models for longitudinal data. In Hagenaars & McCutcheon (Eds.), *Applied latent class analysis* (p. 287-303). Cambridge: Cambridge Univ. Press.

Collins, L., Graham, J., Rousculp, S., & Hansen, W. (1997). Heavy caffeine use and the beginning of the substance use onset process: An illustration of latent transition analysis. In K. Bryant, M. Windle, & S. West (Eds.), *The science of prevention: Methodological advances from alcohol and substance abuse research* (p. 79-99). Washington, DC: American Psychological Assoc.

Collins, L., Schafer, J., & Kam, C. (2001). A comparison of inclusive and restrictive strategies in modern missing data procedures. *Psychological Methods*, *6*, 330-351.

Collins, L., & Wugalter, S. (1992). Latent class models for stage-sequential dynamic latent variables. *Multivariate Behavioral Research*, *27*, 131-157.

Comings, D., Muhleman, D., Ahn, C., Gysin, R., & Flanagan, S. (1994). The dopamine D2 receptor gene: A genetic risk factor in substance abuse. *Drug nad Alcohol Dependence*, *34*(3), 175-180.

Degenhardt, L., Dierker, L., Tat Chiu, W., Medina-MOra, M., Neumark, Y., Sampson, N., et al. (2010). Evaluatin the drug use "gateway" theory using cross-national data: Consistency and associations of the order of initiation of drug use among participants in the WHO World Mental Health Surveys. *Drug and Alcohol Dependence*, *108*, 84-97.

Dempster, A., Laird, N., & Rubin, D. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistic Society*, *39*, 1-38.

Donovan, J. (1996). Problem-behavior theory and the explanation of adolescent marijuana use. *Journal of Drug Issues*, *26*, 379-404.

Donovan, J., & Jessor, R. (1983). Problem drinking and the dimension of involvement with drugs: A Guttman scalogram analysis of adolescent drug use. *American Journal of Public Health*, *73*, 543-552.

Duncan, S., Duncan, T., Biglan, A., & Ary, D. (1998). Contribution of the social context to the development of adolescent substance use: A multivariate latent growth modelling approach. *Drug and Alcohol Dependence*, *50*, 57-71.

Duncan, S., Duncan, T., & Hops, H. (1996). The role of parents and older siblings in predicting adolescent substance use: Modeling development via structural equation latent growth methodology. *Journal of Family Psychology*, *10*(2), 158-172.

Duncan, T., & Duncan, S. (1995). Modeling the processes of development via latent variable growth curve methodology. *Structural Equation Modeling*, *2*, 187-213.

Duncan, T., Duncan, S., Alpert, A., Hops, H., Stoolmiller, M., & Muthen, B. (1997). Latent variable modeling of longitudinal and multilevel substance use data. *Multivariate Behavioral Research*, *32*(3), 275-318.

Duncan, T., Duncan, S., Strycker, L., Li, F., & Alpert, A. (2006). *An introduction to latent variable growth curve modeling: Concepts, issues, and applications.* Mahwah: Lawrence Erlbaum.

Elder, G. (1985). *Life course dynamics. Trajectories and transitions.* Ithaca: Cornell University Press.

Eliason, S. (1993). *Maximum likelihood estimation: logic and practice* (No. 07-096). Newbury Park, CA: Sage.

Ellickson, P., Hays, R., & Bell, R. (1992). Stepping through the drug use sequence: Longitudinal scalogram analysis of initiation and regular use. *Journal of Abnormal Psychology*, *101*, 441-451.

Ellickson, P., Martino, S., & Collins, R. (2004). Marijuana use from adolescence to young adulthood: Multiple developmental trajectories and their associated outcomes. *Health Psychology*, *23*(3), 299-307.

Elliot, D., Huizinga, D., & Ageton, S. (1985). *Explaining delinquency and drug use.* Beverly Hills: Sage Publications.

ESPAD. (2009). *The 2007 ESPAD report. substance use among students in 35 european countries* (Tech. Rep.). The Swedish Council for Information on Alcohol and Other Drugs.

Farrington, D. (2000). Explaining and preventing crime: The globalization of knowledge - the american society of criminology 1999 presidential address. *Criminology*, *38*, 1-24.

Farrington, D. (2003). Developmental and life-course criminology: Key theoretical and empirical issues - the 2002 sutherland award address. *Criminology*, *41*, 221-255.

Farrington, D. (2005). The integrated cognitive antisocial potential (ICAP) theory. In D. Farrington (Ed.), *Integrated developmental & life-course theories of offending.* New Brunswick, New Jersey: Transaction Publisher.

Farrington, D., Loeber, R., Yin, Y., & Anderson, S. (2002). Are within-individual causes of delinquency the same as between-individual causes? *Criminal Behaviour and Mental Health*, *12*, 53-68.

Fergusson, D., Boden, J., & Horwood, J. (2006). Cannabis use and other illicit drug use: Testing the cannabis gateway hypothesis. *Addiction*, *101*, 556-569.

Flisher, A., Parry, C., Muller, M., & Lombard, C. (2002). Stages of substance use among adolescents in Cape Town, South Africa. *Journal of Substance Use*, *7*, 162-167.

Flory, K., Lynam, D., Milich, R., Leukefeld, C., & Clayton, R. (2004). Early adolescent through young adult alcohol and marijuana use trajectories: Early predictors, young adult outcomes, and predictive utility. *Development and Psychopathology*, *16*(1), 193-213.

Golub, A., & Johnson, B. (2002). The misuse of the "gateway theory" in US policy on drug abuse control: A secondary analysis of the muddled deduction. *International Journal of Drug Policy*, *13*, 5-19.

Graham, J., Collins, L., Wugalter, S., Chung, N., & Hansen, W. (1991). Modeling transitions in latent stage-sequential processes: A substance use prevention example. *Journal of Consulting and Clinical Psychology*, *59*, 48-57.

Grinspoon, L., & Bakalar, J. (1992). Marihuana. In J. Lowinson, P. Ruiz, & R. Millman (Eds.), *Substance abuse: a comprehensive textbook* (p. 237-246). Baltimore: Williams & Wilkins.

Guo, B., Aveyard, P., Fielding, A., & Sutton, S. (2009). Using latent class and latent transition analysis to examine the transtheoretical model staging algorithm and sequential stage transition in adolescent smoking. *Substance Use & Misuse*, *44*(14), 2028-2042.

Guo, J., Chung, I., Hill, K., Hawkins, D., Catalano, R., & Abbott, R. (2002). Developmental relationships between adolescent substance use and risky sexual behavior in young adulthood. *Journal of Adolescent Health*, *31*(4), 354-362.

Guo, J., Collins, L., Hill, K., & Hawkins, D. (2000). Developmental pathways to alcohol abuse and dependence in young adulthood. *Juornal of Studies on Alcohol*, *61*, 799-808.

Guy, S., Smith, G., & Bentler, P. (1993). Adolescent socialization and use of licit and illicit substances - impact on adult health. *Psychology & Health*, *8*, 463-487.

Hawkins, D., Catalano, R., & Miller, Y. (1992). Risk and protective factors for alcohol and other drug problems in adolescence and early adulthood: Implications for substance abuse prevention. *Psychological Bulletin*, *112*(1), 64-105.

Hawkins, D., & Weis, J. (1985). The social development model: An integrated approach to delinquency prevention. *Journal of Primary Prevention*, *6*, 73-97.

Heath, A., Meyer, J., Eaves, L., & Martin, N. (1991). The inheritance of alcohol consumption patterns in a general population twin sample: I. multidimensional scaling of quantity/frequency data. *Journal of Studies on Alcohol*, *52*, 345-352.

Hirschi, T. (1969). *Causes of delinquency.* Berkeley, CA: University of California Press.

Hrubec, Z., & Omenn, G. (1981). Evidence of genetic predisposition to alcoholic cirrhosis and psychosis: Twin concordances for alcoholism and its biological end points by zygosity among male veterans. *Alcoholism*, *5*, 207-215.

Hser, Y. (2002). Drug use careers: Recovery and mortality. In S. Korper & C. Council (Eds.), *Substance use by older adults: Estimates of future impact on the treatment system.* Rockville, MD: Substance Abuse and Mental Health Services Administration, Office of Applied Studies.

Hser, Y., Longshore, D., & Anglin, D. (2007). The life course perspective on drug use: A conceptual framework for understanding drug use trajectories. *Evaluation Review*, *31*, 515-547.

Hurrelmann, K., & Hesse, S. (1991). Drogenkonsum als problematische Form der Lebensbewältigung im Jugendalter. *Sucht*, *37*, 240-252.

Hussong, A., Curran, P., Moffit, T., Caspi, A., & Carrig, M. (2004). Substance abuse hinders desistance in young adults' antisocial behavior. *Development and Psychopathology*, *16*, 1029-1046.

Jackson, K., Sher, K., & Schulenberg, J. (2008). Conjoint developmental trajectories of young adult substce use. *Alcoholism: Clinical and*

Experimental Research, *32*(5), 723-737.

Jessor, R., & Jessor, S. (1977). *Problem behavior and psychosocial development: A longitudinal study of youth.* New York: Academic Press.

Jessor, R., & Jessor, S. (1978). Theory testing in longitudinal research on marihuana use. In d. Kandel (Ed.), *Longitudinal research on drug use: Empirical findings and methodological issues* (p. 41-71). Washington, DC.: Hemisphere-Wiley.

Johnston, L., O'Malley, P., Bachman, J., & Schulenberg, J. (2010). *Monitoring the future national results on adolescent drug use: Overview of key findings, 2009* (No. 10-7583). Bethesda, MD: National Institute on Drug Abuse.

Johnston, L., O'Malley, P., & Eveland, L. (1978). Drugs and delinquency: A research for causal connections. In D. Kandel (Ed.), *Longitudinal research on drug use: empirical findings and methodological issues* (p. 137-156). Washington, DC: Hemisphere-Wiley.

Kam, C., & Collins, L. (2000). *Latent transition analysis of substance use among adolescents in the national longitudinal survey of youth* (Tech. Rep. No. 37). The Methodology Center, Technical Report Series.

Kam, J., Matsunaga, M., Hecht, M., & Ndiaye, K. (2009). Extending the theory of planned behavior to predict alcohol, tobacco, and marijuana use among youth of mexican heritage. *Prevention Science*, *10*, 41-53.

Kandel, D. (1975). Reaching the hard to reach: Illicit drug use among high school absentees. *Addictive Diseases*, *1*, 465-480.

Kandel, D. (1978). Homophily, selection, and socialization in adolescent friendships. *American Journal of Sociology*, *84*, 427-436.

Kandel, D. (1980). Drug and drinking behavior among youth. *Annual Review of Sociology*, *6*, 235-285.

Kandel, D. (2002). *Stages and pathways of drug involvement.* Cambridge: Cambridge Univ. Press.

Kandel, D., & Davies, M. (1991). Friendship networks, intimacy, and illicit drug use in young adulthood: A comparison of two competing theories. *Criminology*, *29*, 441-469.

Kandel, D., & Faust, R. (1975). Sequence and stages in patterns of adolescent drug use. *Archives of General Psychology*, *32*, 923-932.

Kandel, D., & Jessor, R. (2002). The gateway hypothesis revisited. In *Stages and pathways of drug involvement: Examining the gateway hypothesis* (p. 365-372). New York: Cambridge University Pres.

Kandel, D., & Logan, J. (1984). Patterns of drug use from adolescence to young adulthood: 1. periods of risk for initiation, continued use, and discontinuation. *American Journal of Public Health*, *74*(7), 660-666.

Kandel, D., Yamaguchi, K., & Chen, K. (1992). Stages of progression in drug involvement from adolescence to adulthood: Further evidence for the gateway theory. *Journal of Studies on Alcohol*, *53*, 447-457.

Kandel, D., Yamaguchi, Y., & Klein, L. (2006). Testing the gateway hypothesis. *Addiction*, *101*(4), 470-476.

Kaplan, D. (2008). An overview of markov chain methods for the study of stage-sequential developmental processes. *Developmental Psychology*, *44*, 457-467.

Kaplan, D., & Walpole, S. (2005). A stage-sequential model of reading transitions: Evidence from the early childhood longitudinal study. *Journal of Educational Psychology*, *97*(4), 551-563.

Kaplan, H. (1975). *Self-attitudes and deviant behavior.* Pacific Palisades, CA: Goodyear.

Kohlberg, L. (1969). Stage and sequence: The cognitive-developmental approach to socialization. In D. Goslin (Ed.), *Handbook of socialization theory and research.* Chicago: Rand McNally.

Kohlberg, L. (1980). *The meaning and measurement of moral development.* Worcester, MA: Clark University Press.

Kreuter, F., & Muthén, B. (2008a). Analyzing criminal trajectory profiles: Bridging multilevel and group-based approaches using growth mixture modelling. *Journal of Quantitative Criminology*, *24*, 1-31.

Kreuter, F., & Muthén, B. (2008b). Longitudinal modeling of population heterogeneity: Methodological challenges to the analysis of empirically derived criminal trajectory profiles. In G. Hancock & K. Samuelsen (Eds.), *Advances in latent variable mixture models* (p. 53-75). Charlotte, NC: Information Age Publishing.

Krohn, M., Lizotte, A., Thornberry, T., Smith, C., & McDowall, D. (1996). Reciprocal causal relationships among drug use, peers, and beliefs: A five-weve panel model. *Journal of Drug Issues*, *26*(2), 405-428.

Kunadt, S. (2011). *Sozialer Raum und Jugendkriminalität.* Münster: Waxmann.

Lanza, S., & Collins, L. (2002). Pubertal timing and the onset of substance use in female during early adolescence. *Prevention Science*, *3*(1), 69-82.

Laub, J., & Sampson, R. (2001). Understanding desistance from crime. In M. Tonry (Ed.), *Crime and justice: An annual review of research* (Vol. 28). Chicago: University of Chicago Press.

Laub, J., & Sampson, R. (2003). *Shared beginnings, divergent lives: Delinquent boys to age 70.* Cambridge, MA: Harvard University Press.

Lazarsfeld, P., & Henry, N. (1968). *Latent structure analysis.* Boston: Houghton Mifflin.

Lee, G., Akers, R., & Borg, M. (2004). Social learning and structural factors in adolescent substance use. *Western Criminology Review*, *5*, 17-34.

Li, F., Barrera, M., Hops, H., & Fisher, J. (2002). The longitudinal influence of peers on the development of alcohol use in late adolescence: A growth mixture analysis. *Journal of Behavioral Medicine*, *25*(3), 293-

315.
Lo, Y., Mendell, N., & Rubin, D. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767-778.
Loeber, R., & Hay, D. (1997). Key issues in the development of aggression and violence from childhood to early adulthood. *Annual Review in Psychology*, *48*, 371-410.
Macleod, J., Oakes, R., Copello, A., Crome, I., Egger, M., Hickman, M., et al. (2004). Psychological and social sequelae of cannabis and other illicit drug use by young people: A systematic review of longitudinal, general population studies. *The Lancet*, *363*, 1579-88.
Maldonado-Molina, M., Collins, L., Lanza, S., Prado, G., Ramirez, R., & Canino. (2007). Patterns of substance use onset among Hispanics in Puero Rico and the United States. *Addictive Behaviors*, *32*, 2434-2437.
Maldonado-Molina, M., & Lanza, S. (2010). A framework to examine gateway relations in drug use: An application of latent transition analysis. *Journal of Drug Issues*, *40*(4), 901-925.
Marcos, A., Bahr, S., & Johnson, R. (1986). Test of bonding/association theory of adolescent drug use. *Social Forces*, *65*, 135-161.
Marcoux, B., & Shope, J. (1997). Application of the theory of planned behavior to adolescent use and misuse of alcohol. *Health Education Research*, *12*, 323-331.
Mariotti, L., & Reinecke, J. (2010). *Wachstum und Mischverteilungsmodelle unter Berücksichtigung unbeobachteter Heterogeneität: Empirische Analysen zum delinquenten Verhalten Jugendlicher in Duisburg.* Münster: Institut für sozialwissenschaftliche Forschung e. V.
Marshall, G. (1998). *Dictionary of sociology* (2nd ed.). Oxford: Oxford University Press.
Matsueda, R. (1982). Testing control theory and differential association: A causal modeling approach. *American Sociological Review*, *47*, 489-504.
McCutcheon, A. (1987). *Latent class analysis* (No. 07-064). Newbury Park, CA: Sage.
McLachlan, G., & Peel, D. (2000). *Finite mixture models.* New York: Wiley and Sons.
Meredith, M., & Tisak, J. (1990). Latent curve analysis. *Psychometrika*, *55*, 107-122.
Moffitt, T. (1993). Adolescence-limited and life-course-persistent antisocial behavior: A developmental taxonomy. *Psychological Review*, *100*, 674-701.
Musto, D. (1992). Historical perspectives on alcohol and drug abuse. In J. Lowinson, P. Ruiz, & R. Millman (Eds.), *Substance abuse: A comprehensive textbook* (p. 2-14). Baltimore: Williams & Wilkins.

Muthén, B. (2001). Second-generation structural equation modeling with a combination of categorical and continuous latent variables: New opportunities for latent class/latent growth modeling. In L. Collins & A. Sayer (Eds.), *New methods for the analysis of change* (p. 291-322). Washington, D.C.: APA.

Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling. *Psychological Methods*, *8*, 369-377.

Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (p. 345-368). Newbury Park, CA: Sage Publications.

Muthén, B., & Asparouhov, T. (2009). Growth mixture modeling: Analysis with non-gaussian random effects. In G. Fitzmaurice, M. Davidian, G. Verbeke, & G. Molenberghs (Eds.), *Longitudinal data analysis.* Boca Raton: Chapman & Hall/CRC Press.

Muthén, B., & Shedden, K. (1999). Finite mixture modeling with mixture outcomes using the EM algorithm. *Biometrics*, *55*, 463-469.

Muthén, L., & Muthén, B. (1998-2010). *Mplus user's guide* (6th ed.). Los Angeles, CA: Muthén and Muthén.

Nagin, D. (1999). Analyzing developmental trajectories: A semiparametric, group-based approach. *Psychological Methods*, *4*, 139-157.

Nagin, D., Farrington, D., & Moffitt, T. (1995). Life-course trajectories of different types of offenders. *Ccriminology*, *33*(1), 111-139.

Nagin, D., & Land, K. (1993). Age, criminal careers, and population heterogeneity: Specification and estimation of a nonparametric, mixed poisson model. *Criminology*, *31*, 327-362.

Nagin, D., & Tremblay, R. (2005). What has been learned from group-based trajectory modeling? examples from physical aggression and other problem behaviors. *The Annals of the American Academy of Political and Social Science*, *602*, 82-117.

Newcomb, M., & Bentler, P. (1986). Frequency and sequence of drug use: A longitudinal study from early adolescence to young adulthood. *Journal of Drug Education*, *16*, 101-120.

Nylund, K. (2007). *Latent transition analysis: Modeling extensions and an application to peer victimisation.* Unpublished doctoral dissertation, University of California, Los Angeles. Available from `www.statmodel.com`

Nylund, K., Muthén, B., Nishina, A., Bellmore, A., & Graham, S. (2006). *Stability and instability of peer victimisation during middle school: Using latent transition analysis with covariates, distal outcomes, and modeling extensions.* Available from `www.statmodel.com` (Submitted for publication)

O'Donnell, J., & Clayton, R. (1982). The stepping-stone hypothesis: A reappraisal. *Chemical Dependencies*, *4*, 229-241.

Patrick, M., Collins, L., Smith, E., Caldwell, L., Flisher, A., & Wegner, L. (2009). A prospective longitudinal model of substance use onset among South African adolescents. *Substance Use & Misuse*, *44*(5), 647-662.

Pöge, A. (2005). Persönliche Codes bei Längsschnittstudien. Ein Erfahrungsbericht. *ZA-Informationen*, *56*, 50-69.

Pöge, A. (2007). *Methodendokumentation der kriminologischen Schülerbefragung in Duisburg 2002 - 2005. Schriftenreihe Kriminalität in der modernen Stadt Methoden* (Vol. 13). Münster, Bielefeld.

Pöge, A. (2008). Persönliches Codes "reloaded". *Metoden - Daten - Analysen. Zeitschrift für Empirische Sozialforschung*, *1*, 59-70.

Piaget, J. (1971). The theory of stages in cognitive development. In R. Green, M. Ford, & G. Flammer (Eds.), *Measurement and Piaget* (p. 1-11). New York: McGraw-Hill.

Piaget, J. (1972). Intellectual evolution from adolescence to adulthood. *Human Development*, *15*, 1-12.

Raftery, A. (1993). Bayesian model selection in structural equation models. In K. Bollen & J. Long (Eds.), *Testing structural equation models* (p. 163-180). Newbury Park, CA: Sage.

Read, T., & Cressie, N. (1988). *Goodness-of-fit statistics for discrete multivariate data*. New York: Springer-Verlag.

Reinecke, J. (1999). Latent class analysis with panel data: Developments and applications. *ZA-Information*, *44*, 137-157.

Reinecke, J. (2006). Longitudinal analysis of adolescents' deviant and delinquent behavior: Applications of latent class growth curves and growth mixture models. *Methodology*, *2*, 100-112.

Resnick, M., Bearman, P., & Blum, R. (1997). Protecting adolescents from harm: Findings from the national longitudinal study on adolescent health. *Journal of American Medical Association*, *278*, 823-832.

Reuband, K. (1994). *Soziale Determinanten des Drogengebrauchs*. Opladen: Westdeutscher Verlag.

Reuband, K. (1999). Drogengebrauch und Drogenabhängigkeit. In G. Albrecht (Ed.), *Handbuch soziale Probleme* (p. 319-336). Opladen: Westdeutsche Verlag.

Robins, L. (1978). The interaction of setting and predisposition in explaining novel behavior: Drug initiation before, in and after Vietnam. In D. Kandel (Ed.), *Longitudinal research on drug use: Empirical findings and methodological issues* (p. 179-196). Washington, DC: Hemisphere-Wiley.

Roeder, K., Lynch, K., & Nagin, D. (1999). Modeling uncertainty in latent class membership: A case study in criminology. *Journal of the American Statistical Association*, *94*(447), 766-776.

Rosenberg, C., Gerrein, J., & Schnell, C. (1978). Cannabis in the treatment of alcoholism. *Journal of Studies on Alcohol*, *39*, 155-158.

Rubin, D. (1987). *Multiple imputation for nonresponse in surveys.* New York: Wiley.

Sampson, R., & Laub, J. (1992). Crime and deviance in the life course. *Annual Review of Sociology*, *18*(1), 63-84.

Schafer, J. (1997). *Analysis of incomplete multivariate data.* London: Chapman & Hall.

Schafer, J., & Graham, J. (2002). Missing data: Our view of the state of the art. *Psychological Methods*, *7*, 147-177.

Schenk, S. (2002). Sensitization as a process underlying the progression of drug use via gateway drugs. In D. Kandel (Ed.), *Stages and pathways of drug involvement: Examining the gateway hypothesis* (p. 318-336). Cambridge, UK: Cambridge University Press.

Schulenberg, J., Merline, A., Johnston, L., O'Malley, P., Bachman, J., & Laetz, V. (2005). Trajectories of marijuana use during the transition to adulthood: The big picture based on national panel data. *Journal of Drug Issues*, *35*, 255-279.

Schumacker, R., & Lomax, R. (2004). *A beginner's guide to structural equation modeling* (2nd ed.). Mahwah: Lawrence Erlbaum.

Sclove, L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, *52*, 333-343.

Smith, G., & Fogg, C. (1978). Psychological predictors of early use, late use, and nonuse of marihuana among teenage students. In D. Kandel (Ed.), *Longitudinal research on drug use: Empirical findings and methodological issues* (p. 101-114). Washington, DC: Hemisphere-Wiley.

Smith, G., & Fogg, C. (1979). Psychological antecedents of teenage drug use. In R. Simmons (Ed.), *Research in community and mental health: An annual compilation of research* (Vol. 1, p. 87-102). Grenwich, Conn: JAI Press.

Smith, S., OHara, B., & Persico, A. (1992). Genetic vulnerability to drug abuse. the D2 dopamine receptorTaqI B1 restriction fragment length polymorphism appears more frequetly in polysubstance abusers. *Archives of General Psychiatry*, *31*, 285-290.

Steiger, J. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*, *25*, 173-180.

Stephens, R., & Cottrell, E. (1972). A follow-up study of 200 narcotic addicts committed for treatment under the Narcotic Addiction Rehabilitation Act (NARA). *British Journal of the Addictions*, *67*, 45-53.

Sutherland, A., & Mariotti, L. (2011). The development of substance use in adolescence: Results from comparing two longitudinal studies in England and Germany. *Rivista di Criminologia, Vittimologia e Sicurezza*, *5*(2), 28-49.

Sutherland, E. (1947). *Principles of criminology.* Chicago: J. B. Lippincott.

Tang, Z., Lanza, S., & Collins, L. (2001). *Modeling adolescent substance use using latent transition analysis: The health for life data set* (Tech. Rep. No. 44). The Methodology Center, Technical Report Series.

Tarter, R., Kirisci, L., & Mezzich, A. (1997). Multivariate typology of adolescents with alcohol use disorder. *The American Journal on Addictions*, *6*, 150-158.

Tofighi, D., & Enders, C. (2008). Identifying the correct number of classes in growth mixture models. In G. Hancook & K. Samuelsen (Eds.), *Advances in latent variable mixture models.* Charlotte, NC: IAP.

Tucker, J., Ellickson, P., Orlando, M., Martino, S., & Klein, D. (2005). Substance use trajectories from early adolescence to emerging adulthood: A comparison of smoking, binge drinking, and marijuana use. *Juornal of Drug Issues*, *35*, 307-331.

Vaillant, G. (1966). A twelve-year follow-up of New York narcotic addicts: Iii. some social and psychiatric characteristics. *Archives of General Psychiatry*, *15*(6), 599-609.

Van de Pol, F., & Langeheine, R. (1989). Mover-stayer models, mixed Markov models and the EM algorithm; with an application to labour market data from the Netherlands Socio-Economic Panel. In R. Coppi & S. Bolasco (Eds.), *Multiway data analysis* (p. 485-495). Amsterdam: North Holland.

Van de Pol, F., & Langeheine, R. (1990). Mixed markov latent class models. *Sociological Methodology*, *20*, 213-247.

Walden, B., Iacono, W., & McGue, M. (2007). Trajectories of change in adolescent substance use and symptomatology: Impact of paternal and maternal substance use disorders. *Psychology of Addictive Behaviors*, *21*(1), 35-43.

Wang, C., Brown, H., & Bandeen-Roche, K. (2005). Residual diagnostics for growth mixture models: Examining the impact of a preventive intervention on multiple trajectories of aggressive behavior. *Journal of the American Statistical Association*, *100*(471), 1054-1076.

Weber, M., Graham, J., Hansen, W., Flay, B., & Johnson, C. (1989). Evidence for two paths of alcohol use onset in adolescents. *Addictive Behaviors*, *14*, 399-408.

Weinstein, N., & Rothman, A. (1998). Stage theories of health behavior: Conceptual and methodological issues. *Health Psychology*, *17*, 290-299.

Werch, C., & Anzalone, D. (1995). Stage theory and research on tobacco, alcohol, and other drug use. *Journal of Drug Education*, *25*, 81-98.

White, H., & Labouvie, E. (1994). Generality versus specificity of problem behavior: Psychological and functional differentces. *Journal of Drug Issues*, *24*, 55-74.

Wiesner, M., Silbereisen, R., & Weichold, K. (2008). Effects of deviant peer association and adolescent alcohol consumption: A growth mixture modeling analysis. *Journal of Youth and Adolescence*, *37*, 537-551.

Wiesner, M., Weichold, K., & Silbereisen, R. (2007). Trajectories of alcohol use among adolescent boys and girls: Identification, validation, and sociodemographic characteristics. *Psychology of Addictive Behaviors*, *21*(1), 62-75.

Wills, T., & Shiffman, S. (1985). *Coping and substance use*. Orlando, FL.: Academic Press.

Windle, M., & Wiesner, M. (2004). Trajectories of marijuana use from adolescence to young adulthood: Predictors and outcomes. *Development and Psychopathology*, *16*(4), 1007-1027.

Yamaguchi, K., & Kandel, D. (1984). Patterns of drug use from adolescence to young adulthood: 3. predictors of progression. *American Journal of Public Health*, *74*(7), 673-681.

Appendix A

Appendices

The following sections will provide some important information about the estimated models and the questionnaire used for this study. The first two sections will report some excerpts from the outputs of the best fitting GMM model presented in Chapter 5 (Section 5.3.3) and the LTA models discussed in Chapter 6 (Section 6.5.1). For each model the complete input code used in Mplus will be reported; for what concerns the outputs, only the most important part of them will be presented. Finally, the third section will contain the translated version of the questions used for the variables of this work.

A.1 Growth mixture model, three classes, random intercept model

```
Mplus VERSION 5.21
MUTHEN & MUTHEN
04/25/2012   4:05 PM

INPUT INSTRUCTIONS

  TITLE: GMM for Drug Use rates 5w
         Logged frequencies
         Model assumption: random intercept

  DATA:     FILE IS ln+1_drug_5w_(1552).dat ;
            TYPE IS INDIVIDUAL ;
            FORMAT IS FREE;
            NOBSERVATIONS ARE 1552 ;

  VARIABLE: NAMES ARE AT0283LN BT0283LN CT0283LN DT0283LN ET0283LN
                      AA0011 ASCHULF ESCHULF;

            USEVARIABLES ARE
                  AT0283LN BT0283LN CT0283LN DT0283LN ET0283LN ;

            MISSING ARE ALL (999) ;

            CLASSES = c(3) ;
```

```
  ANALYSIS: TYPE = MIXTURE MISSING  ;
            ALGORITHM = INTEGRATION ;
            STARTS = 50 10 ;

  SAVEDATA: File is 3classi.dat ;
            Format is free ;
            Save=cprobabilities ;

  MODEL:
         %OVERALL%
         I S Q| AT0283LN@0 BT0283LN@1 CT0283LN@2 DT0283LN@3 ET0283LN@4;

         S-Q@0 ;

  PLOT:
         TYPE = PLOT3;
         Series = AT0283LN(s) BT0283LN(s) CT0283LN(s) DT0283LN(s) ET0283LN(s);

  OUTPUT: RESIDUAL TECH1 TECH7 TECH8 TECH11 TECH12 ;


GMM for Drug Use rates 5w
Logged frequencies
Basic Model, Assumptions: quadratic, Continuous Data

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                        1551

Number of dependent variables                                    5
Number of independent variables                                  0
Number of continuous latent variables                            3
Number of categorical latent variables                           1


THE MODEL ESTIMATION TERMINATED NORMALLY



TESTS OF MODEL FIT

Loglikelihood

          H0 Value                          -6151.452
          H0 Scaling Correction Factor          6.910
            for MLR

Information Criteria

          Number of Free Parameters                17
```

```
          Akaike (AIC)                      12336.904
          Bayesian (BIC)                    12427.797
          Sample-Size Adjusted BIC          12373.793
            (n* = (n + 2) / 24)



FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THE ESTIMATED MODEL

    Latent
   Classes

       1      1410.69982          0.90954
       2        46.51685          0.02999
       3        93.78332          0.06047


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASS PATTERNS
BASED ON ESTIMATED POSTERIOR PROBABILITIES

    Latent
   Classes

       1      1410.67058          0.90952
       2        46.51545          0.02999
       3        93.81397          0.06049


CLASSIFICATION QUALITY

     Entropy                        0.992


CLASSIFICATION OF INDIVIDUALS BASED ON THEIR MOST LIKELY LATENT CLASS
MEMBERSHIP

Class Counts and Proportions

    Latent
   Classes

       1            1412          0.91038
       2              46          0.02966
       3              93          0.05996


Average Latent Class Probabilities for Most Likely Latent Class Membership
(Row) by Latent Class (Column)

           1        2        3
```

```
   1   0.998    0.000    0.002
   2   0.000    1.000    0.000
   3   0.023    0.001    0.975


MODEL RESULTS

                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Latent Class 1

 I        |
    AT0283LN           1.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           1.000      0.000    999.000    999.000
    DT0283LN           1.000      0.000    999.000    999.000
    ET0283LN           1.000      0.000    999.000    999.000

 S        |
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           2.000      0.000    999.000    999.000
    DT0283LN           3.000      0.000    999.000    999.000
    ET0283LN           4.000      0.000    999.000    999.000

 Q        |
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           4.000      0.000    999.000    999.000
    DT0283LN           9.000      0.000    999.000    999.000
    ET0283LN          16.000      0.000    999.000    999.000

 Means
    I                  0.011      0.003      4.400      0.000
    S                  0.054      0.011      4.712      0.000
    Q                  0.001      0.004      0.391      0.696

 Intercepts
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           0.000      0.000    999.000    999.000
    CT0283LN           0.000      0.000    999.000    999.000
    DT0283LN           0.000      0.000    999.000    999.000
    ET0283LN           0.000      0.000    999.000    999.000

 Variances
    I                  0.022      0.006      3.856      0.000
    S                  0.000      0.000    999.000    999.000
    Q                  0.000      0.000    999.000    999.000

 Residual Variances
    AT0283LN           0.007      0.004      1.671      0.095
```

```
    BT0283LN           0.237      0.030      7.794      0.000
    CT0283LN           0.315      0.049      6.426      0.000
    DT0283LN           0.685      0.094      7.274      0.000
    ET0283LN           0.860      0.084     10.272      0.000

Latent Class 2

 I        |
    AT0283LN           1.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           1.000      0.000    999.000    999.000
    DT0283LN           1.000      0.000    999.000    999.000
    ET0283LN           1.000      0.000    999.000    999.000

 S        |
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           2.000      0.000    999.000    999.000
    DT0283LN           3.000      0.000    999.000    999.000
    ET0283LN           4.000      0.000    999.000    999.000

 Q        |
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           4.000      0.000    999.000    999.000
    DT0283LN           9.000      0.000    999.000    999.000
    ET0283LN          16.000      0.000    999.000    999.000

 Means
    I                  2.243      0.103     21.689      0.000
    S                 -0.298      0.235     -1.267      0.205
    Q                 -0.007      0.056     -0.118      0.906

 Intercepts
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           0.000      0.000    999.000    999.000
    CT0283LN           0.000      0.000    999.000    999.000
    DT0283LN           0.000      0.000    999.000    999.000
    ET0283LN           0.000      0.000    999.000    999.000

 Variances
    I                  0.022      0.006      3.856      0.000
    S                  0.000      0.000    999.000    999.000
    Q                  0.000      0.000    999.000    999.000

 Residual Variances
    AT0283LN           0.007      0.004      1.671      0.095
    BT0283LN           0.237      0.030      7.794      0.000
    CT0283LN           0.315      0.049      6.426      0.000
    DT0283LN           0.685      0.094      7.274      0.000
    ET0283LN           0.860      0.084     10.272      0.000
```

```
Latent Class 3

 I        |
    AT0283LN           1.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           1.000      0.000    999.000    999.000
    DT0283LN           1.000      0.000    999.000    999.000
    ET0283LN           1.000      0.000    999.000    999.000

 S        |
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           2.000      0.000    999.000    999.000
    DT0283LN           3.000      0.000    999.000    999.000
    ET0283LN           4.000      0.000    999.000    999.000

 Q        |
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           1.000      0.000    999.000    999.000
    CT0283LN           4.000      0.000    999.000    999.000
    DT0283LN           9.000      0.000    999.000    999.000
    ET0283LN          16.000      0.000    999.000    999.000

 Means
    I                  0.112      0.036      3.103      0.002
    S                  2.359      0.196     12.055      0.000
    Q                 -0.468      0.062     -7.577      0.000

 Intercepts
    AT0283LN           0.000      0.000    999.000    999.000
    BT0283LN           0.000      0.000    999.000    999.000
    CT0283LN           0.000      0.000    999.000    999.000
    DT0283LN           0.000      0.000    999.000    999.000
    ET0283LN           0.000      0.000    999.000    999.000

 Variances
    I                  0.022      0.006      3.856      0.000
    S                  0.000      0.000    999.000    999.000
    Q                  0.000      0.000    999.000    999.000

 Residual Variances
    AT0283LN           0.007      0.004      1.671      0.095
    BT0283LN           0.237      0.030      7.794      0.000
    CT0283LN           0.315      0.049      6.426      0.000
    DT0283LN           0.685      0.094      7.274      0.000
    ET0283LN           0.860      0.084     10.272      0.000

Categorical Latent Variables

 Means
    C#1                2.711      0.127     21.312      0.000
    C#2               -0.701      0.193     -3.636      0.000
```

```
TECHNICAL 11 OUTPUT

     Random Starts Specifications for the k-1 Class Analysis Model
        Number of initial stage random starts                  50
        Number of final stage optimizations                    10



  VUONG-LO-MENDELL-RUBIN LIKELIHOOD RATIO TEST FOR 2 (H0) VERSUS 3 CLASSES

          H0 Loglikelihood Value                        -7106.491
          2 Times the Loglikelihood Difference           1910.078
          Difference in the Number of Parameters                4
          Mean                                            300.422
          Standard Deviation                              661.545
          P-Value                                          0.0171

  LO-MENDELL-RUBIN ADJUSTED LRT TEST

          Value                                          1847.218
          P-Value                                          0.0196
```

A.2 Latent transition analysis between 2005 and 2006 (Model M4)

```
Mplus VERSION 5.21
MUTHEN & MUTHEN
08/29/2011  12:13 PM

INPUT INSTRUCTIONS

  TITLE: LTA - Recent Use Model
         model specification b. (2 Tau fixed)(4 rho)
         T4 --> T5
         Alcohol, Marijuana, Hard Drugs

  DATA: FILE IS lta_5w_drug_+cov.dat ;
        TYPE IS INDIVIDUAL;
        FORMAT IS FREE;
        NOBSERVATIONS ARE 1552;

  VARIABLE:
  NAMES ARE at0343 bt0343 ct0343 dt0343 et0343
  at0295 bt0295 ct0295 dt0295 et0295
  aharddr bharddr charddr dharddr eharddr
  aa0011 aschulf eschulf
```

```
bh0004 bh0041 bh0042 bh0106
ch0004 ch0041 ch0042 ch0106
dh0004 dh0041 dh0042 dh0106
eh0004 eh0041 eh0042 eh0106 ;

USEVARIABLES ARE dt0343 dt0295 dharddr
                 et0343 et0295 eharddr ;

CATEGORICAL ARE dt0343 dt0295 dharddr
                et0343 et0295 eharddr ;

MISSING ARE ALL (999);

CLASSES = c1(4) c2(4) ;

ANALYSIS:
TYPE = MIXTURE MISSING ;
STARTS = 50 10 ;
STITERATIONS = 20 ;

MODEL:

    %OVERALL%           !STRUCTURAL MODEL

    ![c2#1@-15] ;

    c2#1 ON c1#1 ;      !transition prob. t4-->t5
    c2#2 ON c1#1 ;      !cm model taus' matrix
    c2#3 ON c1#1 ;

    c2#1 ON c1#2 ;
    c2#2 ON c1#2 ;
    c2#3 ON c1#2 ;

    c2#1 ON c1#3@-15 ;
    c2#2 ON c1#3 ;
    c2#3 ON c1#3 ;


MODEL c1:               !MEASUREMENT MODEL T4

    %c1#1%              !no use latent status t4
    [dt0343$1*3] (1);
    [dt0295$1*3] (1);   !in () measur. equality constrains across time
    [dharddr$1*3] (1);

    %c1#2%              !alcohol lat. stat. t4
    [dt0343$1*-3] (2);
    [dt0295$1*3] (1);
    [dharddr$1*3] (1);

    %c1#3%              !alcohol+maria lat. stat. t4
```

```
      [dt0343$1*-3] (2);
      [dt0295$1*-3] (2);
      [dharddr$1*3] (1);

      %c1#4%              !a+m+hd lat. stat. t4
      [dt0343$1*-3] (2);
      [dt0295$1*-3] (2);
      [dharddr$1*-3] (2);


  MODEL c2:               !MEASUREMENT MODEL T5

      %c2#1%              !no use latent status t5
      [et0343$1*3] (1);
      [et0295$1*3] (1);   !in () measur. equality constrains across time
      [eharddr$1*3] (1);

      %c2#2%              !alcohol lat. stat. t5
      [et0343$1*-3] (2);
      [et0295$1*3] (1);
      [eharddr$1*3] (1);

      %c2#3%              !alcohol+maria lat. stat. t5
      [et0343$1*-3] (2);
      [et0295$1*-3] (2);
      [eharddr$1*3] (1);

      %c2#4%              !a+m+hd lat. stat. t5
      [et0343$1*-3] (2);
      [et0295$1*-3] (2);
      [eharddr$1*-3] (2);

  OUTPUT: TECH1 TECH10 ;

LTA - Recent Use Model
model specification b. (2 Tau fixed)(4 rho)
T4 --> T5
Alcohol, Marijuana, Hard Drugs

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                        1552

Number of dependent variables                                    6
Number of independent variables                                  0
Number of continuous latent variables                            0
Number of categorical latent variables                           2

THE MODEL ESTIMATION TERMINATED NORMALLY

TESTS OF MODEL FIT
```

```
Loglikelihood

          H0 Value                        -3109.544
          H0 Scaling Correction Factor       1.018
            for MLR

Information Criteria

          Number of Free Parameters             16
          Akaike (AIC)                    6251.088
          Bayesian (BIC)                  6336.645
          Sample-Size Adjusted BIC        6285.816
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit for the Binary and Ordered Categorical
(Ordinal) Outcomes**

          Pearson Chi-Square

          Value                             43.400
          Degrees of Freedom                    46
          P-Value                           0.5818

          Likelihood Ratio Chi-Square

          Value                             37.595
          Degrees of Freedom                    46
          P-Value                           0.8066

** Of the 200 cells in the latent class indicator table, 1
   were deleted in the calculation of chi-square due to extreme values.

Chi-Square Test for MCAR under the Unrestricted Latent Class Indicator
Model

          Pearson Chi-Square

          Value                             59.391
          Degrees of Freedom                   128
          P-Value                           1.0000

          Likelihood Ratio Chi-Square

          Value                             58.947
          Degrees of Freedom                   128
          P-Value                           1.0000

MODEL RESULTS USE THE LATENT CLASS VARIABLE ORDER

   C1  C2
```

```
  Latent Class Variable Patterns

         C1        C2
       Class     Class

          1         1
          1         2
          1         3
          1         4
          2         1
          2         2
          2         3
          2         4
          3         1
          3         2
          3         3
          3         4
          4         1
          4         2
          4         3
          4         4


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASS PATTERNS
BASED ON THE ESTIMATED MODEL

  Latent Class
    Pattern

   1 1       362.76001          0.23374
   1 2       162.61581          0.10478
   1 3         8.77314          0.00565
   1 4         2.93700          0.00189
   2 1        51.71852          0.03332
   2 2       574.54786          0.37020
   2 3        75.17174          0.04844
   2 4        15.33780          0.00988
   3 1         0.00000          0.00000
   3 2       107.84579          0.06949
   3 3       113.05062          0.07284
   3 4        16.01346          0.01032
   4 1         6.16229          0.00397
   4 2        21.26078          0.01370
   4 3        11.69005          0.00753
   4 4        22.11511          0.01425


FINAL CLASS COUNTS AND PROPORTIONS FOR EACH LATENT CLASS VARIABLE
BASED ON THE ESTIMATED MODEL

  Latent Class
    Variable    Class
```

```
  C1            1       537.08600          0.34606
                2       716.77594          0.46184
                3       236.90988          0.15265
                4        61.22823          0.03945
  C2            1       420.64084          0.27103
                2       866.27026          0.55816
                3       208.68556          0.13446
                4        56.40337          0.03634


LATENT TRANSITION PROBABILITIES BASED ON THE ESTIMATED MODEL

  C1 Classes (Rows) by C2 Classes (Columns)

            1        2        3        4

   1     0.675    0.303    0.016    0.005
   2     0.072    0.802    0.105    0.021
   3     0.000    0.455    0.477    0.068
   4     0.101    0.347    0.191    0.361


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON ESTIMATED POSTERIOR PROBABILITIES

  Latent Class
    Pattern

   1 1       362.76001          0.23374
   1 2       162.61582          0.10478
   1 3         8.77314          0.00565
   1 4         2.93700          0.00189
   2 1        51.71852          0.03332
   2 2       574.54786          0.37020
   2 3        75.17174          0.04844
   2 4        15.33780          0.00988
   3 1         0.00000          0.00000
   3 2       107.84579          0.06949
   3 3       113.05062          0.07284
   3 4        16.01346          0.01032
   4 1         6.16229          0.00397
   4 2        21.26079          0.01370
   4 3        11.69005          0.00753
   4 4        22.11511          0.01425


FINAL CLASS COUNTS AND PROPORTIONS FOR EACH LATENT CLASS VARIABLE
BASED ON ESTIMATED POSTERIOR PROBABILITIES

  Latent Class
    Variable    Class
```

C1	1	537.08600	0.34606
	2	716.77594	0.46184
	3	236.90987	0.15265
	4	61.22824	0.03945
C2	1	420.64084	0.27103
	2	866.27026	0.55816
	3	208.68555	0.13446
	4	56.40337	0.03634

CLASSIFICATION QUALITY

Entropy 0.923

CLASSIFICATION OF INDIVIDUALS BASED ON THEIR MOST LIKELY LATENT CLASS PATTERN

Class Counts and Proportions

Latent Class Pattern		
1 1	373	0.24034
1 2	164	0.10567
1 3	10	0.00644
1 4	3	0.00193
2 1	63	0.04059
2 2	557	0.35889
2 3	76	0.04897
2 4	14	0.00902
3 1	0	0.00000
3 2	108	0.06959
3 3	109	0.07023
3 4	15	0.00966
4 1	6	0.00387
4 2	19	0.01224
4 3	12	0.00773
4 4	23	0.01482

Average Latent Class Probabilities for Most Likely Latent Class Pattern (Row) by Latent Class Pattern (Column)

Latent Class Variable Patterns

Latent Class Pattern No.	C1 Class	C2 Class
1	1	1
2	1	2

3	1	3
4	1	4
5	2	1
6	2	2
7	2	3
8	2	4
9	3	1
10	3	2
11	3	3
12	3	4
13	4	1
14	4	2
15	4	3
16	4	4

	1	2	3	4	5	6	7	8
1	0.962	0.023	0.002	0.000	0.008	0.004	0.001	0.000
2	0.007	0.898	0.002	0.001	0.000	0.091	0.000	0.000
3	0.000	0.050	0.745	0.007	0.000	0.005	0.183	0.001
4	0.000	0.001	0.009	0.856	0.000	0.000	0.002	0.128
5	0.019	0.000	0.000	0.000	0.741	0.236	0.001	0.000
6	0.003	0.010	0.000	0.000	0.003	0.968	0.004	0.000
7	0.000	0.000	0.003	0.000	0.001	0.025	0.925	0.005
8	0.000	0.000	0.000	0.001	0.000	0.000	0.017	0.952
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.003	0.000	0.000	0.003	0.018	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003
13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	0.000	0.000	0.000	0.004	0.000	0.000	0.001	0.039

	9	10	11	12	13	14	15	16
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.008	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000
5	0.000	0.002	0.000	0.000	0.001	0.000	0.000	0.000
6	0.000	0.007	0.000	0.000	0.000	0.003	0.000	0.000
7	0.000	0.000	0.040	0.000	0.000	0.000	0.000	0.000
8	0.000	0.000	0.001	0.029	0.000	0.000	0.000	0.001
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.940	0.028	0.000	0.003	0.005	0.000	0.000
11	0.000	0.016	0.972	0.006	0.000	0.000	0.003	0.000
12	0.000	0.000	0.024	0.936	0.000	0.000	0.000	0.037
13	0.000	0.002	0.000	0.000	0.907	0.090	0.001	0.000
14	0.000	0.017	0.001	0.000	0.012	0.953	0.015	0.001
15	0.000	0.000	0.032	0.000	0.000	0.006	0.912	0.050
16	0.000	0.000	0.001	0.039	0.000	0.005	0.002	0.909

CLASSIFICATION OF INDIVIDUALS BASED ON THEIR MOST LIKELY LATENT CLASS MEMBERSHIP FOR EACH LATENT CLASS VARIABLE

Latent Class Variable	Class		
C1	1	550	0.35438
	2	710	0.45747
	3	232	0.14948
	4	60	0.03866
C2	1	442	0.28479
	2	848	0.54639
	3	207	0.13338
	4	55	0.03544

A.3 Translated excerpt from the questionnaire

39. Have you ever taken drugs like ecstasy, cannabis, cocaine, etc. (smoking cigarettes or drinking alcohol is not meant)?

❍ no → go to **question 40**
❍ yes ↓

How old were you the first time?
______years old

Think about the last twelve months. Did it happen this year?

❍ no → go to **question 40**
❍ yes ↓

How many times?
______times

Have you ever used any of these drugs in the last 12 months?	Marijuana, hashish	❍
	Heroin, morphine	❍
	Cocaine, crack	❍
	Speed	❍
	„designer-drugs“, ecstasy	❍
	LSD, mushrooms	❍
	other	❍

44. Have you ever been drunk?

❍ no → go to **question 45**
❍ yes ↓

How old were you the first time you were drunk?
______years old

How often have you been drunk?	several times a week	①
	several times a month	②
	once a month	③
	once or several times a year	④

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