Is it who you know, or how many that counts? Criminal networks and cost avoidance in a sample of young offenders

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Abstract

The aim of the current study is to assess whether criminal networks can help young offenders avoid contacts with the criminal justice system. We examine the association between criminal network and cost avoidance specifically for the crime of cannabis cultivation in a rural region in Quebec, Canada. A self-report delinquency survey, administered to the region's quasi-population of high school students (N = 1262), revealed that a total of 175 adolescents had participated in the cannabis cultivation industry (a 15% lifetime prevalence rate). Forty-seven respondents (27%), including 29 who were arrested, reported having participated in a cultivation site that was detected by the police. Results indicate that "who you know" matters in the cultivation industry, and is an important independent predictor of arrest: very few young growers who were embedded in adult networks were apprehended. Conversely, embeddedness in a youth network emerged as an independent risk factor, especially in larger networks.

Key words: social capital; criminal achievement; cost avoidance; cannabis cultivation; criminal networks;

INTRODUCTION

Criminological research has long been concerned with the social element of crime. Most studies that paid attention to the social aspect of offending examined the role of delinquent peers in explaining involvement in crime (e.g. Sutherland, 1947; Haynie, 2001; 2002; Matsueda and Anderson, 1998; Payne and Cornwell, 2007; Warr, 2002). Interest in delinquent peers and co-offenders has extended to other considerations, especially within research using a criminal career framework. A larger network of accomplices has been linked to longer and more active criminal careers (Piquero et al., 2007). Criminal achievement researchers, whose key object of analysis has been success in crime, have been even more explicit about the importance of co-offenders. First, they argued that co-offenders should be considered as resources or social capital that can be used to get ahead in crime (McCarthy and Hagan, 2001). Second, researchers recognized that not all offenders are equally apt at using this resource, and they examined whether variations in social capital were related to variations in criminal achievement. Results showed that, all else being equal, offenders earned more money from crime if they were open to collaboration (McCarthy and Hagan, 2001), reported knowing more successful offenders (Tremblay and Morselli, 2000), used their criminal network more efficiently (Morselli and Tremblay, 2004), and had mentors in their criminal network (Morselli et al., 2006).

These studies offered insights into the link between criminal networks and illegal earnings. Of importance, researchers suggested a mechanism to understand why that is the case. How offenders build and manage their criminal network is crucial in determining their level of success, because criminal capital, as opposed to human capital, accumulates almost exclusively through contact with others (McCarthy and Hagan, 2001). For example, it was not mere network size, but *effective* size[1] that was associated to higher earnings in Morselli and Tremblay (2004). Similarly, contacts identified specifically as *mentors* were those that facilitated earnings attainment in Morselli et al. (2006), and not just any type of contact.

Yet the question remains whether networks have the same beneficial effects on the other indicator of criminal success: cost avoidance. Success in crime is not just about earnings attainment, but also about cost avoidance, defined broadly as the ability to avoid contact with the criminal justice system (Adler, 1993; Kazemian and Leblanc, 2007; McCarthy and Hagan, 2001; VanNostrand and Tewksbury, 1999). Past research suggests that networks could also play an important role in cost avoidance. In their study of 268 incarcerated offenders, Morselli et al. (2006) also examined the role of mentors in avoiding the costs of crime, which was measured in number of days these offenders were incapacitated in the three years preceding their incarceration. Results showed that having a criminal mentor was a significant negative predictor of the number of days incapacitated. A different set of studies emphasized how key players insulate themselves from detection within their criminal network (Baker and Faulkner, 1993; Dorn et al., 1998; Krebs, 2002; Williams, 2001). For example, Baker and Faulkner (1993) showed how conspiracy managers who decreased their network efficiency by increasing the number of layers (and players) within a decentralized network had lower probabilities of later being found guilty in court. Other studies suggested that illegal endeavors that increased network size, or added "redundant" contacts to a criminal network, enhanced resilience (Williams, 2001), which seems to go against the conventional wisdom of *keeping it small*. Numerous studies have insisted that having the fewest individuals possible who know about ongoing illegal business

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[1] Effective size combines information about the size of the network, and the relative redundancy of the contacts within the network (Morselli and Tremblay, 2004). A greater effective network size means that an offender's contacts lead to other people in other cliques, with few redundant contacts.

activities is a main strategy used by offenders for avoiding detection (Adler, 1993; Desroches, 2005; Jacobs, 1996; Reuter, 1983; VanNostrand and Tewsbury, 1999). On one hand, investing in social relationships may have positive returns for offenders in terms of finding new and interesting criminal opportunities (Tremblay, 1993), even though not all social relationships are equally productive. On the other hand, over-investing in criminal relationships might generate negative returns when the issue of concealment is considered. Such has been the main thrust of a set of studies that tested the so-called "group hazard hypothesis" (Erickson, 1971; 1973; Hindelang, 1976; Feyerherm, 1980; Morash, 1984; Brownfield et al., 2001). Results from these studies indicated that, when offending frequency and crime seriousness variables are taken into account, the positive relationship between arrest risks and co-offending is significantly reduced (or cancelled).

In short, the relationship between criminal network and cost avoidance may be different than the one found for increasing income. A trade-off might exist between ideal network size to maximize criminal gains and opportunities, while minimizing risks. The lack of empirical research linking network measures to relative cost avoidance measures makes it difficult to establish the nature of the trade-off, or whether it exists at all.

On the conceptual level, however, Lin's (2001) network theory of social capital helps us reconcile these apparently contradictory views. Lin (2001) identifies three stages of action associated with an individual's social capital: 1) the creation of social capital, 2) the mobilization of social capital, and 3) the harvest of returns from the mobilization of social capital. Social capital may be mobilized for two types of actions: a) *instrumental* actions, where efforts are aimed at acquiring valued resources not yet at one's disposal; and b) *expressive* actions, where efforts are aimed at maintaining or preserving valued resources already at one's disposal (Lin, 2001, p. 45). The outcomes expected from instrumental actions include the ones associated with earnings or job attainment, while the outcomes expected for expressive actions include maintaining one's health, well-being or, in our case, one's freedom. Expressive returns of social capital have been measured mainly through trust, support (Lai, 2006; Son and Lin, 2008)[2] and social control in the form of discouraging malfeasance (e.g. Colvin et al.2002; Wright and Fitzpatrick, 2006)[3]. According to Lin (1999) instrumental actions and expressive actions reinforce one another, but the factors associated with their returns may differ. Closed networks with homophilious ties (contacts with similar characteristics and resources) reinforce the preservation of resources because it increases solidarity and trust whereas extended networks with heterophilious interactions (contacts with dissimilar characteristics and resources) are more likely to aid in the acquisition of resources (Coleman, 1990; Lin, 1999; 2001; Burt, 2002; Granovetter, 1973). It is these defining features, suggests Lin (2008), which may be fundamental in understanding the utility of social capital, both instrumental and expressive.

For our purposes, this distinction first underscores the fact that criminal networks may be as important in facilitating cost avoidance as they are in facilitating illegal earnings attainment. Second, it suggests that the type of network or contacts who help in monetary success may be different than the ones needed for cost avoidance. For example, it may be that a large number of contacts help in finding interesting criminal opportunities, while also providing more

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[2] Factors such as self esteem and psychological health were considered expressive returns among the residential mobility on social capital urban Shanghai residents (Lai, 2006). Son and Lin (2008) referred to expressive civic action as the preservation of collective goods in a community and instrumental civic actions as mobilization to improve the status quo.

[3] Colvin et al. (2002) refer to instrumental and expressive social support both of which can be used to prevent an individual's participation in crime by reducing strain. Wright and Fitzpatrick (2006) conceptualized expressive returns among a sample of youth as physical and mental well being expecting that it would reduce the incidence of self reported violence. More commonly however, organizations are characterized as serving either instrumental goals (unions, political parties) or expressive goals (sports clubs, religious organizations, neighborhood organizations) (e.g. Bekkers et al., 2007; Gidengel et al., 2003; Miller, 1999).

opportunities for detection. The opposite may also be true: a large number of criminal contacts may provide opportunities for finding both safe and interesting criminal opportunities, as is suggested by Tremblay and Morselli's (2000) finding that high illegal earners had a significantly larger network of offenders who never went to prison. Consider also that, whereas skills learned to increase financial success are different from those for avoiding detection, similar contacts (e.g. criminal mentors) may provide both skill sets (Morselli et al., 2006).

THE CURRENT STUDY

This paper explores how different network and co-offending measures affect the odds of arrest in a sample of juvenile offenders. A self-report delinquency survey was administered to 1262 adolescents aged from 13 to 17 years attending one of four secondary schools in a rural region in Quebec, Canada. Conducting the survey in this location was motivated by the suspected widespread participation of these youth in the large scale marijuana cultivation industry. A total of 175 adolescents reported having participated in marijuana cultivation (a 15% lifetime prevalence rate)—a prevalence rate comparable to the highest ones found for youth drug dealing[4] in the United States (e.g. Altschuler and Brounstein, 1991; Saner et al., 1995; Steinman, 2005), and higher than the ones generally found in Canada in similar samples (Smart et al., 1992). Some of these young growers were arrested as a result of their involvement in cultivation; others were not arrested but participated in sites that were detected by the police; others successfully avoided both detection and arrest. Some of these youths were part of large cultivation networks, whereas others had very few criminal contacts with other growers. The objective of the current study is to uncover whether arrested and non-arrested youths differed in

[4] We compare to rates found for drug dealing because to our knowledge, this is the first self-report delinquency study to include the specific crime of cannabis cultivation.

significant ways, especially with regard to the characteristics of the criminal network in which they were embedded.

Cannabis cultivation presents an interesting opportunity for examining the impact of criminal networks on cost avoidance. First, domestic marijuana cultivation has experienced extraordinary growth in industrialized nations including Canada (Bouchard, 2007; Malm and Tita, 2006), the United States (Harrison et al., 2007; Weisheit, 1991) and New Zealand (Wilkins and Casswell, 2003), and has become a lucrative criminal opportunity for a substantial number of offenders. Police forces recognized the consequences of this growing industry and invested considerable resources to eradicate the problem (Plecas, et al., 2005; Malm and Tita, 2007; Wilkins and Casswell, 2003). Although a few studies have examined the macro-level risks of detection for broadly defined categories of offenders (Bouchard, 2007; Wilkins et al., 2002), differences in risks for individuals have yet to be investigated.

Second, the nature of the offence requires that cost avoidance issues be examined separately. Most predatory offences are short-lived, requiring sporadic involvement, low time and money investment, and instant gratification. Conversely, most of the roles that offender can occupy in the cannabis cultivation industry require rather long-term involvement (a minimum of 3 to 6 months) before uncertain rewards can be obtained. In short, the time frame for being considered "at risk" of being arrested is extended with this offence, even when compared to drug dealers, whose each "dealing cycles" last a few days to a few weeks (Caulkins et al., 1999). Third, the size of co-offending groups involved in cannabis cultivation should be larger than what is usually found for more straightforward offenses. Maintaining a cannabis cultivation site involves numerous tasks often performed by different offenders, such as installing equipment, plant maintenance, harvesting, and manicuring. Hence, Bouchard (2007) found that the average size of offending groups per cultivation site ranged from a minimum of three to more than a dozen individuals involved in larger sites. Studying variations in co-offending dynamics and risks is, therefore, especially meaningful for this particular offense.

Finally, industry growth and the extensive division of labor involved in cultivation both multiply involvement opportunities for women and juveniles (Hafley and Tewksbury, 1996). In fact, it gives adults and youths an opportunity to become co-offenders (Sarnecki, 2001). Juveniles might be motivated to start their own cultivation sites in spite of the numerous obstacles this entails. Examples include the specialized skills required for such sophisticated cultivation, the necessary startup capital for equipment purchases and set up, or simply accessing vehicles needed to carry materials and plants (Weisheit, 1992; Wilkins and Casswell, 2003; Potter, 2006). In short, juveniles may need adult resources for the instrumental needs associated with commercial cannabis cultivation. As for adults, they may need juveniles for both instrumental (e.g. perform low-level tasks) and expressive reasons (e.g. avoid performing risky tasks), as has been found for drug dealing in past studies (Bourgois, 1995; Johnson et al., 2000; Little and Steinberg, 2006; Padilla, 1992).

In this study, we distinguish juvenile growers who are embedded in adult networks from those who are embedded in juvenile networks. We also examine the distinct contribution of different co-offending and network measures on success in avoiding arrest. While most previous studies examined cost avoidance issues in samples of adult offenders (for an exception see Kazemian and Leblanc, 2007), analyzing the patterns in juveniles' contacts with the criminal justice system at an early stage may be especially important in understanding persistence and desistance from crime. The next section provides information on the data and methods allowing us to fulfill the objectives of this study.

DATA AND METHODS

In November 2006, 1262 questionnaires were distributed and administered throughout four secondary schools located in two Regional County Municipalities (RCM) in Quebec. The schools were relatively small, so one trained research assistant covered all the classes for one school in a day. The schools had previously authorized the research and students were guaranteed their answers would remain confidential. Questionnaires were completed using the scantron method. These two RCMs have respective populations of 18,000 and 23,000. Both RCMs are situated in a region that is economically dependent on agriculture and two major industrial plants, and with per capita income ($ 27,000) comparable to the rest of the province ($29,000).[5]

The participation rate was 100 %; however, 4 % of the participants did not have valid questionnaires and were removed from analysis. Therefore, a total of 1166 participants were included in our analysis. A pre-test was conducted in one of the schools before the start of the study to improve the clarity of questions and to limit the number of questions. The questionnaire administered contained 54 multiple-choice questions on criminal activity, victimization, drug use and cannabis cultivation. DEP-ADO instrument version 3.1 was used to measure drug and alcohol use (Germain et al., 2005), while a combination of the Jessness Inventory (1988) and MASPAQ (Leblanc, 1996) was used for self-reported delinquency. The survey objective was to investigate cannabis cultivation among the region's youth, so the last 24 questions were devoted to that particular offense (the cultivation questionnaire was developed by the first author of the current study).

[5] Indicators are based on 2006 census figures from Institut de la Statistique du Quebec (http://www.stat.gouv.qc.ca)

Sample of growers

The last part of the questionnaire had three questions that were designed to be answered by every respondent, whether or not they had participated in cannabis cultivation. The first two questions asked respondents about the number of juveniles and adults they knew who were active cannabis growers. The third question asked respondents the age at which they participated in the cannabis cultivation industry for the first time. If they never participated, the survey was over for them. This third question (or another one about participation that followed) received a positive response from a total of 194 respondents; this group was retained for further consideration. In order to be included in the final sample of growers, participants had to answer a majority of the additional cultivation-related questions, and had to offer consistent and credible answers for the rest of the questionnaire. A total of 19 participants were removed from the sample due to inconsistent or invalid answers[6]; the final sample was composed of 175 growers (we refer to all participants as "growers" for the remainder of the paper). Note that almost all of them were active in the 12 months preceding the survey (12% past year prevalence).

Our sample size of 175 growers indicates that 15 % of these high school students, at one point in their life, had been involved in cannabis cultivation. This impressive prevalence rate compares to the prevalence rates for drug dealing found in early 1990s studies at the peak of the crack era in the United States (Saner et al., 1995), and is much higher than the prevalence rates found in high school samples, whether in the U.S. (e.g. 6.9% in Haynie, 2001) or in Canada (6% in Smart et al., 1992). No previous studies reported prevalence rates for high school sample of this kind, but others reported a prevalence rate of participation in cultivation for samples of cannabis users – all of them lower than the one found here. Cohen and Kaal (2001) found a rate

[6] The most common reason for excluding a participant was missing data. We systematically excluded respondents who did not answer a majority of the cultivation-related questions.

of 8% in a sample of 214 cannabis users in Amsterdam while Field and Casswell (1999) found a 3.4% rate in New Zealand. On the one hand, the high prevalence rate found in our sample was expected, because the region under study has been especially chosen for that reason. On the other hand, the unusually large number of adolescents involved should induce policy makers to further examine the specific circumstances that helped the expansion of the industry (see Bouchard et al., 2008).

Measures

Dependent variables

The study has two dependent variables: arrest and detection. If a respondent was arrested one or more times for cannabis cultivation, they were coded into the "arrested" category. Some respondents were not arrested, but reported that they had participated in a cultivation site that was detected by the police. They were coded in the "detected" category. Detection was chosen as an additional dependent variable for both pragmatic and theoretical reasons. First, arrest for cannabis cultivation is a relatively rare event, and considering the issue of detection allowed us to increase our sample size and statistical power. Previous studies suggested that the risks of detection are far greater than the risks of arrest, even more so for youth. Bouchard (2007) estimated that 19-37 % of outdoor sites result in detection, whereas the risk of arrest for a cultivation offense is only 2-5 %. In this sample, 29 out of 175 (16.6%) respondents reported having been arrested for cannabis cultivation, whereas the sample increases to 47 (26.8%) participants when we include those who participated in a site that was detected, whether or not they were also arrested. These arrest rates are higher than expected, and likely reflect the focused police attention on growers in this region. Second, it is possible that "arrested" and "detected not arrested" participants are different, the latter category having avoided most of the downfall. The differences between these categories will be examined later in the paper.

Main independent variables: criminal networks

We use four variables related to our respondents' criminal network—three are specific to cannabis cultivation. The first measure is the size of the participant's co-offending group the last time they participated in a cultivation site. We asked the following question to all participants: "How many persons have participated (you included) to this cultivation site, from start to finish"?[7] The number of co-offenders was originally a seven category ordinal variables (from none [alone], to more than 15 co-offenders) that was recoded into a five category ordinal variable for better representation of all categories (alone, two, 3-4, 5-6, 7+). Univariate results show that the mode for number of co-offenders is between 3 and 4, which is consistent with previous studies and general offending (Reiss, 1988; Warr, 1996) on cannabis cultivation. Using interview data, Bouchard (2007) found that 4 was the mean number of co-offenders for a typical cannabis cultivation site.

TABLE 1 ABOUT HERE

The other two variables of interest concern the larger criminal network of respondents, as opposed to the more direct co-offending group for a specific venture. All respondents were asked the following question: "Among all of the youth that you personally know (friends and acquaintances) who attend your school, how many have participated in a cannabis cultivation site in the past 12 months?" Then, a similar question was asked, which involved the number of adult growers they personally know. At least two specific features of these questions should be

[7] Translation from the French by the first author of the current study.

underscored. First, they are crime specific, which was important because our dependent variables, arrested and detected, are also crime specific. Second, they are age-specific, as they differentiate between youth and adults networks. We wanted to examine whether embeddedness in an adult or juvenile network had an influence on the odds of being arrested, controlling for the intensity and seriousness of participation.

Initially, network size was a seven category ordinal variable (from none to more than 15 adults/juvenile known). We re-coded the variables in two ways. First, we compared each respondent on the number of adult and juvenile growers they knew. Those respondents who reported knowing more adults than juveniles were considered to have a predominantly adult grower network (19%), and vice-versa (44%). More than one-third (34%) knew the same number of juvenile and adult growers (see Table 1). Second, we also chose to dichotomize the variables, isolating respondents who knew an extensive number of juvenile growers, and those who knew an extensive number of adult growers: (23.5 %) knew more than 15 adults and 53 respondents (31.7 %) knew more than 15 youth. The idea was to verify whether the interaction of network type and large size has an independent impact on the risks of being arrested. We tried grouping the categories in different ways, but found that the only discernible patterns were found with these hyper-connected growers. We used regression tree analyses (CHAID) to test whether the cutting point (15) is a good one. First, it can identify one, or multiple cutting points, if they are found to differ significantly from each other in relation to the dependent variable. Second, both the original and the dichotomized variable can be entered simultaneously in the CHAID model, allowing us to test which variable structure, if any, is the most suitable for the analysis.

Finally, 30 respondents were self-identified gang members. Every respondent was asked the following question: “In the past 12 months were you involved in an organized gang?” Even though group offending is commonly associated with gang membership, the two concepts should be differentiated (Carrington, 2002; Warr, 2002). Status as a gang member and the visibility it provides may induce additional risks independently of co-offending patterns (Brownfield et al., 2001).

Control variables

In order to examine the independent effect of network and co-offending dynamics on arrest and detection, we control for other risk factors which have been identified in past studies. Because risks may originate from sources outside the individual-level, the first set of control variables concern aspects related to the cultivation site in which the respondents participated. First, we controlled for the type of site in which the respondent most recently participated, defined as either outdoor or indoor. The distinction merits attention because outdoor sites have been shown to be at greater risk of detection (Bouchard 2007; Wilkins et al., 2002). In the present study, the reported rate of participation in an outdoor cultivation site was 63.5 % (Table 1). This is consistent with expectations for youth involvement in cultivation, which should be found in the less sophisticated, less capital-intensive outdoor sites (Bouchard, 2007; 2008). It is also not surprising within a region dependant on agriculture and known for outdoor cultivation. Despite its higher detection rate, it is easier for outdoor growers to evade arrest. Unlike indoor sites, outdoor growers can leave the plot unattended for extended periods of time, or only visit the plots at night. Arrest data for Quebec show that only 14 % of outdoor detection lead to arrest, whereas 76-95 % of detection of indoor sites lead to arrest (Bouchard, 2007).

Participants of larger, commercial sites may be at higher risk of detection and arrest than those who cultivate for their personal cannabis consumption (Bouchard, 2007). Consistent with previous research, sites that contained more than 20 plants were considered “commercial sites,” which suggests that some reselling of cannabis is highly likely (Bouchard, 2007; Weisheit, 1992; Hough et al., 2003). Table 1 shows that close to 60 % (59.4) of our sample participated in a commercial site. The role of high school students involved in commercial or indoor cultivation sites may be limited to short-term hired labor, as opposed to full-time “owners” (which means they are accountable for the site, not owners of the land/property). Because these different roles may have an impact on risks, we also control for type of participation (laborers vs. owners) in subsequent analyses. This is the equivalent of controlling for differential crime seriousness. Univariate analysis shows that 61.1 % of respondents in our sample were responsible of their own cultivation site.

Criminal career research has shown that frequency of offending is generally related to higher arrest rates, although some high-rate offenders successfully evade detection (Chaiken and Chaiken, 1985). Two measures of intensity of participation were included: the number of years spent as an active grower (actual age – age of onset), and whether the respondent participated in more than one site in the past year. On one hand, the longer the time spent as a grower, the more opportunities for being known to the police. On the other hand, it is also possible that experienced offenders learn to avoid arrest (Saner et al., 1995), which would increase the arrest risks of novice growers, especially if they occupy lower, more risky roles. The median number of years of experience in our sample is 1.5 and 47.4 % of the respondents participated in multiple sites. We also expect a positive relationship between participation in multiple sites and arrest.

A second set of control variables includes typical risky behaviors identified in prior research on risks: involvement in other crimes, involvement in drug dealing over the previous 12-month period, regular hard drug use, and regular cannabis use. Involvement in other crimes is a dichotomous variable that indicates whether respondents also participated in any of the following crimes in the past 12 months: mischief, assault, theft, possession of firearms fraud, and sexual offenses. Specialization in crimes has been shown to be beneficial in criminal achievement, at least as it relates to criminal earnings (Tremblay and Morselli, 2000; Hagan and McCarthy, 1997; McCarthy and Hagan, 2001). As for arrest, individuals who were involved in non-drug related crimes were also more likely to be arrested for marijuana related offenses (Fergusson et al., 2003). A little more than half the sample (57.5 %) reported involvement in other crimes. We also examined whether growers were involved in drug dealing, which can attract additional attention from law enforcement and increase the likelihood of detection for participation in other offenses, such as cannabis cultivation. Half the respondents (50.3 %) in the present study reported selling drugs.

Past research on drug markets suggested that hard drug users can become unreliable and sloppy in their business dealings and are not trusted by higher-level dealers (Adler, 1993; Johnson and Natarajan, 1995; Matrix Knowledge Group, 2007). Kazemian and LeBlanc (2007) found that drug use was a significant negative correlate of differential cost avoidance in late adolescence or early adulthood. Respondents were considered as regular users of hard drugs if they reported using either/or cocaine, hallucinogens, heroin, amphetamines, or other drugs at least once a week[8]. Table 1 shows that a little more than 20 % of our sample admitted to using hard drugs on a weekly basis. Regular use of cannabis was more common with a 58.3 % prevalence rate. As expected, cannabis use rates are markedly higher in our sample than among a typical high school sample. For instance, a survey administered among Ontario high school students found that 4.8 % use cannabis weekly (Adlaf and Paglia-Boak, 2007). Traditionally,

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[8] Occasional hard drug use and cannabis use was prevalent with 21.7% and 19.6% of the sample respectively. Respondents were considered occasional users of hard drugs if they reported using either/or cocaine, hallucinogens, heroin, amphetamines, or other drugs once a month. Occasional cannabis use was also defined as once a month.

drug use is extremely high among young offenders (Newburn, 1998). In a self-report survey of Canadian adolescents, Smart et al. (1992), matched a group of drug dealers with a group of non-sellers, and found that 97% of the dealers used cannabis in the last 12 months compared to only 16.3% of non drug sellers. The drug dealing sample also had a significantly higher rate of hard drug use. Inciardi and Pottieger (1991) interviewed 254 crime-involved youths in Miami and found 87% used marijuana daily and 11% used marijuana occasionally (3+ times per week). Drug use is also associated with heightened risks of arrest: For example, Fergusson et al. (2003) found that increased cannabis use and other illicit drug use were associated with increased rates of arrest for cannabis related offenses.

The final set of control variables includes two demographic variables, age and gender. There were 58 females and 115 males in the sample: the mean age is 15.7 years. Regarding risk, younger adult offenders have been shown to take more risks than older adults and they tend to be involved with larger groups than their older counterparts (Morselli and Tremblay, 2004; Bouchard, 2006; Natarajan and Belanger, 1998; Reiss, 1988). It is not clear whether the same relationship can be found in a sample of juveniles only. Gender may also be related to detection. Fergusson et al. (2003) discovered that males are significantly more likely than females to be arrested for cannabis related offenses.

Analytical strategy

The small number of respondents in the reference category of our dependent variables presented an analytical challenge. We addressed this challenge in three ways. First, we assessed the relationship between each independent variable against the dependent variables at the bivariate level[9] and we chose only the most significant predictors for multivariate analyses. Second, we determined the most efficient and parsimonious logistic regression model through an iterative process, not overloading the models at each stage. Third, we validated these analytical choices by comparing the logistic regression results to those obtained with a classification tree/ recursive partitioning procedure (CHAID). Both methods are suitable for the prediction of categorical dependent variables.

To prepare for logistic regression analyses, we tested for multivariate outliers, and found that no variables had a standardized malahanobis distance greater than 3.29. Nested logistic regression models predicting arrest for cannabis cultivation were performed in three stages, running two models at each step. The first stage examines the role of network type on arrest; the second stage considers the interaction of network type and large size; and the third stage is the best model, including only variables that were shown to be significant or close to significance. The same models were used for detection.

Classification tree models were developed using CHAID in SPSS 16.0, which stands for Chi-square Automatic Interaction Detector. As the name suggests, this method is designed for uncovering sometimes complex interactions, which would be more difficult to detect using traditional techniques. The CHAID algorithm starts by examining the statistical significance between each predictor and the dependent variable, until the most statistically significant Chi-Square value is found (Kass, 1980). The sample is then divided further according to the values of

[9] Before bivariate analyses we tested for the pattern of missing values. Little's MCAR test revealed that there was no significant deviation from a pattern of values that are "missing completely at random" ($p > .05$). Because none of the variables had a significant number of missing values, we considered running our models using listwise deletion. Doing so resulted in a loss of 65 respondents, something we could not afford given the small sample size. Strategies available for imputation of missing values for dichotomous variables are limited, and none of the ones available are truly satisfying. Because missing values were few and randomly distributed, we opted for the straightforward median (for ordinal variables) and mode (for dichotomous variables) imputation. Note that none of our dependent variables had missing values.

that predictor and the selection procedure is repeated for each partition, until the most significant predictor is found. The tree stops developing once no further partitioning can be accomplished within the specified level of significance. The outcome of the partitioning process is the creation of more or less homogeneous groups with regard to the dependent variable (Silver and Chow-Martin, 2002). One of the advantages of CHAID is that it is a nonparametric method; it thus performs well with non linear, highly skewed variables, or those with an ordinal structure (Lewis, 2000), such as the ones considered in the current study. CHAID is especially useful for exploratory analyses, or when used in interaction with other methods, testing more theoretically-driven models (as we do here).

RESULTS

We start by examining the bivariate relationship between arrest and each of our independent variables (Table 2, columns 1-4). Table 2 shows that only 3 of 18 variables are significantly related to arrest: years of experience, type of site, and predominantly adult network. That is, the odds of being arrested were higher for growers who were active for a longer period, who participated in indoor cultivation sites (26.3 vs. 11.9%), and for those who were not embedded in an adult grower network (19.4 vs. 3.2%). Note that only one grower embedded in an adult network was arrested overall. We also considered variables that were moderately significant and found that being embedded in a predominantly youth network was related to arrest. Contrary to the results for adult network, the relationship was positive: growers who were embedded in a youth network were arrested more often than others (21.4 vs. 13.3%). Those with a balanced network were also on par in regards to arrest: they were no more, or no less likely to be arrested than their counterparts (14.5 vs. 17.5%).

The interaction of type and large size of network may also matter. Table 2 shows that being embedded in a large adult grower network was moderately associated to arrest: the larger the adult network, the lower the odds of being arrested (10.3 vs. 18.4%). No such effect was found for large youth networks. Regular cannabis use (19.6 vs. 11.8%) and participation in a commercial site (18.8 vs. 12.7%) were the only other variables positively associated to arrest.

Note that similar results were found once we extended our analysis to also consider the respondents who participated in a detected site but who were not arrested (Table 2, last 3 columns). New variables emerged as potentially associated to detection: gang membership, large youth grower network, and drug dealing. The relationship between detection and the first two variables was positive, whereas drug dealing appeared to be a protective rather than a risk factor. Overall, we found that gender, age, regular use of hard drugs, site ownership, working in multiple sites, belonging to a balanced network, and direct number of co-offenders were not associated to arrest or detection at the bivariate level. The absence of a relationship between direct co-offending and our dependent variables might indicate that an offender's larger criminal network is more pertinent to cost avoidance issues.

TABLE 2 ABOUT HERE

Next, we tested the relationship between arrest/detection and our independent variables at the multivariate level using a nested logistic regression model. In order to limit the number of predictors for multivariate analyses, we did not consider the variables with significance levels over .30 in a two-tailed test of significance (for either arrest or detection) in Table 2. We used this cut-off point in order to make sure that we do not miss potentially significant variables in later analyses. Additional analyses showed that some variables in the .10 to .30 range ended up having an impact at the multivariate level, while none of the variables above that cut-off point had such an effect on the dependent variables. Moreover, CHAID analyses will allow us to include all variables and verify whether some of the discarded predictors become important when considered in interaction with others. We performed the analysis in three stages, running two models at each step. The first stage examines the role of network type (predominantly youth/ adult) on arrest, the second stage looks at the interaction of network type and large size, and the third one is the best model, which only included variables shown to be significant or close to significance. At each stage, criminal network variables (including gang membership) were entered in model 2, after the controls were entered in model 1.[10]

Models that did not include information on the respondent's criminal network (model 1) were generally poor in accounting for arrest. Consider the first stage of model 1, on the extreme left of Table 3. The model is only marginally significant (χ^2 = 9.9 (5) p=.08), and only one significant predictor emerged: type of site (*B* = .86, p≤.01). The coefficient is positive, indicating that working on an indoor site is associated with a higher risk of arrest. The model greatly improved when we added the criminal network variables in the second block (χ^2 = 19.4 (8) p ≤ .01). The Cox and Snell pseudo R^2 almost doubled, explaining 11 % of the total variance. Two of our network variables are marginally significant: gang membership (*B*=-1.06, p≤.10) and being embedded in an adult network (*B*=-1.84, p≤.10). The negative coefficient suggests that gang membership may be a protective, rather than risk factor in regards to arrest. The negative

[10] We tested for multicollinearity with two standard methods. First, correlation coefficients were assessed using Spearman's rho (Appendix A). Results show that no correlations were higher than .42 (between large youth networks, and large adult networks). To further test if multicollinearity would pose a problem, we entered the variables from our logistic regression model into a linear regression model and we examined the tolerance levels for each of the predictors. All the variables had a tolerance level of above .7, which indicates that multicollinearity is not a hindrance (Meyers et al., 2006).

relationship between adult network and arrest is consistent with findings at the bivariate level. These growers working, or surrounded by adult growers are rarely arrested as a consequence of participation in the cultivation industry. The *B* coefficient for youth networks is positive, but not significant after controlling for other factors.

Similar results were found when we interacted network type with size, at stage 2: having a large adult grower network was negatively related to arrest, whereas the opposite was true for large youth networks (columns 4-5, Table 3). Here, however, none of the variables were statistically significant, suggesting that network type seems to matter more than size. These results still highlight the fact that specifying the age-specific composition of youth network is important in assessing their level of success, at least in avoiding the costs of crime.

The best model solution (last two columns, Table 3) warrants two additional observations. First, years of experience and regular use of cannabis both emerged as marginally significant, positive predictors of arrest. We interpret the result with regard to experience as a consequence of the increased opportunities for apprehension associated with a longer participation in the cultivation industry. The positive result for cannabis use could reflect the increased visibility and recklessness that might come with heavy use, increasing the likelihood of law enforcement apprehension compared with simply being involved in cultivation.

TABLE 3 ABOUT HERE

We ran the same models using detection as the dependent variable, in hope of increasing statistical power. There were many similarities with the arrested model but some differences are worth noting (see Table 4). First, growers who were also involved in drug dealing were less likely to be detected than others. This result may reflect the kind of environment in which grower-dealer operates, something that will be explicitly considered in the CHAID analysis. Second, gang membership no longer appeared to be a protective factor. Gang membership remained non-significant throughout all stages, indicating that many gang members participated in a site that was eventually detected, without being arrested themselves (see Table 3). Third, being embedded in a youth network does not appear to be a risk factor as such (stage 1), but it can become risky with large sizes (stage 2): being embedded in a large youth network significantly increased the odds of having participated in a detected site ($B=.9$, $p\leq.05$). The significant effect was lost, however, once we ran the best model solution. Years of experience, drug dealing, and predominantly adult network emerged as the most significant predictors at that last stage. Yet, the same reverse effect remains: a large grower network size is only risky when network members include a majority of youths.

TABLE 4 ABOUT HERE

CHAID ANALYSIS

We tested the relationship between criminal network and cost avoidance with a classification tree analysis, using the CHAID algorithm. CHAID allows us to uncover interaction effects and relationships that may not have been discovered with logistic regression. One feature of CHAID is that we can enter all variables in the model at the same time and let the algorithm specify the combination of predictors and variable splits that are pertinent to cost avoidance. We used the p.≤ 10 level instead of the $p\leq.05$ level as a necessary condition for variable selection in order to be consistent with the small statistical power allowed by our sample size. Parent nodes could not be split further if they contained fewer than 25 cases, and the minimum number of child nodes for inclusion was set at 10 cases. No maximum tree depth was specified. The results are illustrated in Figure 1 and Figure 2.

FIGURE 1 ABOUT HERE

FIGURE 2 ABOUT HERE

Figure 1 shows the results of the CHAID analysis for arrest. Consistent with the results of the logistic regression (best model, Table 3), the analysis suggests that type of site is the most significant variable to take into account. Indoor growers are arrested more than twice as often as outdoor growers (26.3 vs. 11.9%). Yet, each variable interacts with one or two additional variables, suggesting the presence of interaction effects and distinct profiles within each category. This is where we uncover that risks are equally low for every outdoor grower. For example, outdoor growers who also use cannabis regularly and who are embedded in youth networks have moderately high risks of being arrested (20.3%, n = 59). Conversely, none of the regular users of cannabis who are embedded in adult networks were arrested (0%, n = 14). This finding confirms the importance of network type in assessing the odds of being arrested. Interestingly, it also specifies the circumstances in which the network is likely to have an impact.

Figure 1 shows that indoor cultivation is much riskier, but most importantly, it shows for whom it is riskier: growers embedded in youth networks. Risks are almost three times lower for indoor growers who are embedded in adult networks or who have a balanced network (42.9 vs. 16.7%). The risks are further reduced even more if one’s involvement is limited to being a hired laborer who is embedded in an adult network: none of the 14 indoor growers who fit this description were arrested.

The classification tree developed for detection reveals a slightly different picture (Figure 2). First, the most important variable is type of criminal network, not type of site. Those growers who are embedded in adult networks rarely participated in cultivation sites that were detected (9.7%), even though nearly one third of the other respondents were detected (30.6%). Risks are high for most of these growers embedded in youth or in balanced networks, except for those non regular cannabis users involved in outdoor sites (20.3%), who represent the majority of growers in the sample (n = 79). Second, the CHAID analysis for detection parallels the finding of the logistic regression that drug dealing may be a protective rather than a risk factor. However, the CHAID analysis specifies for whom this is especially the case: grower-dealers who are embedded in adult networks (n = 16). None of these respondents were arrested or participated in a detected site, which further illustrates the important role that adults might play in the criminal career of juveniles.

Discussion

Lin's (2001) network theory of social capital proposes that individuals mobilize resources embedded in their social networks for two types of actions: instrumental actions (such as obtaining better jobs), and expressive actions, where social networks help preserve something individuals already have (such as health or freedom). A core implication of Lin's theory for our present purpose is that social relations that facilitate instrumental needs, such as making money, may differ from the relations that facilitate preserving expressive needs, such as one's freedom. Research on criminal achievement has mainly been concerned with examining the relationship between social capital and instrumental actions, using earnings attainment as the outcome variable. The findings of these studies were clear: offenders who are open to collaboration with others and who manage their criminal network more effectively earn more money from crime than others (McCarthy and Hagan, 2001; Morselli and Tremblay, 2004; Morselli et al., 2006). The current study turned to the role of criminal networks in fulfilling offenders' expressive need of avoiding the costs of crime, something that has been overlooked in previous research.

Our analysis focused on young offenders, particularly those involved in cannabis cultivation. We were fortunate in that we had access to data on a region known for its extensive cannabis industry. The data offer rich and offense-specific information on the nature of youth participation and on the size and type of grower network in which these youths are embedded. Realizing that the cultivation industry constitutes an opportunity for contact between adolescents and adult growers, we examined the impact of different network dynamics (predominantly adult, or youth grower networks) on growers' relative success in cost avoidance. Initially, it was difficult to predict whether being embedded in an adult grower network would be more, or less risky than being enmeshed in a more homogeneous youth network. On one hand, we expected that adolescents surrounded by adult growers would occupy low-level, risky jobs that could more frequently lead to contacts with the police. On the other hand, we also expected that being close to more experienced growers would lead these young growers to work in more sophisticated cultivation sites, that is, sites that are better protected from detection.

Our results clearly indicate that the latter hypothesis is the most likely scenario. Only 1 of 31 respondents who reported being embedded in adult networks was arrested as a result of his involvement in cannabis cultivation. The CHAID analysis reveals that most of the other respondents fit two different profiles. The first group described their involvement as hired laborers on indoor sites. Most of the tasks for which growers are typically hired, with the exception of daily maintenance (which is unlikely for most youths), only requires between one and a few days of work: installing equipment, harvesting plants, trimming buds (Weisheit, 1992).

Such sporadic or irregular involvement might not be enough for them to be linked to a particular site, if detected. The possibility that many of these adolescents actually help out their parents, on a cultivation site situated in their own home is also likely. Even in the case of a seizure, these youths would not be held responsible for the site, and would avoid apprehension.

The other group of non-arrested growers embedded in adult networks is of a different kind: outdoor growers who use cannabis regularly. Regular cannabis use is a risk factor for most youths, but it is not for those embedded in adult networks. More importantly, 11 of 14 of these growers reported being owners of their own outdoor site, instead of being hired laborers on sites of others. Sporadic involvement thus cannot explain why none of these growers were arrested, compared to the 12 (out of 59) growers arrested who fit this profile, but who were embedded in youth networks. Instead, we turn to social capital and the role of mentors as the most likely explanation for this result. Past studies have shown that young drug dealers or novices sometimes benefit from the tutelage of more experienced offenders (e.g. Adler, 1993; Bourgois, 1995; McCarthy, 1996; Padilla, 1992; Ruggiero, 1995). Few studies have linked such apprenticeship to outcomes, such as whether mentored offenders were more successful than others at cost avoidance. One notable exception is Morselli et al.'s (2006) study, which found that mentors were independently related to the number of days that inmates were incarcerated in the three years preceding their current incarceration.

Being surrounded by more experienced growers might increase young growers' criminal capital and accelerate their learning curve (Kleiman 1989; Caulkins, 2001). Offences like cannabis cultivation require a certain amount of learning before growers are considered comfortable, competent, or completely independent (Weisheit, 1992). The process involves trial and error, and young growers and novices in general are prone to mistakes. Some of these mistakes have more consequences than others, including some that lead to detection. Being co-opted in adult networks might help growers avoid some of these mistakes, and start them higher on the learning curve. Young offenders are especially likely to learn and be influenced by other offenders when the latter are older. Bayer et al.'s (2008) analysis of recidivism among a sample of over 8,000 incarcerated juvenile offenders showed that exposure to older peers exerts more influence on young offenders' behavior upon release than exposure to peers similar in age. This was especially the case for burglary, robbery, and drug offences. Future research would benefit from incorporating criminal capital and social capital measures in a longitudinal framework, where the impact of both concepts on a performance outcome could be assessed systematically.

The current study is also interested in the size of respondents' networks. Size usually implies a risky connotation in illegal drug markets (Adler, 1993; Desroches, 2005; Jacobs, 1996; Reuter, 1985). However, other research suggests that larger network sizes might increase security for certain players in the network who can use their advantageous position to "hide" from detection (Baker and Faulkner, 1993; Dorn et al., 1998). In Morselli et al.'s (2006) mentor and criminal achievement study, an offender's effective network size was positively associated to illegal earnings, but not to the number of days incapacitated. Nonetheless, who these offenders knew (having a mentor, or not) was important for both criminal achievement indicators. Interestingly, as far as cost avoidance is concerned, the current study also finds that *who you know* might matter more than *how many you know*. First, the size of the cultivation site (in the number of co-offenders, or number of plants) was not directly related to arrest or detection. This non result is interesting, as it suggests that not mere organizational size, but other individual (e.g. network size) and contextual factors (e.g. type of site) play important roles in detection. Second, we found that having a large adult network is also a protective factor, but one that is less strongly associated to arrest risks than being embedded in an adult network. However, the results regarding youth networks suggest that size matters. Although being embedded in a youth network is not found is a risk factor per say, having a large youth network is a significant predictor of detection in at least one of the logistic regression models. Additional analyses (not shown) suggested that these youths are more likely to be involved in predatory crimes and to be gang members than growers embedded in adult networks. Although involvement in other crime and gang membership does not appear as independent risk factor in our analyses, their effect on arrest might be channeled through the network. Uncovering those mechanisms that hinder or facilitate cost avoidance through a longitudinal research design should be the focus of future research.

The current study has limitations that should be taken into account when interpreting these findings. First, our sample size is smaller than we would prefer. We addressed this issue by comparing the results of two multivariate methods, which confirmed the robust finding regarding the protective effect of adult grower networks. We hope future research can conduct similar analyses using larger samples. Second, our data relies exclusively on self-reported delinquency and while self-report measures provide many advantages over the use of official data, our study would have benefited from cross-informant validity measures. In particular, cross-validation with official data would have been especially useful for the main dependent variables. Nevertheless, past research showed that compared to official statistics, youths who have officially been involved with the system self-report their delinquency at a substantial rate (Thornberry and Krohn, 2000; Huizinga and Elliott, 1986)[11] . Third, our data does not indicate specifically

[11] Correlation between official and self-reported delinquency rates for African-American males (.35) are considerably lower than for African American females and Caucasian males (.58-.65) (Thornberry and Krohn, 2000).

whether a respondent was mentored or not, or whether respondents can identify such mentors in their networks. Our data is limited to identifying those respondents whose grower network includes a majority of adults or youths. Given our findings, we can only conjecture on the impact of that proximity to experienced growers might bring to these young offenders. This finding might be interesting enough to induce future research in incorporating more detailed questions on the nature of such relationships. Fourth, our data allow us to assess the size and composition of an offender's network but does not allow us to consider a respondent's position within their network. Recent studies on youth networks have examined the influence of peers on offending behavior (Haynie, 2001; Haynie, 2002; Payne and Cornwell, 2007) and found that network structure matters. For example, using data from a representative sample of 13,000 adolescents in the United States, Haynie (2001) found a stronger association between peers and delinquency for adolescents who are located in a central position within their friendship network, as well for those who are enmeshed in denser networks (p. 1048). The influence of different network measures on cost avoidance have yet to be investigated, but offer a promising avenue for research. Last, one should be careful in generalizing the findings of this study to other populations. As mentioned earlier, the location was chosen for its high prevalence of youth participation in the cultivation industry. It is unclear whether similar patterns would be found in other samples where cannabis cultivation is not as prevalent. Similar studies should be undertaken in order to verify whether the general patterns that we found holds when analyzing different samples, and different types of crime.

Despite these limitations, the current study contributes to the criminal achievement literature by showing the importance of criminal networks on early criminal career success. The next step is to analyze the implications for the residual careers of these young offenders (see

Kazemian and Leblanc, 2007). Both the ability to earn significant money from crime and the ability to avoid the costs of crime have been linked to persistence in crime and recidivism (Robitaille, 2004; Shover and Thompson, 1992). Young offenders working with older offenders have been shown to progress and occupy leadership roles later on in their career (Morselli et al., 2006; Sullivan, 1989). The frequency, or even the existence of contacts between young and older offenders, largely been overlooked by criminological research, might emerge as one of the most important predictors of success and persistence in crime.

References

Adler, P. A. (1993). *Wheeling and Dealing: An Ethnography of an Upper-Level Drug Dealing and Smuggling Community*. New York: Columbia University Press.

Altschuler, D. M., & Brounstein, P. J. (1991). Patterns of drug use, drug trafficking, and other delinquency among inner-city adolescent males in Washington, D.C. *Criminology*, *29*(4), 589-622.

Baker, W. E., & Faulkner, R. R. (1993). The social organization of conspiracy: Illegal networks in the heavy electrical equipment industry. *American Sociological Review, 58*(6), 837-860.

Bayer, P. J., Hjalmarsson, R. and Pozen, D. E. (2008). *Building Criminal Capital Behind Bars: Peer Effects in Juvenile Corrections*. Forthcoming in *Quarterly Journal of Economics*.

Bekkers, R., Volker, B., Gaag, M., & Flap, H. (2007). Social networks of participants in voluntary associations. Amsterdam: Utrecht University.

Bouchard, M. (2007). A capture-recapture model to estimate the size of criminal populations and the risks of detection in a marijuana cultivation industry. *Journal of Quantitative Criminology*, *23*, 221-241.

Bouchard, M. (2008). Towards a realistic method to estimate cannabis production in industrialized countries. Forthcoming in *Contemporary Drug Problems*.

Bourgois, P. (1995). In *Search of Respect: Selling Crack in El Barrio*. Cambridge: Cambridge University Press.

Brownfield, D., Sorenson, A. M., and Thompson, K. M. (2001). Gang membership, race, and social class: a test of the group hazard and master status hypotheses. *Deviant Behavior, 22*, 73-89.

Burt, R. S. (1992). Structural Holes: The Social Structure of Competition. Cambridge, MA: Harvard University Press.

Carrington, P. J. (2002). Group crime in Canada. *Canadian Journal of Criminology, July*, 277-315.

Caulkins, J., Taylor, A., Johnson, B., and Taylor, L.J. (1999). What drug dealers tell us about the costs of doing business. *Journal of Drug Issues*, 29(2): 323-340.

Caulkins, J. P. (2001). The dynamic character of drug problems. Bulletin on Narcotics, vol. LIII, Nos 1 and 2.

Chaiken, J. M., & Chaiken, M. R. (Eds.). (1985). *Who gets caught doing crime?* Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics.

Coleman, J. S. (1988). Social capital in the creation of human capital. *The American Journal of Sociology, 94*, S95-S120.

Coleman, J. (1990). *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.

Colvin, M., Cullen, F. T., & Vander Ven, T. (2002). Coercion, social support, and crime: An emerging theoretical consensus. Criminology, 40(1), 19-42.

Desroches, F. J. (2005). *The Crime That Pays: Drug Trafficking and Organized Crime in Canada*. Toronto: Canadian Scholar's Press Inc.

Dorn, N., Oette, L., & White, S. (1998). Drug importation and the bifurcation of risks: Capitalization, cut outs and organized crime. *British Journal of Criminology*, 38(4), 537-560.

Erickson, M. L. (1971). The group context of delinquent behavior. *Social Problems, 19*(1), 114-129.

Erickson, M. L. (1973). Group violations and official delinquency: The group hazard hypothesis. *Criminology, 11*(2), 127-160.

Erickson, M. L., and Jenson, G. F. (1977). "Delinquency is still a group behaviour!": Toward revitalizing the group premise in the sociology of deviance. *The Journal of Criminal Law and Criminology, 68*(2), 262-273.

Fergusson, D.M., Swain-Campbell, N.R. and Horwood, L.J. (2002). Arrests and convictions for cannabis related offences in a New Zealand birth cohort. *Drug and Alcohol Dependence, 70*, 53-63.

Feyerherm, W. (1980). The group hazard hypthesis: a Reexamination *Journal of Research in Crime and Delinquency, January*, 58-68.

Germain, M., Guyon, L., Landry, M., Tremblay, J., Brunelle, N., Bergeron, J. (2005). DEP-ADO Grille de dépistage de consommation problématique d'alcool et de drogues chez les adolescents et les adolescentes. Version 3.1, October 2005. Recherche et intervention sur les substances psychoactives - Québec (RISQ)

Gidengel, E., Goodyear-Grant, E., Nevitte, N., Blais, A., & Nadeau, R. (2003). Gender, knowledge and social capital. Paper presented at the Gender and Social Capital, University of Manitoba.

Granovetter, M. (1973). The strength of weak ties. The American Journal of Sociology, 78(6), 1360-1380.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *The American Journal of Sociology, 91*(3), 481-510.

Hafley, S.R and Tewksbury, R. (1996). Reefer madness in Bluegrass County: Community structure and roles in the rural Kentucky marijuana industry. *Journal of Crime and Justice, 19*(1), 75-94.

Harrison, L. D., Erickson, P. G., Korf, D. J., Brochu, S., and Benschop, A. (2007). How much for a dime bag? An exploration of youth drug markets. *Drug and Alcohol Dependence, 90S*, S27–S39.

Haynie, D. L. (2001). Delinquent peers revisited: Does network structure matter? *American Journal of Sociology, 106* (4), 1013–1057.

Haynie, D. L. (2002). Friendship networks and delinquency: The relative nature of peer delinquency. *Journal of Quantitative Criminology, 18*(2), 99-134.

Hindelang, M. J. (1976). With a little help from their friends: Group participation in reported delinquent behaviour. *The British Journal of Criminology, 16*(2), 109-125.

Hough, M., Warburton, H., Few, B., May, T., Man, L-H., Witton, J., and Turnbull, P. (2003). *A Growing Market: The Domestic Cultivation of Marijuana*. York: Joseph Rowntree Foundation.

Huizinga, D., & Elliott, D. S. (1986). Reassessing the reliability and validity of self-report and official measures. *Journal of Quantitative Criminology*, 2(4), 293-327.

Inciardi, J. A., & Pottieger, A. E. (1991). Kids, crack and crime. *Journal of Drug Issues*, 21(2), 257-270.

Jacobs, B. (1996). Crack dealers' apprehension avoidance techniques: A case of restrictive deterrence. *Justice Quarterly*. 12(3), 359-381.

Jesness, C. F. (1988). The Jesness Inventory classification system. *Criminal Justice and Behavior*, 15(1), 78-91.

Johnson, B. D., and Natarajan, M. (1995). Strategies to avoid arrest: Crack sellers' response to intensified policing. *American Journal of Police, 14*(3/4), 49-69.

Johnson, B.D., Dunlap, E., & Tourigny, S.C. (2000). Crack distribution and abuse in New York. In *Illegal Drug Markets: From Research to Prevention Policy*. Edited by Mangai Natarajan, and Mike Hough. Monsey, Ny: Criminal Justice Press.

Kass, G. (1980). An Exploratory Technique for Investigating Large Quantities of Categorical Data. *Applied Statistics*, 29: 119-127.

Kazemian, L., and Le Blanc, M. (2007). Differential cost avoidance and successful criminal areers: random or rational? *Crime and Delinquency, 53*(1), 38-63.

Krebs, V. (2002). Mapping networks of terrorist cells. *Connections*, 24(3), 43-52.

Lai, G., & Siu, Y.-M. (2006). Residential mobility and social capital in urban Shanghai. *Asian Journal of Social Science, 34*(4), 573-599.

Leblanc,M.(1996). MASPAQ, mesures de l'adaptation sociale et personnelle pour les adolescents québécois : manuel et guide d'utilisation (3rd ed.).Montréal, Ecole de psychoéducation, Groupe de recherche sur les adolescents en difficulté, Université de Montréal.

Lewis, R. (2000). An introduction to classification and regression tree (CART) analysis. Conference presented at the 2000 Annual meeting of the society for Academic Emergency Medecine, San Francisco, CA. Available at: http://www.saem.org/download/lewis1.pdf

Lin, N. (2001). *Social Capital: A Theory of Social Structure and Action*. Cambridge: Cambridge University Press.

Lin, N. (2008). A network theory of social capital. In C. D, J. W. van Deth & G. Wolleb (Eds.), The Handbook of Social Capital (pp. 50-69). Oxford: Oxford University Press.

Little, M., and Steinberg, L. (2006). Psychosocial correlates of adolescent drug dealing in the inner city - potential roles of opportunity, conventional commitments, and maturity. *Journal of Research in Crime and Delinquency, 43*(4), 357-386.

Malm, A. E., and Tita, G. E. (2006). A spatial analysis of green teams: A tactical response to marijuana production in British Columbia. *Policy Sciences, 39*, 361-377.

Matrix Knowledge Group. (2007). *The illicit drug trade in the United Kingdom*. London.

Matsueda, R. L., and Anderson, K. (1998). The dynamics of delinquent peers and delinquent behavior. *Criminology, 36*(2), 269-308.

McCarthy, B. (1996). The attitudes and actions of others: Tutelage and Sutherland's theory of Differential Association. *British Journal of Criminology, 36*(1), 135-147.

McCarthy, B., and Hagan, J. (1995). Getting into street crime: The structure and process of criminal embeddedness. *Social Science Research, 24*, 63-95.

McCarthy, B., and Hagan, J. (2001). When crime pays: Capital, competence, and criminal success. *Social Forces, 79*(3), 1035-1059.

Meyers, L., Gamst, G., & Guarino, A.J. (2006). *Applied Multivariate Research: Design and Interpretation*. Thousand Oaks, CA: Sage Publications.

Morash, M. (1984). Establishment of a juvenile police record: The influence of individual and peer group characteristics. *Criminology, 22*(1), 97-111.

Morselli, C., and Tremblay, P. (2004). Criminal achievement, offender networks and the benefits of low self-control. *Criminology, 42*(3), 773-804.

Morselli, C., Tremblay, P., and McCarthy, B. (2006). Mentors and criminal achievement. *Criminology*, *44*(1), 17-43.

Natarajan, M., and Belanger, M. (1998). Varieties of drug trafficking organizations: A typology of cases prosecuted in New York City. *Journal of Drug Issues, 28*(4), 1005-1026.

Newburn, T. (1998). Young offenders, drugs and prevention. *Drugs: Education, Prevention and Policy*, 5(3), 233-243.

Padilla, F. M. (1992). *The Gang as an American Enterprise*. New Brunswick, New Jersey: Rutgers University Press.

Payne, D. C., and Cornwell, B. (2007). Reconsidering peer influences on delinquency: Do less proximate contacts matter? *Journal of Quantitative Criminology, 23*, 127-149.

Piquero, A., Farrington, D., Blumstein A. (2007). *Key issues in criminal career research*. New York: Cambridge University Press.

Plecas, D., Malm, A., Kinney, B. (2005). *Marihuana Growing Operations in British Columbia Revisited*. Department of Criminology and Criminal Justice, University of the Fraser Valley, Abbotsford.

Potter, G. R. (2006). *Weed, Need and Greed: Domestic Marijuana Production and the UK Cannabis Market.* University of Sheffield, Sheffield.

Reiss, A. J. (1988). Co-offending and Criminal Careers. *Crime and Justice, 117*, 117-170.

Reuter, P. (1983). *Disorganized Crime - The Economics of the Visible Hand*. Cambridge, MA: MIT Press.

Reuter, P. (1985). *The organization of illegal markets: An economic analysis*. Washington, D.C.: National Institute of Justice US Department of Justice.

Robitaille, C. (2004). A qui profite le crime? Les facteurs individuels de la reussite criminelle (Who benefits from crime? Individual predictors of criminal success). *Criminologie,* 37(2), 33-62.

Ruggiero, V. (1995). Drug economics: A Fordist model of criminal capital? *Capital and Class, Spring*(55), 131-150.

Saner, H., MacCoun, R., and Reuter, P. (1995). On the ubiquity of drug selling among youthful offenders in Washington, D.C., 1985-1991: Age, period, or cohort effect? *Journal of Quantitative Criminology, 11*(4), 337-362.

Sarnecki, J. (2001). *Delinquent networks: youth co-offending in Sweden*. Cambridge: Cambridge University Press.

Sharp, C., Aldridge, J., and Medina, J. (2006). *Delinquent youth groups and offending behaviour: findings from the 2004 Offending, Crime and Justice Survey*. London, : Home Office.

Shover, N., & Thompson, C. Y. (1992). Age, differential expectations, and crime desistance. *Criminology*, 30(1), 89-104.

Silver, E. Chow-Martin, L. (2002). A multiple modes approach to assessing recidivism risk: Implications for judicial decision making. *Criminal Justice and Behavior,* 29(5): 538-568.

Smart, R. G., Adlaf, E., M., and Walsh, G., W. (1992). Adolescent drug sellers: trends, characteristies and profiles. *British Journal of Addiction, 87,* 1561-1570.

Son, J., & Lin, N. (2008). Social capital and civic action: A network-based approach. *Social Science Research, 37,* 330-349.

SPSS for Windows, Rel. 16.0.1. (2007). Chicago: SPSS Inc.

Steinman, K. J. (2005). Drug selling among high school students: related risk behaviors and psychosocial characteristics. *Journal of Adolescent Health, 36*, 71.e71–71.e78.

Sullivan, M. L. (1989). *"Getting Paid" Youth Crime and Work in the Inner City*. Ithica: Cornell University.

Sutherland, E. H. (1947). *Principles of Criminology* (4 ed.). New York: Lippineott.

Thornberry, T. P., & Krohn, M. D. (2000). The self-report method for measuring delinquency and crime. *Criminal Justice,* 4, 33-83.

Tremblay, P. (1993). Searching for suitable co-offenders. In R. Clarke, V & M. Felson (Eds.), *Routine Activity and Rational Choice* (Vol. 5, pp. 17-38). New Brunswick, New Jersey: Transaction Publishers.

Tremblay, P., and Morselli, C. (2000). Patterns in criminal achievement: Wilson and Abrahamse revisted. *Criminology, 38*(2), 633-659.

Uggen, C., and Thompson, M. (2003). The socioeconomic determinants of ill-gotten gains: Within-person changes in drug use and illegal earnings. *American Journal of Sociology, 109*(1), 146-185.

VanNostrand, L. M., & Tewksbury, R. (1999). The motives and mechanics of operating an illegal drug enterprise. *Deviant Behavior, 20*, 57-83.

Warr, M. (1996). Organization and instigation in delinquent groups. *Criminology, 34*(1), 11-37.

Warr, M. (2002). *Companions in Crime: The Social Aspects of Criminal Conduct*. Cambridge: Cambridge University Press.

Weisheit, R. A. (1991). The intangible rewards from crime: The case of domestic marijuana cultivation. *Crime and Delinquency, 37*(4), 506-527.

Weisheit, R. A. (1992). *Domestic Marijuana: A Neglected Industry*. Westport: Greenwood Press.

Wilkins, C. and Casswell, S. (2003). Organized crime in cannabis cultivation in New Zealand: an economic analysis. *Contemporary Drug Problems*, *30*, 757-777.

Wilkins, C., Bhatta, K., & Casswell, S. (2002). The effectiveness of cannabis crop eradication operations in New Zealand. *Drug and Alcohol Review, 21*(4), 369-374.

Williams, P. (2001). Transnational Criminal Networks. in J. Arquilla and D. Ronfeldt (eds), *Networks and Netwars: The Future of Terror, Crime and Militancy*. Santa Monica: Rand Corporation, pp. 61–97.

Wright, D. R., & Fitzpatrick, K. (2006). Social capital and adolescent violent behavior: Correlates of fighting and weapon use among secondary school students. Social Forces, 84(3), 1435-1453.

Table 1. Coding of the variables and description of the sample of growers (n = 175)

	% (n)
Demographics:	
Gender (Females =1)	33.5 (58)
Mean age	15.7 (SD .99)
Risk factors:	
Involvement in other crimes=1 (Theft, fraud, possession of firearms, sexual offences, assault and mischief =1)	57.5 (96)
Drug dealing=1 (in last 12 months)	50.3 (88)
Regular hard drug use=1 (Use cocaine, hallucinogens, heroin, amphetamines or other drugs at least once a week)	20.8 (33)
Regular cannabis use=1 (Use cannabis at least once a week)	58.3 (95)
Gang member=1 (Member of organized gang)	17.8 (30)
Type of site (Last participation, indoor =1)	36.5 (57)
Intensity of involvement (Owner of cultivation site = 1, hired labour=0)	61.1 (96)
Commercial site =1 (21+ plants)	59.4 (92)
Mean years of exp growing	1.9 (SD 1.49)
Multiple sites=1 (2+ sites)	47.4 (81)
Network variables:	
Predominantly adult network (greater adults than youth in network)	19.4 (31)
Predominantly youth network (greater youth than adults in network)	43.8 (70)
Balanced network (equal adults and youth)	34.4 (55)
Large adult grower network =1 (Knowing more than 15 adults involved with cultivation)	23.5 (39)
Large youth grower network =1 (Knowing more than 15 youth involved with cultivation)	31.7 (53)
Median number of co-offenders (Number of immediate co-offenders)	3-4
Dependent variables:	
Arrested (Arrested for cultivation)	16.6 (29)
Detected (Arrested themselves or someone from the same site arrested)	27.3 (47)

Table 2. Bivariate results predicting arrest for cannabis cultivation and having participated in a detected cultivation site

	% Arrested			% Detection		
	YES (%)	NO (%)	$\chi2$(p)	YES (%)	NO (%)	$\chi2$(p)
Demographics:						
Gender (female=1)	17.2	16.2	.03 (.87)	25.9	27.4	.04 (83)
Age (mean)	15.9 (arr.)	15.7 (n-arr)	.44 (.93)	15.8 (det)	15.8 (n-det)	1.45 (.70)
Risk behaviours:						
Other crimes	15.4	18.3	.26 (.61)	26.0	28.2	.11 (.75)
Drug dealing (last year)	18.2	14.9	.33 (.56)	22.7	31.0	1.54 (.22)
Regular hard drug use	18.8	15.7	.08 (.78)	29.2	26.0	.25 (.62)
Regular cannabis use	19.6	11.8	1.86 (.17)	29.0	23.5	.63 (.43)
Gang member	13.3	17.2	.275 (.60)	36.7	24.8	1.77 (.18)
Type of site (indoor =1)	26.3	11.9	5.81 (.02)*	36.8	22.0	4.29 (.04)*
Intensity of involvement (Owner = 1)	18.4	13.1	.81 (.37)	27.2	26.2	.02 (.89)
Commercial site	18.8	12.7	1.07 (.3)	29.5	22.2	1.08 (.3)
Multiple sites (2+)	14.8	18.1	.34 (.56)	27.2	26.6	.01 (.93)
Years of exp growing (mean)	2.5 (arr)	1.8 (n-arr)	16.38 (.01)*	2.4 (det)	1.7 (n-det)	15.46 (.02)*
Network variables:						
Predominantly adult network	3.2	19.4	4.85 (.03)*	9.7	30.6	5.67 (.02)*
Predominantly youth network	21.4	13.3	1.99 (.16)	31.4	23.8	1.24 (.27)
Balanced network	14.5	17.5	.24 (.63)	27.3	26.7	.01 (.93)
Large adult grower network	10.3	18.4	1.45 (.29)	20.5	28.7	1.03 (.31)
Large youth grower network	18.9	15.6	.29 (.59)	34.0	23.8	1.95 (.16)
Number of co-offenders	3-4 (arr)	3-4 (n-arr)	2.24 (.69)	3-4 (det)	3-4 (n-det)	2.47 (.65)

*p < .05 **p < .01 (two-tailed)

Table 3 Logistic regression predicting arrest for cannabis cultivation

	Network type		Network size + type		Best model	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
	B (S.E.)	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**
Years of experience	.19(.14)	.27(.16) †	.19(.14)	.23(.15)	.2(.14)	.29(.16)†
Drug dealing	-.13(.5)	-.19(.52)	-.13(.5)	-.12(.52)	-	-
Type of site	.86(.43)*	.93(.45)*	.86(.43)*	1.09(.46)*	.9(.43)*	.99(.45)*
Regular cannabis use	.7(.52)	.89(.55)	.7(.52)	.87(.56)	.64(.46)	.87(.49)†
Commercial site	.3(.49)	.34(.5)	.3(.49)	.35(.5)	-	-
Gang member	-	-1.06(.65)†	-	-1.1(.65)†	-	-.97(.65)
Predominantly adult network	-	-1.84(1.08)†	-	-	-	-1.91(1.06)†
Predominantly youth network	-	.22(.45)	-	-	-	-
Large adult network	-	-	-	-1.07(.66)	-	-.74(.62)
Large youth network	-	-	-	.5(.53)	-	-
Constant	-2.92(.58)**	-2.98(.64)**	-2.92(.58)**	-3.05(.61)**	-2.78(.51)**	-2.68(.54)**
Overall % predicted	83.4	84	83.4	84.6	83.4	84.6
$\chi 2(p)$	9.93(.08)†	19.38(.01)**	9.93(.08)†	16.34(.04)*	9.54(.02)*	20.16(.00)**
Cox and Snell pseudo R^2	.06	.11	.06	.09	.05	.11

† p≤.10 *p<.05 **p<.001

Table 4 Logistic regression models predicting participation to a detected cultivation site

	Network type		**Network size + type**		**Best model**	
	Model 1 B (S.E.)	**Model 2 B (S.E.)**	**Model 1 B (S.E.)**	**Model 2 B (S.E.)**	**Model 1 B (S.E.)**	**Model 2 B (S.E.)**
Years of experience	.22(.13)†	.25(.14)†	.22(.13)†	.20(.13)	.24(.12)†	.26(.13)*
Drug dealing	-.92(.43)*	-.97(.44)*	-.92(.43)*	-.98(.44)*	-.78(.41)*	-88(.43)*
Type of site	.55(.37)	.51(.38)	.55(.37)	.63(.38)†	.59(.37)	.6(.38)
Regular cannabis use	.74(.43)†	.73(.45)†	.74(.43)†	.63(.45)	.67(.42)	.63(.44)
Commercial site	.46(.4)	.38(.41)	.46(.4)	.39(.41)	-	-
Gang member	-	.12(.49)	-	.07(.49)	-	-
Predominantly adult network	-	-1.39(.69)*	-	-	-	-1.23(.7)†
Predominantly youth network	-	.17(.38)	-	-	-	-
Large adult network	-	-	-	-.93(.52)†	-	-.74(.56)
Large youth network	-	-	-	.9(.46)*	-	.63(.48)
Constant	-1.96(.46)**	-1.83(.5)**	-1.96(.46)**	-1.92(.47)**	-1.73(.4)**	-1.61(.41)**
Overall % predicted	73.1	72.6	73.1	74.3	72.6	74.3
$\chi2$(p)	12.95(.02)*	19.76(.01)**	12.95(.02)*	18.18(.02)*	11.62(.02)*	20.84(.00)**
Cox and Snell pseudo R^2	.07	.11	.07	.10	.06	.11

† p≤.10 *p<.05 **p<.001

Figure 1. Classification tree (CHAID) analysis with arrest as the predicted outcome

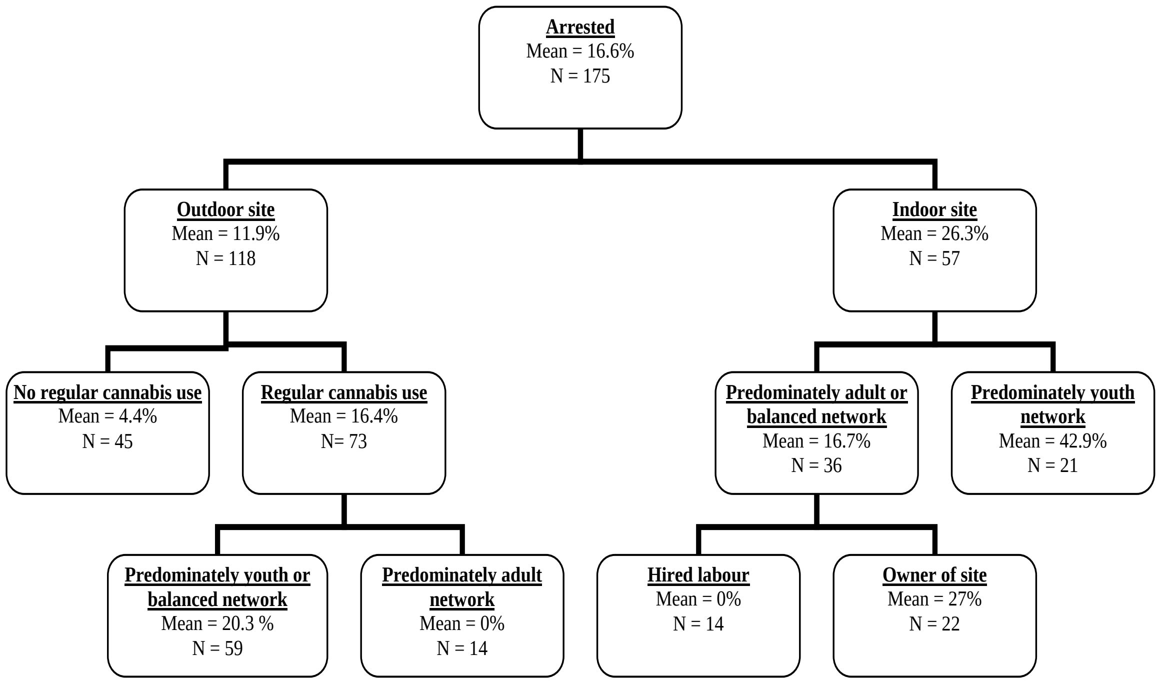
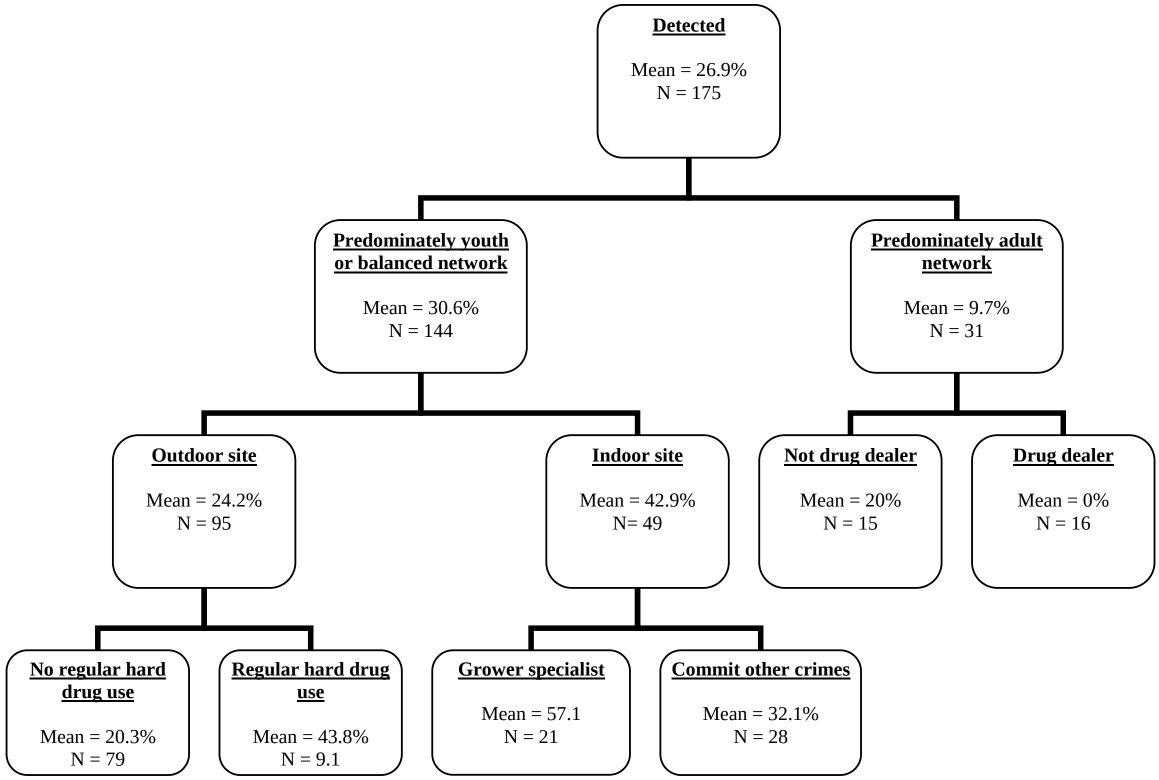


Figure 2. Classification tree (CHAID) analysis with having participated in a detected cultivation site as the predicted outcome



Appendix A. Table 5. Correlation matrix (Spearman's rho)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Arrested	1.000																			
2.Detected	.735**	1.000																		
3. Gender (f=1)	.013	-.016	1.000																	
4. Age	.043	.022	.053	1.000																
5. Other crimes	-.039	-.024	-.012	.004	1.000															
6. Drug dealing	.044	-.094	-.174*	-.144	.249**	1.000														
7. Hard drug	.021	.037	.002	-.052	.101	.216**	1.000													
8. Cannabis	.103	.060	-.111	-.030	.177*	.473**	.264**	1.000												
9. Gang member	-.040	.101	-.095	-.038	.129	.119	.207**	.207**	1.000											
10 Type of site	.182*	.157*	.055	.079	-.071	-.065	.101	-.021	.169*	1.000										
11. Owner	.068	.010	-.224**	.012	.079	.088	-.046	-.017	.110	-.157*	1.000									
12 Commercial	.078	.078	-.054	.048	.059	.230**	.209**	-.012	.152*	.115	.026	1.000								
13 Yrs exp	.126	.156*	.011	.169*	.073	.097	.090	-.011	.258**	.153*	.066	.182*	1.000							
14. Multiple sites	-.044	.006	-.142	-.101	.043	.281**	.080	.152*	.186*	-.058	.054	.290**	.046	1.000						
15. Co-offenders	-.016	.038	.171*	-.048	.136	.159*	.075	.096	.185*	.066	-.145	.266**	.114	.204**	1.000					
16 Predom adults	-.167*	-.180*	.150*	-.104	-.074	.012	-.032	-.029	-.052	-.067	.025	.005	-.003	-.070	.024	1.000				
17. Predom youth	.107	.084	-.079	.028	.128	.065	-.006	.029	-.031	-.045	-.088	.102	.008	.014	-.116	-.379**	1.000			
18. Balanced Net	-.037	.006	-.032	.118	.008	-.065	.051	.009	.117	.134	.056	-.133	-.047	.063	.096	-.314**	-.553**	1.000		
19. +15 adults	-.091	-.077	.002	.079	-.005	.148	.023	.145	.084	.038	.017	.030	.038	.109	.169*	.147	-.437**	.406**	1.000	.
20. +15 youth	.041	.106	-.068	.090	.241**	.257**	.159*	.270**	.195**	-.007	.143	.106	.115	.186*	.190*	-.306**	.071	.250**	.424**	1.000

*p<.05 **p<.01 ***p<.001