Candidate number: 3076D

Purity and Proximity: An investigation into illegal drug markets using US data

ABSTRACT:

This paper measures the extent to which the proximity from the main drug entry points into the US, namely its border with Mexico, is a key variable in determining cocaine purity. Data from the Drug Enforcement Administration's STRIDE dataset is used in conjunction with estimated distances and travel times from four key drug entry points. I establish a relationship between purity and proximity and assess the extent to which proximity can help explain variation in the rate of cocaine overdoses between states.

Word count: 7,447

Contents

1 Introduction

Illegal drug purity should be a key consideration of policy makers because of its potential impact on the health outcomes of users. Yet this feature of illegal drug markets has often been ignored by the literature which tends to focus on the price of illegal drugs (Arkes et al., 2008; Caulkins, 2007; Caulkins et al., 2003; Caulkins, 1995; Horowitz, 2001; Hyatt and Rhodes, 1995; Saffer and Chaloupka, 1999).

To establish whether there is a connection between the overdose rate and the purity of the drugs taken I have first looked at the relationship between drug purity and the proximity to the US-Mexico border (the 'source'). A simple relationship such as this would allow me to determine whether the health outcomes of users in the US varies systematically based on geographic location. Previous efforts to estimate this relationship have relied on using drug purity data obtained from the Drug Enforcement Administration's (DEA) STRIDE dataset and the distances from the main entry points along the US-Mexico border (Cunningham et al., 2010).

As distance is time-invariant, the work by Cunningham et al. (2010) fails to control for state fixed effects. This is arguably a serious weakness in the current literature which I have attempted to resolve. The approach taken in this paper is to instead use the travel time between the main entry points and the most populous cities in each state. For my estimation strategy to work the travel time needs to vary across time, I have accordingly used the relaxation of the National Maximum Speed Law (NMSL) introduced in 1974 as a natural experiment causing variation in these travel times. What is more, using the relaxation of the NMSL enables me to explore the relationship between the rate of overdoses resulting from cocaine abuse and purity without having to rely on the purity data from STRIDE which is unlikely to reflect street purity.

To save space, the following is a brief survey of the most relevant papers in the literature for my investigation. Caulkins et al. (2003) (writing for the Executive Office of the President) describe a significant increase in the purity of cocaine between 1986-88; this is the period when the NMSL was relaxed, motivating my investiga-

tion. They find that this increase in purity 'appears fairly robust' across the US, meanwhile prices only tended to fall systematically in particular cities and regions. Davies (2010) estimates a 52% increase in cocaine purity after the introduction of Mandatory Minimum (MM) sentences–part of the Anti-Drug Abuse Act of 1986–across the period 1977-2001. These laws meant that the minimum length of time a drug trafficker was required to serve in prison depended entirely on the weight of drugs they were caught in possession of and not their purity. Davies argues that as a result of these laws, traffickers would rather transport lower quantities of higher purity drugs[1].

Caulkins (1995) also investigates how drug prices vary with geographic location across the US due to the significant transaction costs associated with their distribution; in the case of cocaine, he finds evidence that it is distributed through an urban hierarchy. Levitt and Venkatesh (1998) find a very organised hierarchy even within drug-selling gangs. The theory I put forward in Section 2.1 depends on there being a distribution structure of this nature. Coomber (1997) presents evidence that the disorganised nature of the UK drugs market means less adulteration takes place compared with continental markets which are tightly controlled by organised crime groups. What is more, Coomber argues both on logical grounds and using evidence from the UK that adulteration of illicit drugs using toxic substances is incredibly rare.

With regards to cocaine overdoses, Bohnert et al. (2010) find a significant relationship between ambient temperature and the risk of overdosing from cocaine due to its effects on the body. As my investigation relies on using proximity to the US-Mexico border, it is important to keep temperature considerations in mind as we move away from the Equator. Hyatt and Rhodes (1995) controversially find that the number of cocaine overdoses is negatively related to cocaine prices obtained from the STRIDE dataset. Although these findings are potentially significant for my investigation, the weakness of STRIDE price data (discussed in Section 3.2) prevents me from incorporating this into my theory and investigation.

[1]The two thresholds for MM sentences in the case of powder cocaine are 0.5kg and 5kg.

2 Theory

2.1 Purity

One of the most important questions to first address when considering drug purity is what drives variation in it. The three main factors affecting illicit drug purity are impurities from production, added adulterants and diluting agents. The production process of cocaine has remained rudimentary to this day; Mejia and Posada (2008) find that most of the world's supply comes from small-scale local producers in Colombia. The purity of cocaine produced in these jungle laboratories will often be very close to 100%. It is only when cocaine moves through the supply chain that adulterants and diluting agents are added to increase profits.

To understand why the purity of illegal drugs should vary with the proximity to the source, it is important to first understand how the drug supply chain works. Drug transactions either on the street or in distribution are conducted according to weight; for example, street dealers will sell cocaine in grams while distributors will sell cocaine in kilos. This feature of illegal drug markets combined with the difficulty of accurately determining the purity of a substance makes weight the principle variable in many drug transactions and legislation (Davies, 2010). Consequently, as drugs move down the supply chain closer to the end user they are cut to increase profits.

Almost all cocaine in the world is produced in South America, with Colombia being the focal point. Once produced, traffickers have three possible distribution options to get the drugs into the US. The most common transport method is by land across the US-Mexico border; the other methods are by sea to ports such as Miami, or by air on private planes or commercial flights. It is for these two reasons I have restricted the focus of this paper to cocaine: cocaine is only produced in meaningful quantities in South America and flows upwards into the US primarily through the US-Mexico border providing us with a clear idea of the entry points into the US.

The reason drug purity should vary with geographic location within the US is that the further away a city is from the entry point of the drugs, the less likely

it will be that a single trafficker will transport the drugs the entire length of the journey. Given this reasoning, we would expect to see the furthest regions having lower purity as a result of this lengthening in the supply chain.

> **Proposition 1:** The longer it takes for cocaine to reach its destination, the lower its expected purity.

2.2 Proximity

Ideally an estimation strategy should control for unobserved heterogeneity between the states, this however creates problems when estimating a relationship for distance or travel time. Including state fixed effects is essential insofar as they are able to control for factors that are likely to affect purity: potentially disparate DEA strategies across regional offices, the presence of ports and airports, and the established distribution networks between dealers and traffickers[2]. Critically, including fixed effects allows us to control for differences in cocaine purity as a result of other transportation methods. Consider the example of Florida, which has long been a key entry point for drugs smuggled by sea, we would expect to observe higher levels of purity as a result of the more direct route and shorter journey time.

To overcome the problem of fixed effects removing time-constant variables I have used the relaxation of the NMSL introduced in 1974 to create exogenous variation in the time taken to travel. In response to the 1973 oil crisis the US government imposed a federal speed limit of 55mph that applied to all states. Before this federal speed limit was imposed every state had been allowed to set their own speed limits; these pre-NMSL speed limits ranged from a low of 60mph to an open speed limit in Nevada. The NMSL existed until 1987 when the federal government allowed states to apply to increase their speed limit to 65mph. The first state to raise its speed limit to 65mph was New Mexico on 02/04/1987, and the last to relax the speed limit during this period was Georgia on 22/02/1988[3]. During this period of relaxation only nine states kept the 55mph speed limit, choosing to relax it in the 90s or later.

The nine states that kept the 55mph speed limit after 1988 were Connecticut, Delaware, Hawaii, Maryland, Massachusetts, New Jersey, New York, Pennsylvania

[2]It is worth noting that although the DEA's strategies and the distribution networks used by traffickers are potentially endogenous and change over time, it is likely that these things are approximately fixed over short time periods. In any case, models (E) and (F) presented in Section 4 allow for state trends.

[3]Only Georgia and Alaska raised their speed limits in 1988.

and Rhode Island. Aside from Hawaii, all of these states are located in the North East which crucially means that the relaxation of the speed limits between 1987-88 changed the travel time from the US-Mexico border for every state. Had it been the states bordering Mexico that did not raise their speed limits during this period, their travel times would have remained the same throughout and would therefore be excluded from my sample. For clarity, consider the example of only Texas relaxing its speed limit and the effect this has on the travel time to Vermont: to reach Vermont a trafficker leaving from Nuevo Laredo must pass through Texas and so the travel time to New Hampshire, VT also changes.

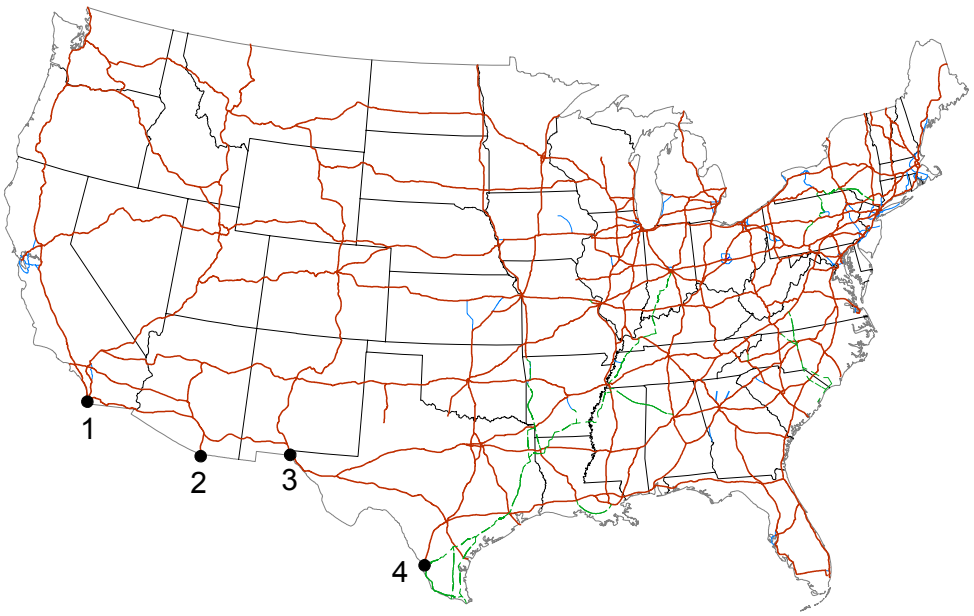
The four border entry points considered in this paper were selected because they are commonly cited as key drug entry points into the US from Mexico[4]. More importantly, they constitute the minimum number of entry points required to minimise the travel times to the most populous cities in every US state; this is directly as a result of their connectedness to the US Interstate Highway System (see Figure 2.1). It is arguably as a result of their connectedness that they are commonly cited as the key entry points. The four entry points are:

1. Tijuana, borders California (6)
2. Nogales, borders Arizona (1)
3. Ciudad Juárez, borders Texas (4)
4. Nuevo Laredo, borders Texas (37)

Note: The number in parentheses represents the total number of cities for which each border point is the start of the shortest route.

[4]These four entry points are highlighted in the US Department of Justice's National Drug Threat Assessment 2011 report. Dell (2011) also makes mention of the strategic importance of these entry points in her analysis on the networked nature of drug trafficking.

Figure 2.1: Map of the US indicating the four key border entry points considered in my analysis as well as the US Interstate Highway System.



I have chosen to restrict my analysis to the most populous cities in each state for two reasons. The first reason is that the STRIDE dataset includes observations for many cities in each state and so collecting the relevant data on travel times and distances would be time consuming and arguably of limited value. The second reason is that we would expect to see the most observations for each state–both acquisitions of cocaine and overdoses resulting from its abuse–in its most populous city. Alaska and Hawaii were excluded from the analysis because they are not part of the contiguous US hampering my estimation strategy. In addition to this, I have excluded the District of Columbia for data reasons outlined in Section 3.2.

Using speed limits to construct the theoretical minimum travel time requires the strong assumption that all drug traffickers drive at the speed limit for their entire journey. Although this assumption is strong, it can be justified for a rational trafficker. A trafficker wants to minimise their time in possession of any illegal drugs whilst also drawing as little attention to themselves as possible. By traveling below the speed limit they increase the time they are in possession of the drugs as well as

the opportunity cost of the job. Although traveling above the speed limit reduces their travel time, it would also significantly increase the likelihood that they will be stopped by law enforcement officials.

An important feature of the estimated travel times, much like the shortest distances, is that they represent a binding constraint for all drug traffickers. We therefore do not need to know the network of routes used by drug traffickers, how long each journey takes, or even whether several traffickers were involved (an implicit assumption made in Section 2.1). What we are essentially analysing is the effect relaxing this constraint has on purity.

2.3 Health

Interestingly, purity affects the health of drug users in two very different ways. An overdose is the main risk associated with insufflating cocaine in its purest form. Drug users develop routines of abuse that vary with tolerance, and so users concerned about their health should vary intake with purity as well as weight. If users are unable to accurately determine the purity of their drugs or purify the substance themselves, which applies to many if not most users, they may overdose as a result of consuming drugs of unusually high purity. In this sense, the variance of drug purity is important in determining the likelihood of an overdose just as much as the absolute purity. In the case of heroin, when 'rogue' batches of unusually high purity appear on the streets, public health warnings are often issued[5].

Proposition 2: High purity cocaine is more likely to cause overdoses, as is highly variable purity if users fail to regulate intake with purity.

The risks associated with low purity cocaine centre on the cutting agents used to 'bulk-up' the product before it reaches the end user. If the cutting agents are toxic, there is a clear risk to the health of users who are unable to distil the drug. How this impacts the health of users is determined by the cutting agents used; we can therefore distinguish between the risk of overdoses and other health complications.

However, the use of toxic cutting agents cannot be in the interests of a drug dealer; a dealer cutting or selling drugs cut with toxic substances would lose out

[5] A search on Google will reveal articles in local or national newspapers highlighting warnings issued by police forces. It is also possible, and more common, to find internet forums where users warn each other about unusually high purity heroin. The street purity of cocaine today is considerably lower than it was in the 80s and does not warrant such warnings anymore.

on future business directly as a result of the deaths of their addicted customers and through competition with other dealers. In fact, cutting agents used today are usually cheaper chemicals that partially mimic the effects of the desired drug (Coomber, 1997). It is worth noting that these added chemicals may still cause health complications but that it is difficult to discern these impacts precisely because there exists very little data about what these chemicals are and their effects on human health. For these reasons, unlike highly variable and high purity cocaine, we would not expect to observe overdoses with lower purity cocaine. In terms of what we are able to observe, data is available for accidental overdoses caused by cocaine meanwhile, due to the vast spectrum of possibilities, data on long-term health complications resulting from cocaine abuse is not. This restricts the type of analysis we are able to engage in.

What I will attempt to test is whether the number of overdoses occurring in the most populous cities in each state can be explained through differences in the variance of drug purity and travel times to that city. We would expect to see more overdoses in cities closer to the US-Mexico border due to Proposition 1, but also more overdoses in cities with higher drug variance as a result of Proposition 2.

Another variable of interest is the total quantity of cocaine acquired by the DEA annually in every city (computed using the STRIDE dataset). This is interesting because of the effect acquisitions by the DEA have on supply and/or purity. Taking large quantities of cocaine off the streets reduces supply and may lead to lower purity cocaine if dealers choose to cut their cocaine to compensate and meet demand. The effect of this would be to reduce overdoses in the city due to lower purity or supply, a likely objective for government if not the DEA.

3 Data

3.1 Overview

For my analysis I created two entirely new datasets using data obtained from the DEA's STRIDE dataset, Google Maps, the speed limit history of the US and the CDC WONDER dataset. The first dataset, *Purity and Proximity*, is designed to test Proposition 1 and uses data from STRIDE, Google Maps and the speed limit history of the US. This dataset spans 1986-88 and includes the following variables for each acquisition: the city and state where it was made; the date; the purity and quantity; whether it was a seizure or purchase; and the distance and travel time from the nearest entry point along the US-Mexico border.

The second dataset, *Overdoses*, is used to investigate whether the rate of cocaine overdoses in US states can be explained through differences in proximity and purity variance (Proposition 2) as well as the total acquisitions made by the DEA. For this dataset I consolidated data from all of the sources listed above. This dataset spans 1986-89 and includes the following variables for each state-year pair: the number of cocaine overdoses; the population; the rate of cocaine overdose deaths; the travel time from the nearest entry point along the US-Mexico border; the purity variance; and the total quantity of cocaine acquired by the DEA.

3.2 STRIDE Dataset

The cocaine purity data comes from the DEA's STRIDE (System to Retrieve Information from Drug Evidence) dataset which is an administrative record of all acquisitions of illegal drugs made by the DEA. For each acquisition the following variables are recorded: the type of acquisition (seizure or purchase), the price paid if it was a purchase, the chemical found, the date and location, the purity and the quantity. For my *Purity and Proximity* dataset, all observations in years outside the period 1986-88 were dropped as well as any observations between April 1987 and

February 1988[6]. Alaska and Hawaii were also excluded from the sample because they are not part of the contiguous US; the District of Columbia was also excluded for data reasons outlined at the end of this section. Any observations made outside of the most populous cities in these states or in airports were also removed.

Although the STRIDE dataset is ubiquitous in studies conducted on the market for illegal drugs in the US because of the sheer number of observations it contains, it is not without its problems. The STRIDE dataset is an administrative record of all acquisitions of illegal drugs made by the DEA; the direct implication of this is that the observations contained within it are not generated by a random process but are instead driven by the objectives of the DEA. For these reasons it has been argued that the price data in STRIDE does not reflect the true distribution of the market prices for illegal drugs (Horowitz, 2001). If it were the case that the DEA systematically targets high profile dealers and distributors to create maximum disruption in illegal drug markets, we would expect to observe acquisitions of large quantities and high purity. Evidence from my sample shows that the average quantity acquired by the DEA is more than a kilogram–considerably more than a retail quantity–lending support to this theory.

Table 3.1: Summary statistics for cocaine acquisitions and purity in my sample

Variable	Obs.	Mean	Std. deviation	Minimum	Maximum
Acquisitions (grams)	9,592	1349.94	27677.71	.0001	2287660
Purity (percent)	9,592	65.16	34.93	0	100

In any case, at what point in the cocaine supply chain the DEA chooses to intervene is irrelevant as long as it is consistent across or within states. A confounding story could be that DEA offices in the regions furthest away from the US-Mexico border choose to target dealers lower down the supply chain with lower purity cocaine. For example, between 1986-88 the DEA made the greatest number of acquisitions in New York City which, at the time, had the toughest anti-drug legislation in the country. If the DEA in New York chose to target smaller dealers because of the legal environment elevating their criminal status, without controlling for state fixed effects it is conceivable that this may lead us to incorrectly accepting Proposition 1. It is plausible that DEA regional offices may have differed in their objectives despite

[6]These two dates demarcate the exact period in which the NMSL was relaxed by 41 states.

the federal nature of the organisation. This would underpin the need for state fixed effects in any estimation strategy to control for these differences.

Although true prices are likely to influence the overdose rate and purity, I have taken the decision to ignore the price data in STRIDE because of the issues highlighted with it. One issue raised by Horowitz (2001) is that informants or undercover agents are used to conduct these purchases which may lead to differences in the agreed price due to negotiation, experience and budgets. I have instead created a *Purchase* dummy variable to indicate whether the acquisition was a seizure or purchase. Purity data is more robust over prices in that it is not directly observable ex-ante and is only accurately determined through laboratory testing afterwards. This also means that the DEA cannot be targeting purity–and why should it? The DEA, and other drug enforcement agencies around the world, often measure their success by the number of acquisitions and the total quantity of drugs taken off the streets.

Although the overwhelming majority of the data present in STRIDE is collected by the DEA, additional observations are included for the District of Columbia made by the Metropolitan Police of the District of Columbia (MPDC). Horowitz (2001) finds that there are significant systematic differences between the data collected by these two organisations driven by their individual strategies: there is evidence that the MPDC is more oriented towards making retail purchases compared with the DEA. My dataset does not differentiate between acquisitions made by the DEA and the MPDC and hence the decision was made to exclude Washington D.C. from my analysis.

3.3 Google Maps and the Proximity Data

The distance and travel time data required for my analysis had to be generated using data from Google Maps in conjunction with the speed limit history of the US. The four entry points along the US-Mexico border chosen were Ciudad Juárez, Nogales, Nuevo Laredo and Tijuana. The first step was to calculate which entry point would minimise the journey time to the most populous city in each state. Once this was established, it was straightforward to compute the distance between the optimal entry point and the most populous city for each state. These distances calculated by Google maps are the minimum distances using the road network in the US.

To generate the hypothetical travel times used in my analysis I had to first consider

the history of the NMSL. While the NMSL was still in force between 1986 and early 1987, the hypothetical travel time could be found by dividing the distance by the 55mph speed limit for each journey.

Of the 48 contiguous states, only eight did not raise their speed limits between 1987-88 and all were concentrated in the North Eastern US. While this meant that the journey times for all contiguous states changed post the relaxation period, it also meant that it would not be possible to simply divide the distance by 65mph. In total there were 10 journeys[7] for which some distance had to be covered at 55mph. Each of these journeys had to be deconstructed into the constituent distances travelled in each state and have the correct speed limit applied to each section to generate the new travel times. Simply put, 38 of the of the hypothetical journeys took place at 65mph after this relaxation period and 10 took place under a combination of 65mph and 55mph.

3.4 CDC WONDER Dataset

The particular dataset used in my analysis is the Compressed Mortality File from the WONDER dataset, which includes mortality and population counts for all US counties. For our period of interest, the underlying cause of death is specified using the International Classification of Diseases 9th revision code. An accidental cocaine overdose is denoted by the code E855.2: Accidental poisoning by local anaesthetics. The code applies not only to cocaine but also lidocaine, procaine and tetracaine. It is worth noting however that the other three chemicals included in E855.2 are used primarily in minor surgery and dentistry as local anaesthetics and are not used recreationally as they do not induce a high. It is therefore unlikely that these other chemicals may bias up the overdose count.

A problem with the WONDER dataset is that it is disaggregated down only to the county level whereas the STRIDE data is released by cities, in addition to this it is only a yearly count as opposed to STRIDE which includes the date of any acquisition made by the DEA[8]. To unite the WONDER and STRIDE datasets, I attributed the mortality of the county (or counties) encompassing the most populous city to the most populous city. Again, this introduces a measurement error whenever an overdose took place outside of the most populous city but in the county. For

[7] These comprised of the eight states that kept the 55mph speed limit as well as the North Eastern states of Maine and New Hampshire.

[8] The date of mortalities is omitted to preserve confidentiality.

example, suppose we have a very large county relative to the city, if the death takes place in the county but far away from the city there is measurement error because we are using the travel time, variance and seizure data for the city.

The NMSL was relaxed between 1987-88, with Georgia the only contiguous state that relaxed its speed limit in 1988; this meant that all observations in 1987 had to be excluded but not all observations made in 1988. The relaxation of Georgia's speed limit only affected the travel time to Georgia and North Carolina and so the 1988 observations for GA and NC were excluded. In addition to this issue, when estimating the sample variance, many city-year pairs were excluded because they lacked enough observations (30) to accurately estimate the sample variance. To counter balance this reduction in sample size I included 1989 in my *Overdoses* dataset. It is worth noting that many observations for 1989 were suppressed by the CDC for confidentiality reasons.

4 Purity and Proximity

What we are interested in measuring is the effect travel time has on purity, especially after controlling for state fixed effects. Using the Estimated Travel Time (ETT) data in conjunction with the STRIDE dataset allows us to estimate this effect. The first pair of regressions, (A) and (B), will be simple OLS regressions contrasting the coefficients estimated with ETT and distance; this will give us a good indication of whether a relationship exists between purity and proximity at all. By construction of the ETT variable, we would expect very similar coefficient estimates and significance results.

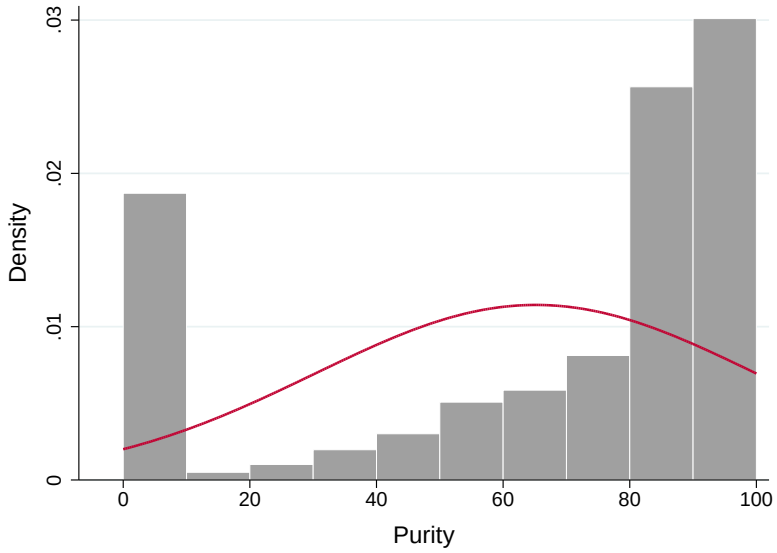
- **Purity and Proximity models (A) and (B):**

$$\begin{aligned} Purity_{ist} = \alpha_0 + \alpha_1 Distance_s + \alpha_2 Purchase_{ist} \\ + \alpha_3 Weight_{ist} + \alpha_4 1987_t + \alpha_5 1988_t + \epsilon_{ist} \end{aligned} \tag{A}$$

$$\begin{aligned} Purity_{ist} = \alpha_0 + \alpha_1 ETT_{st} + \alpha_2 Purchase_{ist} \\ + \alpha_3 Weight_{ist} + \alpha_4 1987_t + \alpha_5 1988_t + \epsilon_{ist} \end{aligned} \tag{B}$$

Note: ETT will be reported in hours and $Distance$ will be reported in 100km units to make the coefficients comparable. A car traveling at a speed of 60mph will cover approximately 100km in an hour. The $Purchase$ variable will be a dummy variable indicating whether the acquisition was a purchase ($Purchase = 1$) or seizure ($Purchase = 0$). The variables 1987 and 1988 are time dummies.

Figure 4.1: Purity density



There exist two concerns when modelling purity using OLS. The first relates to the bounded nature of purity meaning that we never observe values above 100 or below 0: OLS is not constrained to make predictions in this interval. The second issue is the concentration of purity observations at the extremes. Consider the distribution of purity in Figure 4.1, there are many observations concentrated in the top and bottom deciles. My proposed solution to these two problems is a Tobit regression model censored at 0 and 100. It is worth noting that an additional assumption of normality is required to employ a Tobit regression model (Wooldridge, 2009).

The next set of regressions, (C) and (D), introduce state fixed effects and we can interpret the coefficient on ETT as the change in purity that occurs when the travel time from the US-Mexico border increases. This coefficient will be informative when comparing states that are equidistant from the US-Mexico border but have different travel times due to speed limit disparities, for example, North Eastern and Midwest states[9]. The coefficient will also be capturing the effect on purity the relaxation of the NMSL had. My final two regressions, (E) and (F), will allow for state specific time trends instead of separate state and year fixed effects; this removes the restriction that every state follows the same time trend.

[9]The states that did not relax the NMSL between 1987-88 were all concentrated in the Northeast. Although the distance from Nuevo Laredo and a state in the Northeast or Midwest may be similar, their ETTs are different post-NMSL.

- **Purity and Proximity models (C) to (F):**

Model (B) with state fixed effects	(C)
Tobit of (C)	(D)
Model (B) with state-year fixed effects	(E)
Tobit of (E)	(F)

The standard errors for each of my models will be heteroskedasticity robust and clustered by state. Clustering allows us to account for within state correlation in some unspecified way (Nichols and Schaffer, 2007) and although OLS estimates are unbiased in the presence of clustering, the reported standard errors are unlikely to be correct causing inference problems. Kezdi (2005) finds that approximately 50 roughly equal sized clusters are enough for asymptotic results to be valid in finite samples: our sample has 48 clusters. In addition to this, Kezdi demonstrates that even in the absence of clustering, so long as the above is not violated, there is little cost of using the CRSE estimator.

Results are reported on the next two pages.

Table 4.1: Regression results for Purity and Proximity models (A) to (D)

	(A) OLS	(B) OLS	(C) OLS	(D) Tobit
Constant	64.350*** (2.788)	65.369*** (2.705)	-	-
ETT (hours)	-	-.367*** (.120)	-4.479** (2.019)	-5.864** (2.871)
Distance (100 km)	-.372*** (.124)	-	-	-
Weight (kg)	.033*** (0.011)	.033*** (.011)	.032*** (.010)	.037*** (.011)
Purchase (dummy)	12.671*** (2.760)	12.633*** (2.714)	11.303*** (2.801)	14.825*** (4.013)
1987	2.348 (3.079)	2.371 (3.061)	2.005 (2.698)	1.998 (3.307)
1988	11.913*** (4.376)	10.526*** (3.940)	-4.852 (5.348)	-7.619 (6.977)
Fixed effects	No	No	Yes	Yes
R^2	0.069	0.070	0.111	0.118[a]
$\log \mathcal{L}$	-	-	-	-41820.913
AIC	9.875	9.873	9.839	8.731

Robust, clustered standard errors reported in parentheses.

*, **, *** indicates significance at the 90%, 95% and 99% level, respectively.

Number of observations 9,592.

[a]McKelvey & Zavoina's R^2

Table 4.2: Regression results for Purity and Proximity models (E) and (F)

	(E)	(F)
	OLS	Tobit
ETT	-1.002**	-1.254**
(hours)	(.402)	(.547)
Weight	.028***	.033***
(kg)	(.009)	(.009)
Purchase	11.661***	15.219***
(dummy)	(2.743)	(3.946)
Fixed effects (state-year)	Yes	Yes
R^2	0.141	0.151[a]
$\log \mathcal{L}$	-	-41650.241
AIC	9.821	8.712

Robust, clustered standard errors reported in parentheses.

*, **, *** indicates significance at the 90%, 95% and 99% level, respectively.

Number of observations 9,592.

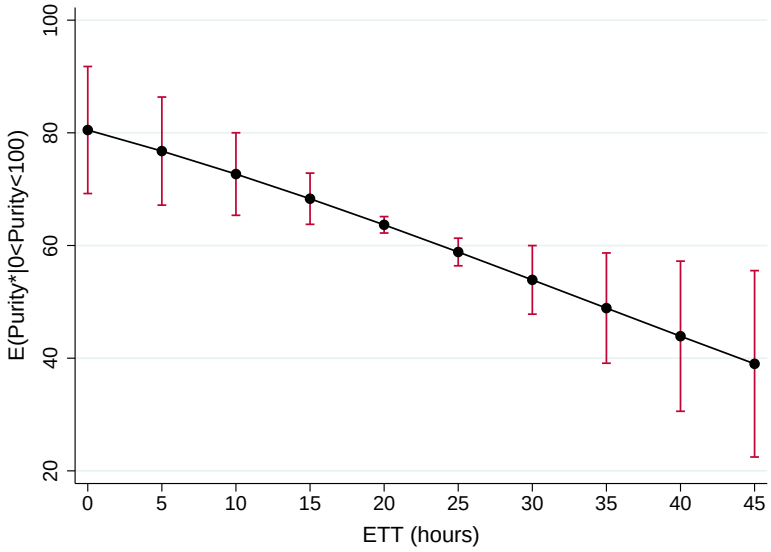
[a]McKelvey & Zavoina's R^2

Note: McKelvey & Zavoina's R^2 is chosen for its performance in matching the OLS R^2 in simulations (Hox, 2010; Long, 1997) and because it attempts to capture explained variability much like the OLS R^2.

$$R^2_{M\&Z} = \frac{Var\left(\hat{y}^*\right)}{Var\left(\hat{y}^*\right) + Var\left(\varepsilon\right)} \quad , \quad R^2_{OLS} = \frac{ESS}{TSS}$$

These results clearly identify a negative association between purity and ETT in support of Proposition 1. By the Akaike information criterion (AIC), the model that appears to provide the best description of this relationship is (F). Figure 6.1 shows that expected purity varies almost linearly with ETT at the means in model (F). Table 6.1 shows the conditional changes in expected purity resulting from the relaxation of the NMSL for Vermont and California, which experienced the largest and smallest absolute change in ETT, respectively. The relationship described is almost 1:1 between purity and ETT, i.e. increasing the travel time constraint by 1 hour reduces purity by 1%.

Figure 4.2: Expected value of purity for model (F)



Note: The bars represent the 95% confidence interval.

Another interesting finding from my results is the positive and significant coefficient on the *Purchase* dummy variable. To understand why this is the case it is important to consider the difference between a seizure and a purchase. The DEA uses purchases to obtain evidence in order to support a prosecution against someone. It should therefore follow that the DEA only chooses to use purchases as a means of securing convictions against high profile distributors due to the risks involved[10]. The higher up the distributor is in the supply chain, the more likely they are to have

[10]Purchases are made using undercover agents or informants, who may be placed in danger, and also requires the DEA to risk losing a substantial sum of money if the transaction 'goes wrong'.

higher purity drugs. As purity is not observable ex-ante, there are few other ways to explain why this coefficient should have such a large, positive and significant value. If this is true, it also lends support to my theory about the drug supply chain and hierarchy outlined in Section 2.1.

Table 4.3: Expected change in purity due to the relaxation of the NMSL

State	Old ETT	New ETT	Difference	Expected change in purity
VT (largest)	39.42	33.35	6.07	6.07
CA (smallest)	2.49	2.10	0.39	0.36
Average	22.86	19.51	3.35	3.20

5 Overdoses

Proposition 2 suggested that high purity and variance should lead to more overdoses and so our first regressions, as before, are preliminary OLS regressions to establish whether or not there exists a link between the two. However, the purity data from STRIDE does not reflect street purity because of the nature of the DEA's operations as discussed in Section 3.2. Average purity from STRIDE reflects purity higher up in the supply chain which may not be well correlated with street purity. One reason for this may be regional differences in the way in which street dealers choose to cut the cocaine before selling it to the end user: an example could be differences in the availability of adulterants or diluents. Yet the minimum travel time required to transport the drugs across the US represents a binding constraint for everyone and imposes structural differences in purity. Essentially our model should be attempting to isolate the effect geographic location has on the rate of overdoses through its effect on purity.

For the same reasons average purity estimated from STRIDE may not be representative of street purity, the sample variance may not be representative either. However, there is little alternative to test the tolerance and abuse hypothesis (part of Proposition 2) other than using the estimated variance from STRIDE.

- **Overdoses models (A) and (B):**

$$Overdose\,Rate_{st} = \beta_0 + \beta_1 ETT_{st} + \beta_2 Var_{st} + \beta_3 Acquistions_{st} + \beta_4 1988_t + \beta_5 1989_t + \epsilon_{st} \quad \text{(A)}$$

Model (A) with state fixed effects (B)

Figure 5.1: Histogram of cocaine overdoses between 1986-89

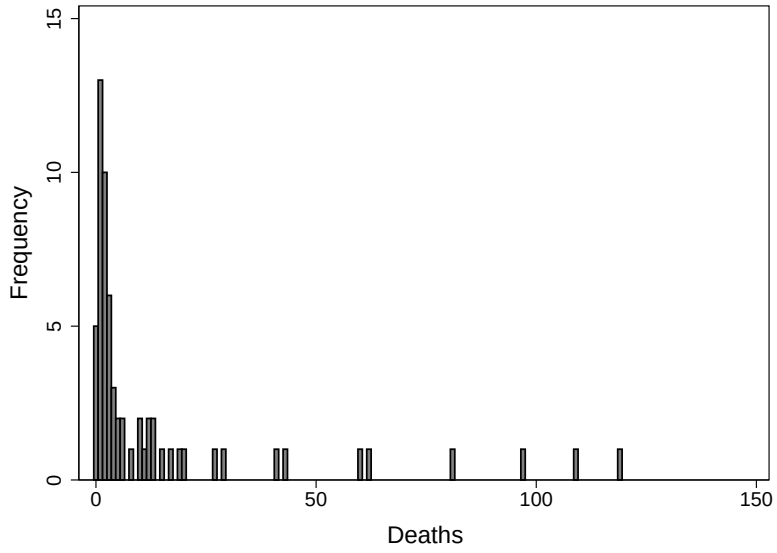


Table 5.1: Summary statistics for cocaine overdoses

Variable	Obs.	Mean	Variance	Minimum	Maximum
Deaths	63	14.49	707.87	0	119

The number of cocaine overdoses occurring every year in each city is inherently count data, it is therefore possible to model it using a Poisson regression model. An issue with the Poisson model is that it only has a single free parameter and requires that the mean and variance be equal. Table 4.1 and Figure 4.2 suggest that this is not the case with our dataset[11]. The negative binomial model is a more generalised alternative to allow for overdispersion and will be estimated instead. To make the analysis between the OLS and negative binomial models equivalent we must control for the exposure (the amount of times the event could have happened) which in our case is the population count. To do this I will include $\ln(Population)$ as an independent variable on the right hand side and restrict its coefficient to 1. Essentially this transformation changes the focus of our analysis into the effect proximity, variance or seizures have on the rate of overdoses (Cameron and Trivedi, 1998). Furthermore, this makes the comparison with models (A) and (B) more straightforward.

[11] A test for Poisson goodness of fit is conducted in the Appendix.

$$\begin{aligned} \ln(Deaths) &= X\beta + \ln(Population) + \epsilon \\ \ln(Deaths) - \ln(Population) &= X\beta + \epsilon \\ \ln(Rate) &= X\beta + \epsilon \end{aligned}$$

- **Overdoses models (C) and (D):**

Negative binomial: (C)

$$\begin{aligned} \ln(Deaths_{st}) = \beta_0 + \beta_1 ETT_{st} + \beta_2 Var_{st} + \beta_3 Acquistions_{st} \\ + \beta_4 1988_t + \beta_5 1989_t + \ln(Population_{st}) + \epsilon_{st} \end{aligned}$$

Model (C) with state fixed effects (D)

Note: Our dataset is unbalanced and small because of the data issues outlined in Section 3.4. This restricts our ability to use clustered standard errors (Kezdi, 2005), hence all reported standard errors are therefore heteroskedasticity robust only.

Results are reported on the next page.

Table 5.2: Regression results for Overdoses models (A) to (D)

	Dependent variable:			
	Rate	Rate	Count	Count
	(A)	(B)	(C)	(D)
	OLS	OLS	Negative Binomial	Negative Binomial
Constant	4.568***	-	-11.957***	-
	(1.511)		(.376)	
ETT	-.105**	-.483	-.030***	-.156***
(hours)	(.050)	(.651)	(.009)	(.067)
Variance	.00098	.00321*	-.00006	-.00008
	(.00129)	(.00165)	(.00033)	(.00034)
Acquisitions	.347	1.356***	.020	.254***
(1000 kg)	(.471)	(.406)	(.050)	(.046)
1988	1.764*	1.190	.444**	.287
	(.988)	(1.845)	(.202)	(.234)
1989	7.967***	1.989	1.173***	.190
	(2.280)	(2.290)	(.291)	(.138)
$\ln(Population)$	-	-	1	1
Fixed effects	No	Yes	No	Yes
R^2	0.438	0.8749	0.347[b]	0.848[b]
$\log \mathcal{L}$	-	-	-172.6888	-127.1051
AIC	5.613	5.062	5.704	5.210

Robust standard errors reported in parentheses.

*, **, *** indicates significance at the 90%, 95% and 99% level, respectively.

Number of observations 63.

[b]Nagelkerke's generalised R^2

6 Discussion

With regards to Proposition 2, there is some evidence to support a relationship between the rate of overdoses and the ETT. Model (B) minimises the AIC but fails to find a significant relationship between the rate of overdoses and the ETT. The second best model by the AIC, model (D), is able to find a significant negative relationship: an increase in the ETT of 1 hour leads to a reduction in the rate of overdoses by a factor of 0.86 (Incident Rate Ratio).

A major concern with this result is that we are not controlling for climate. Bohnert et al. (2010) finds there to be a significant relationship between the occurrence of cocaine overdoses and temperature in New York city. As we move further away from the US-Mexico border we are also moving further away from the Equator which means that average temperatures are falling. Although my model includes state and year fixed effects, it may still be picking up these climate differences as well as, or instead of, differences in purity: this would lead us to overestimate the effect purity has on the rate of overdoses. It may be possible to control for this if we had the exact date of each overdose and included a measure of temperature for that day (the date of each overdose is suppressed by the CDC for confidentiality reasons). The models also fail to find any consistent–or in most cases significant–relationship between the variance of purity and the rate of overdoses. As suggested in Section 5, this may be due to a weak link between STRIDE data and actual street purity.

Models (B) and (D) both find a significant positive relationship between the total acquisitions made by the DEA and overdoses which contradicts the hypothesised relationship in Section 5. However, if we assume that luck is not responsible for the volume of acquisitions made, this variable captures the intensity of DEA operations in the city. Consequently an issue with including this variable is endogeneity: if a city is 'blighted' with a drug problem, it is likely that the DEA will concentrate resources in that city. Therefore the chain of causality between the overdose rate and total acquisitions arguably runs in both directions creating a simultaneity bias.

Nevertheless, this paper establishes a link between cocaine purity and proximity,

introduces an estimation strategy that permitted the inclusion of state fixed effects and shows the extent to which proximity can help explain variation in the rate of overdoses. The results presented show that there is indeed a negative relationship between travel time and cocaine purity. Going forward, it would be possible to test these findings by including more cities or by studying the effect on purity of speed limit relaxation in the 90s. On the issue of cocaine overdoses, it has been more difficult to establish any clear relationship between proximity and the rate of overdoses. This is largely due to data limitations: the small sample size, an inability to control for temperature and a lack of retail purity data. Future studies should attempt to overcome these data issues and test whether both propositions hold in the case of heroin.

The findings for purity and proximity, if applicable at a more localised level, could be useful for law enforcement officials in determining the direction of distribution routes for illegal drugs within a state. If a clear relationship is established for purity and overdoses, policy makers may find it useful in making healthcare spending decisions and preventing overdose deaths through purity monitoring programmes.

Acknowledgments

(1) The DEA STRIDE dataset was obtained under a freedom of information request to the US Department of Justice (FOIA 13-00123-F). The views expressed in this paper are those of the author and do not necessarily represent the views of, and should not be attributed to, the US Department of Justice or the Drug Enforcement Administration.

(2) Speed limit data was obtained from the following URL which cites as sources the Federal Highway Administration, National Coalition Against Speed Limits, National Motorists Association and the American Automobile Association. All efforts were made to verify the data.

URL: http://www.ibiblio.org/rdu/sl-attud/list.html

(3) The CDC WONDER data is available at the following URL. Cocaine overdoses are recorded in the Compressed Mortality File under the code E855.2.

URL: http://wonder.cdc.gov

Appendix

- Below are the confidence interval estimates for α (the overdispersion parameter) in the *Overdoses* models (C) and (D):

Model	α	95% confidence interval for α
(C)	.367602 (.079087)	[.241128, .560413]
(D)	.007495 (.027476)	[5.68×10^{-6}, 9.894147]

Note: α is distributed $\chi^2\,(52)$. Overdispersion exists in the data when $\alpha > 0$.

- Below are the goodness of fit tests for models (C) and (D) when estimated using the Poisson regression model:

Model	P-value for Deviance GOF	P-value for Pearson GOF
(C)	0.0000	0.0000
(D)	0.0246	0.0444

Note: The null hypothesis is that the Poisson model is suitable (no overdispersion). We therefore reject the Poisson model at the 95% significance level for both models.

Bibliography

Arkes, J., R. L. Pacula, S. M. Paddock, J. P. Caulkins, and P. Reuter: 2008, 'Why the DEA STRIDE Data are Still Useful for Understanding Drug Markets'. Working Paper 14224, National Bureau of Economic Research.

Bohnert, A. S. B., M. R. Prescott, D. Vlahov, K. J. Tardiff, and S. Galea: 2010, 'Ambient temperature and risk of death from accidental drug overdose in New York City, 1990-2006'. *Addiction* **105**(6), 1049–1054.

Cameron, A. C. and P. K. Trivedi: 1998, *Regression Analysis of Count Data*. Cambridge University Press.

Caulkins, J.: 2007, 'Price and purity analysis for illicit drug: data and conceptual issues.'. *Drug and Alcohol Dependence* **90**(S1), pp. S61–S68.

Caulkins, J. P.: 1993, 'Zero-Tolerance Policies: Do They Inhibit or Stimulate Illicit Drug Consumption?'. *Management Science* **39**(4), 458–476.

Caulkins, J. P.: 1995, 'Domestic Geographic Variation in Illicit Drug Prices'. *Journal of Urban Economics* **37**(1), 38 – 56.

Caulkins, J. P.: 1997, 'Modeling the Domestic Distribution Network for Illicit Drugs'. *Management Science* **43**(10), 1364–1371.

Caulkins, J. P. and H. Hao: 2008, 'Modelling drug market supply disruptions: Where do all the drugs not go?'. *Journal of Policy Modeling* **30**(2), 251–270.

Caulkins, J. P., R. L. Pacula, J. Arkes, P. Reuter, S. Paddock, M. Iguchi, and J. Riley: 2003, 'The Price and Purity of Illicit Drugs: 1981 Through the Second Quarter of 2003'. *Office of National Drug Control Policy*.

Chaloupka, F. J., M. Grossman, and J. A. Tauras: 1999, 'The Demand for Cocaine and Marijuana by Youth'. In: *The Economic Analysis of Substance Use*

and Abuse: An Integration of Econometrics and Behavioral Economic Research, NBER Chapters. National Bureau of Economic Research, Inc, pp. 133–156.

Coomber, R.: 1997, 'Vim in the Veins - Fantasy or Fact: The Adulteration of Illicit Drugs'. *Addiction Research* **5**(3), pp. 195–212.

Cunningham, J. K., J. C. Maxwell, O. Campollo, K. I. Cunningham, L.-M. Liu, and H.-L. Lin: 2010, 'Proximity to the USA-Mexico border: a key to explaining geographic variation in US methamphetamine, cocaine and heroin purity'. *Addiction* **105**(10), pp. 1785–1798.

Davies, R. B.: 2010, 'Mandatory Minimum Sentencing, Drug Purity and Overdose Rates'. *The Economic and Social Review* **41**(4), pp. 429–457.

Dell, M.: 2011, 'Trafficking Networks and the Mexican Drug War'. Working Paper, Harvard University.

Horowitz, J. L.: 2001, 'Should the DEA's STRIDE Data Be Used for Economic Analyses of Markets for Illegal Drugs?'. *Journal of the American Statistical Association* **96**(456), pp. 1254–1262.

Hox, J.: 2010, *Multilevel Analysis: Techniques and Applications, Second Edition*, Quantitative Methodology Series. Taylor & Francis.

Hyatt, R. R. and W. Rhodes: 1995, 'The price and purity of cocaine: The relationship to emergency room visits and death, and to drug use among arrestees'. *Statistics in Medicine* **14**(5-7), 655–668.

Kezdi, G.: 2005, 'Robust Standard Error Estimation in Fixed-Effects Panel Models'. Econometrics 0508018, EconWPA.

Lakhdar, C. B., H. Leleu, N. G. Vaillant, and F.-C. Wolff: 2011, 'Efficiency of purchasing and selling agents in markets with quality uncertainty: The case of illicit drug transactions'. Working Papers 2011-ECO-02, IESEG School of Management.

Levitt, S. D. and S. A. Venkatesh: 1998, 'An Economic Analysis of a Drug-Selling Gang's Finances'. Working Paper 6592, National Bureau of Economic Research.

Long, J.: 1997, *Regression Models for Categorical and Limited Dependent Variables*, Advanced Quantitative Techniques in the Social Sciences. SAGE Publications.

Mejia, D. and C. E. Posada: 2008, 'Cocaine production and trafficking : what do we know ?'. Policy Research Working Paper Series 4618, The World Bank.

Nandi, A., S. Galea, J. Ahern, A. Bucciarelli, D. Vlahov, and K. Tardiff: 2006, 'What explains the association between neighborhood-level income inequality and the risk of fatal overdose in New York City?'. *Social Science & Medicine* **63**(3), 662–674.

Nichols, A. and M. E. Schaffer: 2007, 'Clustered standard errors in Stata'. United Kingdom Stata Users' Group Meetings 2007 07, Stata Users Group.

Saffer, H. and F. Chaloupka: 1999, 'The Demand for Illicit Drugs'. *Economic Inquiry* **37**(3), 401–411.

Stolzenberg, L. and S. J. D'Alessio: 2003, 'A multilevel analysis of the effect of cocaine price on cocaine use among arrestees'. *Journal of Criminal Justice* **31**(2), 185–195.

Wooldridge, J. M.: 2009, *Introductory Econometrics: A Modern Approach*, ISE - International Student Edition. South-Western.