An Evaluation of Prescription Drug Monitoring Programs

Ronald Simeone and Lynn Holland
Simeone Associates, Inc.
September 1, 2006[1]

Abstract

This research examines the effects of Prescription Drug Monitoring Programs (PDMPs) on the supply and abuse of prescription drugs. Information from the Automation of Reports and Consolidated Orders System (ARCOS) is used to develop measures of supply, and information from the Treatment Episode Data Set (TEDS) is used to develop measures of abuse. Practical considerations lead us to focus on Schedule II pain relievers and stimulants, and composite measures for these two classes of drugs are developed. We estimate both aggregate and individual response models. The aggregate model suggests that PDMPs reduce the per capita supply of prescription pain relievers and stimulants and in so doing reduce the probability of abuse for these drugs. The evidence also suggests that states which are proactive in their approach to regulation are more effective in reducing the per capita supply of prescription pain relievers and stimulants than states which are reactive in their approach to regulation. The individual response model confirms these findings. It is important to note that the probability of pain reliever abuse is actually higher in states that have PDMPs than in states that do not. But our analysis demonstrates that in the absence of such programs the probability of abuse would be higher still.

Key words: drug abuse, multilevel model, binary response model.

[1] We would like to thank Dr. Roger Vaughan, Department of Biostatistics, Columbia University for his review and comments. Please direct all correspondence to Dr. Ronald Simeone, Simeone Associates Inc., 220 Lancaster Street, Albany, New York, 12210 (email ron@simeoneassociates.com). This project was sponsored by the United States Department of Justice, Office of Justice Programs, Bureau of Justice Assistance (No. 2005PMBXK189).

1 Introduction

Twenty states have implemented systems to monitor the prescription and sale of drugs identified as controlled substances by the Drug Enforcement Administration (DEA). Another twenty-three states are in the process of designing or planning to design such systems. This growth is fueled in part by the Harold Rogers Prescription Drug Monitoring Program (PDMP). The competitive grant program, managed by the Bureau of Justice Assistance (BJA) in the Office of Justice Programs (OJP), is intended to support states wishing to enhance local capabilities to monitor the prescription and sale of controlled substances.

States are eligible for these grants if they have in place, or have pending, an enabling statute or regulation requiring the submission of prescription data on controlled substances to a central database. States may also apply if they can introduce legislation or regulations for a prescription monitoring program before the annual OJP Hal Rogers Program grant cycle begins. Prescription Drug Monitoring Programs as they exist at the state level serve a variety of ends, but all are intended ultimately to reduce the abuse of controlled pharmaceutical substances.

We focus on two possible channels by which a PDMP might affect the probability of prescription drug abuse. The first is indirect, operating through the supply of controlled substances. If a PDMP reduces the supply of prescription drugs, then this in turn may reduce the probability of abuse. The second is direct: when supply is held constant, a PDMP may itself reduce the probability of abuse. The former may be indicative principally of the effect that regulation has on prescribing behavior, whereas the latter may be indicative principally of the effect that regulation has on dispensing behavior.

The purpose of this research is to provide a statistical basis for assessing these effects. To this end, we propose a series of multilevel models for estimating the relationships among the presence of a PDMP, supply, and abuse.

The specification of a two-equation multilevel model that makes use of repeated measurements of state characteristics provides a starting point for our analysis, and allows both the supply and abuse measures to be treated as endogenous to the PDMP measures. These relationships are examined while controlling for other state-level characteristics that may be relevant to our task.

But individuals, not states, choose to abuse drugs. Hence, results based on aggregate data can at best only suggest causality. At worst, they allow us to fall victim to the classic ecological fallacy (Robinson [1]; for discussion of circumstances under which generalization from aggregate to individual data is appropriate see Freedman *et al.* [2]; Greenland and Robins [3]; Freedman *et al.* [4]; Neeleman and Lewis [5]). To address this problem, we propose another multilevel model that makes use of repeated measurements made of individual characteristics that are likely to affect behavior.

Both our aggregate and our individual response models will allow relationships to be examined over time. Therefore, it is necessary that we select a common period during which data from all of our sources will be available for use in our analysis. This is the interval beginning January 1, 1997 and ending December 31, 2003.

We begin by discussing issues related to measurement in Section 2. An aggregate model involving equations for supply and abuse is presented and estimated in Section 3. An individual response model for abuse is presented and estimated in Section 4. Findings are discussed and directions for future research are suggested in Section 5.

2 Measurement

The fundamental structure of our model, whether aggregate or individual response, involves three sets of measures: those related to the PDMP, those related to supply, and those related to abuse. Our ability to define these measures is constrained by data that are currently available for use in our analysis. The actual choices that we make are guided by our desire to develop a parsimonious model that avoids misspecification.

PDMP data. In support of our research the National Alliance for Model State Drug Laws (NAMSDL) has assembled data that allow sources of variation in PDMP implementation to be examined over time. One of the most important of these is the manner in which cases are identified and investigated. In some states the PDMP is "reactive" in nature, generating "solicited reports" only in response to a specific inquiry made by a prescriber, dispenser, or other party with appropriate authority. In other states the PDMP is "proactive" in nature, identifying and investigating cases, and generating "unsolicited reports" when it deems that this is warranted. It is important to maintain this distinction since program effects may vary by mode of implementation. Two measures of PDMP status are therefore constructed for each state, for each year. The first involves coding the presence or absence of *any* PDMP as 1 or 0 (respectively). The second involves coding the presence or absence of a *proactively monitoring* PDMP in the same manner.

Prescription Drug Monitoring Programs also differ in their scope of coverage, at one extreme including only Schedule II drugs, and at the other including Schedule II-V drugs. Coverage is cumulative; any state that regulates the prescription and sale of Schedule III drugs also regulates the prescription and sale of Schedule II drugs; any state that regulates the prescription and sale of Schedule IV drugs also regulates the prescription and sale of Schedule II and III drugs, and so on.

Because we seek to examine whether the presence of a PDMP reduces supply it is reasonable to define supply in a manner consistent with the scope of its influence. The most straightforward way of accomplishing this is to limit elements of supply to Schedule II drugs. But the consequences associated with excluding Schedule III-V drugs from our analysis warrants additional consideration.

Supply data. Our source of data on supply is the Automation of Reports and Consolidated Orders System (ARCOS) maintained by the DEA Office of Diversion Control (ODC). ARCOS includes records on retail sales of twelve controlled substances (amphetamine, cocaine, codeine, fentanyl, hydrocodone, hydromorphone, methamphetamine, methylphenidate, meperidine, methadone, morphine, and oxycodone). In support of our research the ODC has aggregated transactions for these drugs to the zip-code and state level and provided data on the number of grams sold for each year during our observation period.

Tables I-IV provide information on the relationship between drug schedule and four types of drugs: "pain relievers", "tranquilizers", "stimulants" and "sedatives." This categorization scheme appears often in drug abuse research and has been adopted as a convention by the National Survey on Drug Use and Health (NSDUH) and other federal reporting systems. The tables were developed by Carnevale Associates, LLC (CALLC) using the Centers for Disease Control (CDC) National Drug Code (NDC) database. Generic drugs (shaded rows) and brand-name products are cross-classified by schedule for pain relievers, tranquilizers, stimulants and sedatives.

Looking at the tables we see that the ARCOS drugs are principally Schedule II pain relievers (opioid agonists including codeine, fentanyl, hydrocodone, hydromorphone, meperidine, methadone, morphine, and oxycodone) and Schedule II stimulants (dopamine agonists and reuptake inhibitors including amphetamine, cocaine, methamphetamine, and methylphenidate).

Table I: Pain Relievers

Drug	Schedule II	Schedule III	Schedule IV	Schedule V
buprenorphine				x
Buprenex®				x
codeine	x			
Tylenol with Codeine®		x		
dextropropoxyphene	x			
Darvocet®			x	
Darvon®			x	
fentanyl	x			
Actiq®	x			
Duragesic®	x			
Oralet®	x			
Sublimaze®	x			
hydrocodone	x			
Hycomine®		x		
Lorcet®		x		
Lortab®		x		
Lortab ASA®		x		
Vicodin®		x		
Vicoprofen®		x		
hydromorphone	x			
Dilaudid®	x			
Palladone®	x			
meperidine	x			
Demerol®	x			
Mepergan®	x			
methadone	x			
Dolophine®	x			
morphine	x			
Kadian®	x			
MS-Contin®	x			
MSIR®	x			
Oramorph SR®	x			
RMS®	x			
Roxanol®	x			
oxycodone	x			
OxyContin®	x			
OxyIR®	x			
Percocet®	x			
Percodan®	x			
Tylox®	x			
pentazocine			x	
Talacen®			x	
Talwin®			x	
Talwin Nx®			x	

Table II: Tranquilizers

Drug	Schedule II	Schedule III	Schedule IV	Schedule V
alprazolam			x	
Xanax®			x	
chlordiazepoxide			x	
Librium®			x	
Limbitrol®			x	
clonazepam			x	
Klonopin®			x	
clorazepate			x	
Tranxene®			x	
diazepam			x	
Valium®			x	
halazepam			x	
Paxipam®			x	
lorazepam			x	
Ativan®			x	
oxazepam			x	
Serax®			x	
prazepam			x	
Centrax®			x	
quazepam			x	
Doral®			x	
meprobamate			x	
Equanil®			x	
Miltown®			x	

Our research focuses on the indirect and direct effects of PDMPs on abuse. When assessing the indirect effects we estimate the relationship between the presence of a PDMP and supply, and the relationship between supply and abuse. It is therefore not unreasonable to limit our definition to include only drugs that are subject to PDMP control and which have significant abuse potential. Defining supply in terms of Schedule II drugs leads us to exclude codeine and hydrocodone since they are Schedule II drugs only in their generic forms. The most common brand name products for codeine (Tylenol with Codeine®) and hydrocodone (Lortab®, Lorcet® and Vicodin®) are regarded as having less potential for abuse, thus their status as Schedule III drugs.

Table III: Stimulants

Drug	Schedule II	Schedule III	Schedule IV	Schedule V
amphetamine	x			
Adderall®	x			
Biphetamine®	x			
Dexedrine®	x			
Dextrostat®	x			
benzphetamine		x		
Didrex®		x		
diethylpropion			x	
Tenuate®			x	
Tepanil®			x	
mazindol		x		
Mazanor®			x	
Sanorex®			x	
methamphetamine	x			
Desoxyn®	x			
methylphenidate	x			
Concerta®	x			
Methylin®	x			
Ritalin®	x			
phendimetrazine		x		
Bontril®		x		
Plegine®		x		
Prelu-27®		x		
phentermine			x	
Adipex®			x	
Fastin®			x	
Ionamin®			x	
Lonamin®			x	

There may be another argument for limiting our analysis to include Schedule II pain relievers and stimulants only. In examining the impact of PDMPs on supply we would ideally make use of information on all sources of prescription drugs that might become candidates for abuse. Internet sales therefore become a concern because they constitute an unmeasured component of supply in each state. From a statistical perspective this problem would be less serious if the preponderance of internet sales involved Schedule III-V rather than Schedule II drugs.

There is some limited evidence to suggest that this may be the case. As the result of a massive investigation (Cyber Chase) conducted by the Organized Crime Drug Enforcement Task Force (OCDETF) a number of significant insights were gained into the operation of the Bansal organization, an India-based group that supplied controlled substances to rogue pharmacies operating Internet Facilitation Centers (IFCs) in the United States.

The indictment (filed in the United States District Court for the Eastern District of Pennsylvania) indicates that during the period from "August 2004...(to)...March 2005 the defendants and others sold at least 400,000 dosage units of controlled substance pharmaceutical drugs in Schedule II, at least 2,700,000 dosage units of controlled substance pharmaceutical drugs in Schedule III, and at least 12,287,000 dosage units of controlled substance pharmaceutical drugs in Schedule IV..." to IFCs.

In this case the preponderance of sales clearly involved Schedule III and IV drugs; and the majority of Schedule II sales involved codeine liquid. If this portfolio were representative of all internet-based trafficking activity, then our operational definition of supply would effectively eliminate at least one confounding factor.

It is also important to differentiate drugs that are produced and distributed legally from drugs that are produced and distributed illegally. Prescription Drug Monitoring Programs do not regulate the production and distribution of illicit drugs. And this leads us to limit our definition of supply further, excluding cocaine and methamphetamine from consideration.

The elements of supply thus become fentanyl, hydromorphone, meperidine, methadone, morphine and oxycodone (which we define collectively as pain relievers in subsequent sections) and amphetamine and methylphenidate (which we define collectively as stimulants in subsequent sections).

Table IV: Sedatives

Drug	Schedule II	Schedule III	Schedule IV	Schedule V
amobarbital	x			
Amytal®	x			
Tuinal®	x			
aprobarbital		x		
Alurate®		x		
butabarbital		x		
Butisol®		x		
butalbital		x		
Fiorina®		x		
chloral hydrate			x	
Aquachloral®			x	
Noctec®			x	
estazolam			x	
ProSom®			x	
flurazepam			x	
Dalmane®			x	
mephobarbital			x	
Mebaral®			x	
methohexital			x	
Brevital®			x	
pentobarbital	x			
Nembutal®	x			
phenobarbital			x	
Luminal®			x	
secobarbital	x			
Seconal®	x			
talbutal		x		
Lotusate®		x		
temazepam			x	
Restoril®			x	
thiamylal		x		
Surital®		x		
thiopental		x		
Pentothal®		x		
triazolam			x	
Halcion®			x	
zaleplon			x	
Sonata®			x	
zolpidem			x	
Ambien®			x	

Because states differ in population size it is necessary to establish some appropriate basis for making comparisons among them. Thus, our measures of supply are defined as grams per capita for fentanyl, hydromorphone, meperidine, methadone, morphine and oxycodone (pain relievers); and amphetamine and methylphenidate (stimulants). These are calculated for each state, for each year.

The fact that there are a number of controlled substances under investigation and that each may be regarded as endogenous relative to the presence of a PDMP causes us to consider whether there are any methods that might be used to summarize our drug-specific per capita measures as one or more composite measures.

Fentanyl, hydromorphone, meperidine, methadone, morphine and oxycodone are all opioid agonists that have therapeutic utility because of their analgesic properties. The relative potency of these drugs has been examined in some detail and therefore provides guidance to the construction of a general measure of supply for pain relievers.

Findings from several surveys of studies that have attempted to establish equianalgesic dose ratios for opioid agonists are presented in Table V (Gordon *et al.* [6]; Anderson *et al.* [7]; Pereira *et al.* [8]). Since research in this area often involves substitution of one drug for another, the order of rotation is regarded as important and therefore reported both in the literature and in our table.

All ratios presented are expressed by route of administration (PO = oral, SC = subcutaneous, IV = intravenous) and relative to morphine. Therefore (reading across the first row entry in Table V) when rotating between morphine and fentanyl 1 mg. fentanyl administered subcutaneously is equivalent to 68 mg. morphine administered subcutaneously.

Table V: Equianalgesic Doses for Pain Relievers

Drug	Rotation	PO	[ref]	SC	[ref]	IV	[ref]
Fentanyl	Morphine-Fentanyl			68.00	[9]		
	Morphine-Fentanyl			84.50	[10]		
	Morphine-Fentanyl			70.00	[11]		
(mean)		74.17		74.17			
Hydromorphone	Morphine-Hydromorphone	5.33	[12]	4.92	[13]	3.55	[14]
	Morphine-Hydromorphone	5.71	[13]				
	Hydromorphone-Morphine	3.80	[12]	4.00	[13]		
	Hydromorphone-Morphine	3.45	[13]				
(mean)		4.57		4.46		3.55	
Meperidine	N/A	0.10	[6]	0.13	[6]		
(mean)		0.10		0.13			
Methadone	Morphine-Methadone	11.36	[15]				
	Morphine-Methadone	11.11	[16]				
	Morphine-Methadone	8.25	[15]				
(mean)		10.24					
Oxycodone	N/A			0.71	[17]		
	Morphine-Oxycodone	1.33	[18]			0.70	[19]
	Morphine-Oxycodone	1.50	[20]				
	Oxycodone-Morphine	1.50	[18]	0.70	[19]		
	Oxycodone-Morphine	1.50	[20]				
(mean)		1.46		0.71		0.70	

We use the information presented in Table V to develop a composite measure for pain relievers, weighting the number of grams for each drug (fentanyl, hydromorphone, meperidine, methadone, and oxycodone) by the corresponding mean equianalgesic oral dose ratio presented there. Morphine serves as our calibration measure and receives a weight of 1. Summing over the weighted values and dividing by the corresponding population produces a composite per capita measure for pain relievers ("PR composite"). The composite measure is calculated for each state, for each year.[1]

Fentanyl poses a problem because it is not ordinarily administered orally (although there is a lozenge available that is intended for sublingual use). We assume the relative potency of fentanyl administered orally to be equal to its relative potency when administered subcutaneously. While there is no direct evidence in support of this calculation, there is indirect evidence demonstrating similarity of equianalgesic dose ratios between hydromorphone administered orally and subcutaneously, and fentanyl and hydromorphone administered subcutaneously. By deduction, the assignment of this value seems reasonable. In any case, since our objective is simply to maintain some approximation to relative potency our assumption is not likely to introduce a significant source of measurement error.

A measure comparable to PR composite is developed for stimulants ("ST composite") where, following convention established by standard dose-equivalence tables, the ratio of amphetamine to methylphenidate is assumed to be $2:1$. As before, the composite measure is calculated for each state, for each year.

[1] This approach is conceptually similar to various methods that have been used to estimate the availability of illicit drugs (heroin and cocaine). In such cases it is necessary to control for the presence of dilutants and adulterants. Standard measures of "grams pure" are therefore developed that can be examined over time and relative to other factors such as price (see for example Arkes *et al.* [21] who make use of a somewhat more refined model that incorporates information on consumer expectations).

The composites are intended to provide potency-adjusted measures of the total supply of pain relievers and stimulants in each state. Since the drugs in a particular group differ in potency and may not all move together in the same direction over time they may exert mutually offsetting effects on supply. The composites allow us to compensate for this. They also offer substantial consistency with the treatment admission-based measures of pain reliever and stimulant abuse that will be used in our analysis (we discuss this issue at length below).

There are some general limitations associated with defining supply in terms of grams per capita. Anecdotal evidence suggests that drugs are not necessarily sold to patients in the same area in which they are purchased by dispensers. A large mail-order pharmaceutical house located in a particular state may thus distort estimates of supply that are based on purchases made by dispensers alone. At the same time, research on psychostimulants has produced empirical evidence demonstrating a strong relationship between per capita measures of grams ordered and the number of prescriptions filled at the zip code level (Bokhari *et al.* [22]).

Abuse data. The Treatment Episode Data Set (TEDS) maintained by the Substance Abuse and Mental Health Services Administration (SAMHSA) constitutes our source of data on abuse. The system includes all individuals admitted to state-licensed drug treatment programs in the United States. Data are captured on state, Metropolitan Statistical Area (MSA), and Core-Based Statistical Area (CBSA); on demographics and prior treatment history; and perhaps most importantly for our purposes, on primary, secondary and tertiary substances of abuse. Since our measures of supply are limited to include Schedule II pain relievers and stimulants we constrain abuse accordingly.

Our measure for pain relievers is defined by TEDS codes for "non-prescription methadone" and "other opiates and synthetics" (which implicitly includes hydromorphone, meperidine, morphine and oxycodone); and our measure for stimulants is defined by TEDS codes for "other amphetamines" (which explicitly excludes methamphetamine) and "other stimulants" (which is assumed to include methylphenidate). Any individual admitted to treatment with an indication that the primary, secondary or tertiary substance of abuse is a prescription pain reliever receives a value of 1 for the pain reliever measure (0 otherwise); and any individual admitted to treatment with an indication that the primary, secondary or tertiary substance of abuse is a prescription stimulant receives a value of 1 for the stimulant measure (0 otherwise). Per capita measures of pain reliever and stimulant abuse are constructed by summing over these individual values and dividing by the corresponding population for each state, for each year.

Defining abuse based upon treatment admissions carries with it some limitations as well. Although TEDS includes records on "first admissions" only (thereby excluding all transfer activity) there is still some tendency for one individual to experience multiple admissions during a calendar year. This is not common; nonetheless, the phenomenon does occur. Throughout the text we refer to "individuals admitted to treatment" with this caveat in mind.

It is also important to remember that admission to treatment represents the culmination of a pattern of behavior in which experimentation leads to abuse and eventually to dependence. But many people who abuse drugs never seek treatment. And our own research shows that the probability of seeking treatment varies as a function of individual characteristics (Simeone *et al.* [23,24]). Thus, without modeling in some way the conditional probability of admission to treatment, we may be able to generalize only to those who actually seek treatment during a particular period of time.

3 A Multilevel Aggregate Model

One factor that figures prominently in the decision to use a particular drug is the local availability of that drug. A relatively low supply may indicate a reduced probability of prescription for the drug; it may indicate a reduced probability that the drug will be diverted to the illicit market; and it may indicate a reduced level of convenience associated with obtaining the drug via illicit means.

Figures 1-8 provide information on supply over time for each pain reliever and stimulant included in our analysis. Per capita measures are transformed to rates per 100,000 as an aid to the reader. We distinguish between states that do not have a PDMP program ("non-PDMP") and states that do ("PDMP"). There are upward secular trends for all pain relievers with the exception of meperidine; and rates for pain relievers are higher in non-PDMP states than in PDMP states for all pain relievers with the exception of hydromorphone.[2] The difference in rates between non-PDMP and PDMP states appears to be especially pronounced for oxycodone (Figure 6). Findings are similar for stimulants. There are secular trends for amphetamine and methylphenidate; and in both cases the rates are higher for non-PDMP states than for PDMP states.

Figures 9-16 provide the same information presented in Figures 1-8 with the exception being that here we distinguish between states that do not have a PDMP which monitors proactively ("non-XPDMP") and states that do ("XPDMP"). The findings are similar although the differences in rates that exist between non-XPDMP states and XPDMP states may be more pronounced than the differences in rates that exist between non-PDMP and PDMP states.

[2] Methadone is something of a special case since it is prescribed both as a pain reliever and as a treatment for heroin addiction. Figure 4 depicts sales to pharmacies only. If we examine sales to Narcotics Treatment Providers (NTPs) we see an upward secular trend in non-PDMP states; but a higher per capita rate generally in PDMP states. This likely reflects the relative sizes of heroin-using populations in non-PDMP and PDMP states.

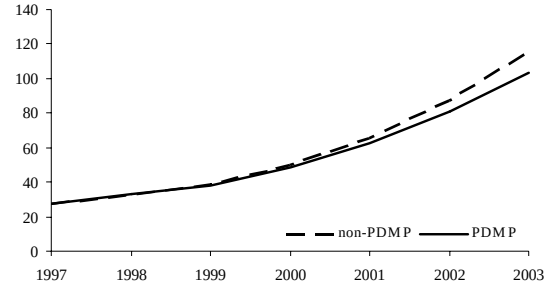

Figure 1. Fentanyl (Grams per 100,000)

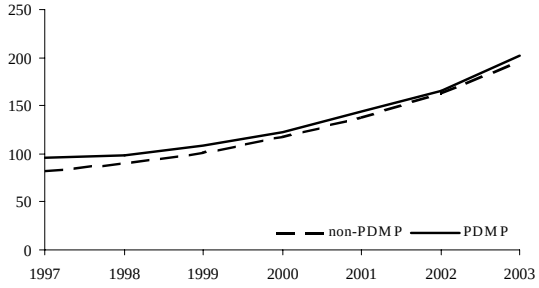

Figure 2. Hydromorphone (Grams per 100,000)

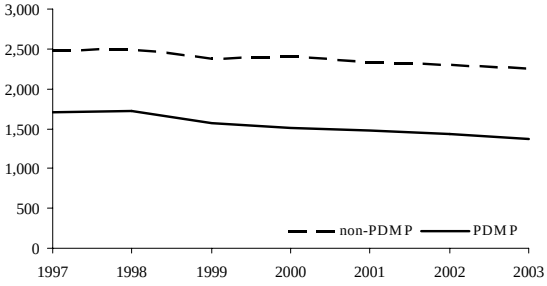

Figure 3. Meperidine (Grams per 100,000)

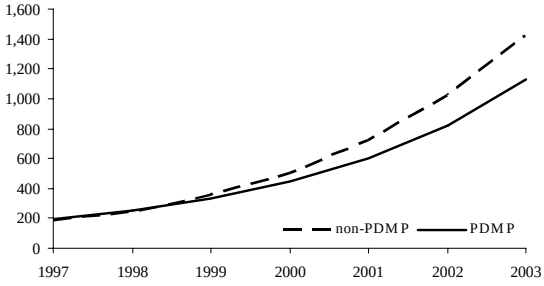

Figure 4. Methadone (Grams per 100,000)

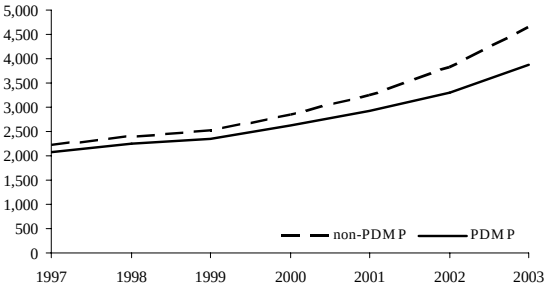

Figure 5. Morphine (Grams per 100,000)

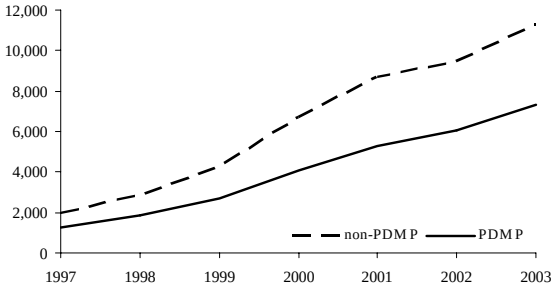

Figure 6. Oxycodone (Grams per 100,000)

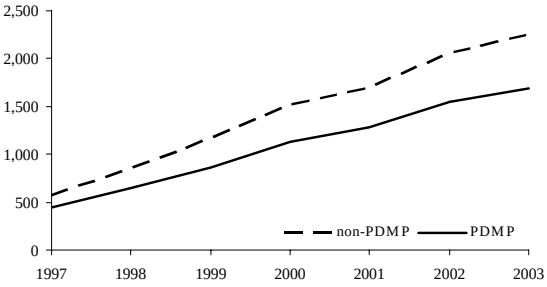

Figure 7. Amphetamine (Grams per 100,000)

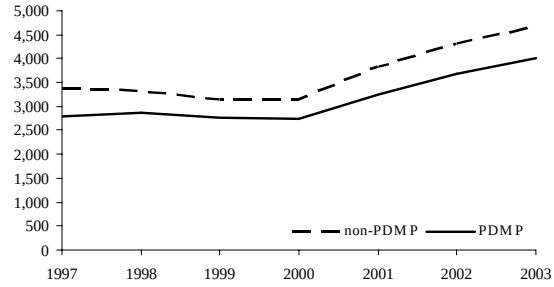

Figure 8. Methylphenidate (Grams per 100,000)

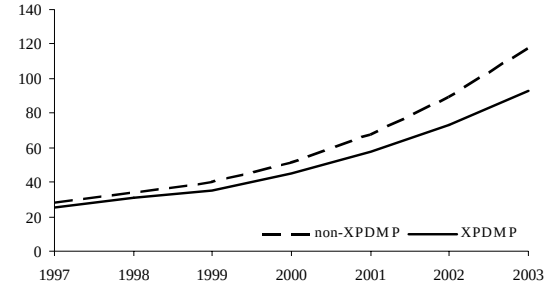

Figure 9. Fentanyl (Grams per 100,000)

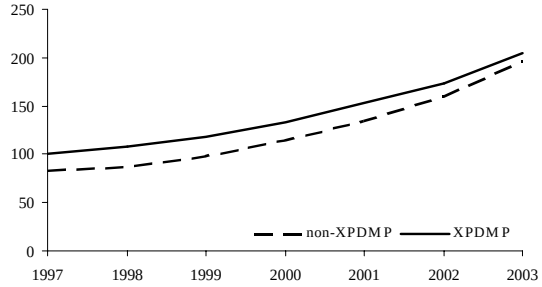

Figure 10. Hydromorphone (Grams per 100,000)

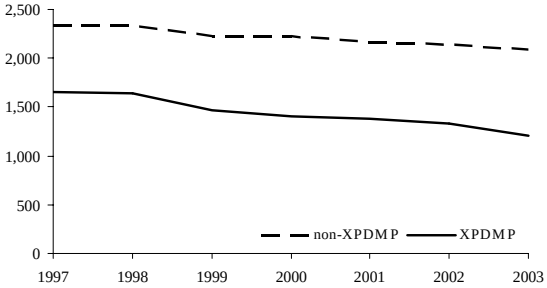

Figure 11. Meperidine (Grams per 100,000)

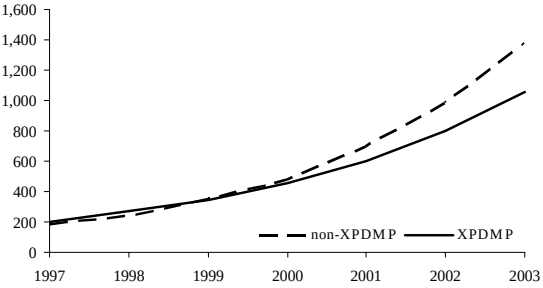

Figure 12. Methadone (Grams per 100,000)

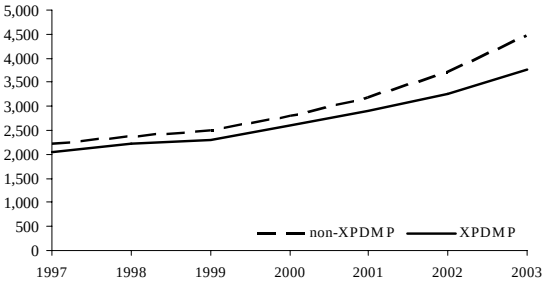

Figure 13. Morphine (Grams per 100,000)

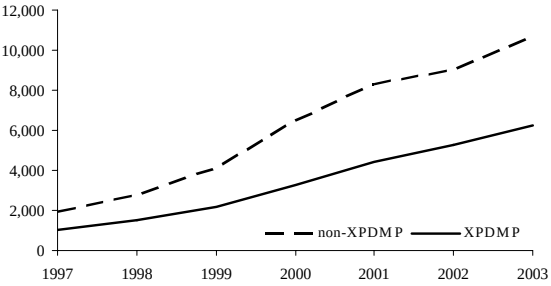

Figure 14. Oxycodone (Grams per 100,000)

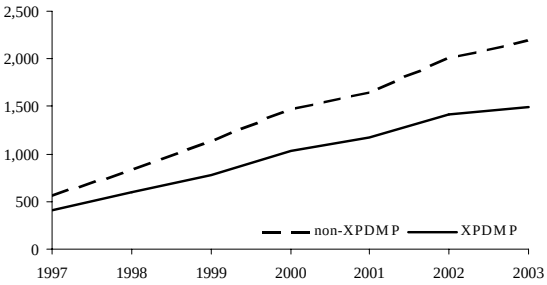

Figure 15. Amphetamine (Grams per 100,000)

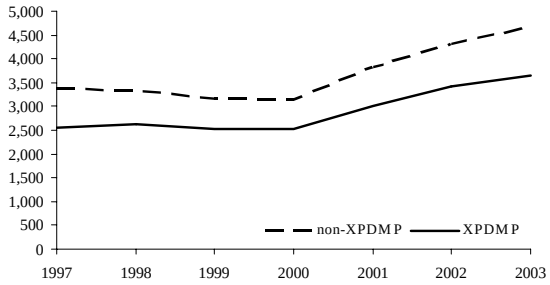

Figure 16. Methylphenidate (Grams per 100,000)

Figures 17-18 provide information on our summary measures for pain relievers (PR composite) and stimulants (ST composite). As before, we differentiate between non-PDMP and PDMP states. We see that the combination and weighting of individual measures produces greater linearization for both pain relievers and stimulants. In each case there is a strong secular trend with rates higher in non-PDMP states than in PDMP states.

Figures 19-20 provide the same information on our summary measures as that presented in Figures 17-18 but here we distinguish between non-XPDMP and XPDMP states. We see that the patterns initially identified in Figures 17-18 persist and are perhaps more pronounced for both pain relievers and stimulants.

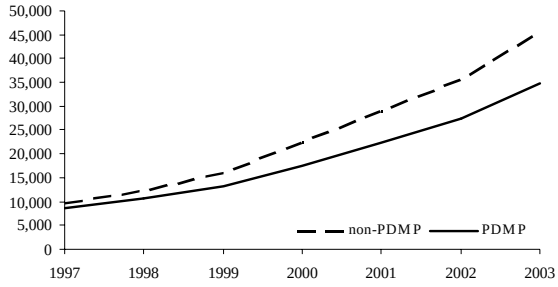

Figure 17. PR Composite (Grams per 100,000)

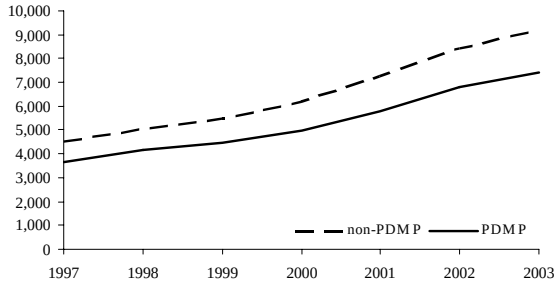

Figure 18. ST Composite (Grams per 100,000)

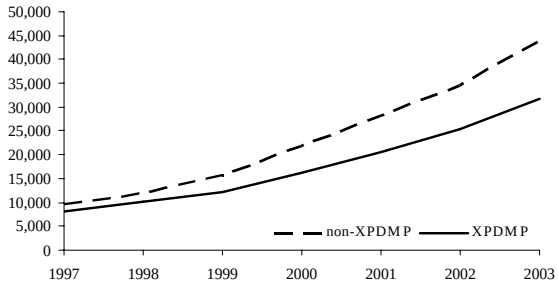

Figure 19. PR Composite (Grams per 100,000)

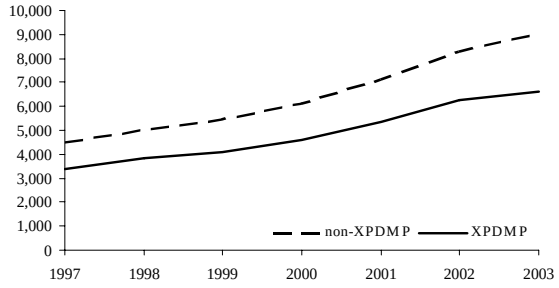

Figure 20. ST Composite (Grams per 100,000)

Figures 21-22 provide information on abuse involving pain relievers ("PR admissions") or stimulants ("ST admissions"). Per capita measures are again transformed to rates per 100,000 and we begin by distinguishing between non-PDMP states and PDMP states. There is a secular trend for pain relievers but not for stimulants. The rate of pain reliever admissions is lower in non-PDMP states than in PDMP states; and the rate of stimulant admissions is higher in non-PDMP states than in PDMP states. Figures 23-24 provide the same information as that presented in Figures 21-22 except that here we distinguish between non-XPDMP and XPDMP states. The findings essentially mirror those described above.

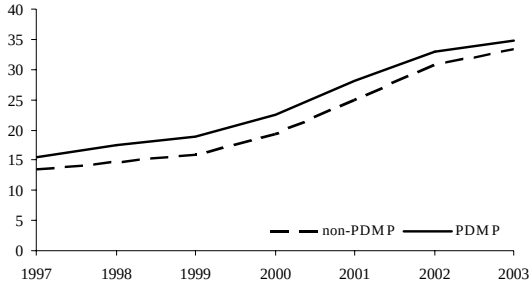

Figure 21. PR Admissions (Number per 100,000)

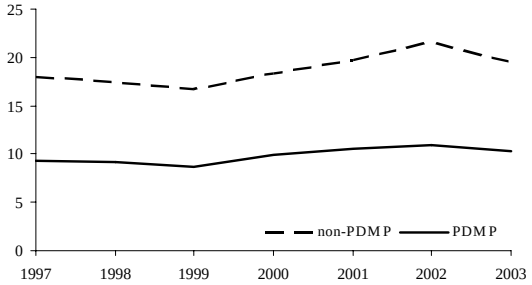

Figure 22. ST Admissions (Number per 100,000)

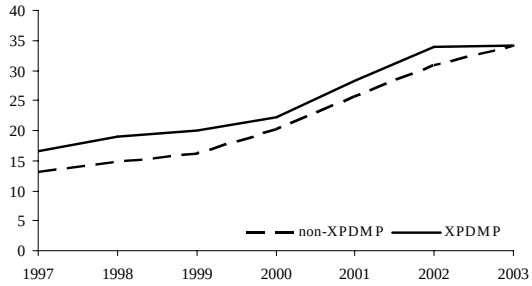

Figure 23. PR Admissions (Number per 100,000)

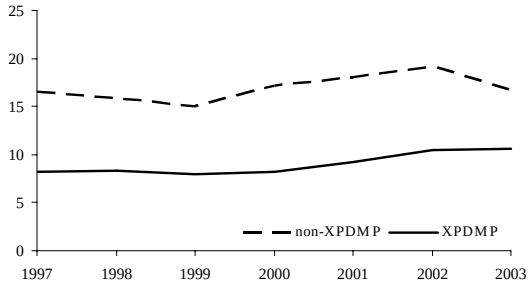

Figure 24. ST Admissions (Number per 100,000)

For completeness we provide numerical information in Table VI related to the trends that have been discussed in this section. Material is presented there on rates per 100,000 for the separate drugs that we have characterized as pain relievers and stimulants, for our composite measures of pain relievers and stimulants, and for treatment admissions that involve pain relievers and stimulants.

Table VI: Summary of Rates per 100,000

	non-PDMP			PDMP		
	1997	2003	Change	1997	2003	Change
Pain Relievers						
Fentanyl	28	115	88	27	103	76
Hydromorphone	83	196	113	96	202	107
Meperidine	2,488	2,259	-229	1,708	1,375	-333
Methadone	188	1,422	1,234	193	1,132	939
Morphine	2,235	4,648	2,413	2,075	3,863	1,788
Oxycodone	1,973	11,263	9,291	1,249	7,314	6,064
Stimulants						
Amphetamine	576	2,254	1,679	444	1,690	1,246
Methylphenidate	3,387	4,671	1,283	2,783	4,013	1,231
Composites						
PR composite	9,714	45,333	35,619	8,503	34,857	26,354
ST composite	4,539	9,179	4,641	3,671	7,394	3,724
Admissions						
PR admissions	13	33	20	15	35	19
ST admissions	18	20	1	9	10	1
	non-XPDMP			XPDMP		
	1997	2003	Change	1997	2003	Change
Pain Relievers						
Fentanyl	28	117	89	25	93	67
Hydromorphone	83	196	113	100	205	104
Meperidine	2,336	2,085	-251	1,650	1,208	-442
Methadone	186	1,375	1,189	200	1,057	858
Morphine	2,219	4,469	2,250	2,034	3,762	1,727
Oxycodone	1,936	10,664	8,727	1,004	6,223	5,218
Stimulants						
Amphetamine	562	2,190	1,628	413	1,494	1,081
Methylphenidate	3,373	4,673	1,299	2,548	3,636	1,088
Composites						
PR composite	9,671	43,924	34,253	8,059	31,613	23,553
ST composite	4,497	9,052	4,555	3,374	6,624	3,250
Admissions						
PR admissions	13	34	21	17	34	18
ST admissions	17	17	0	8	11	2

Figures 1-24 would seem to indicate that PDMPs reduce supply while having a mixed impact on abuse. But visual inspection alone does not allow us to identify mediating factors or to determine whether PDMPs account for the differences that we observe. For this we will need a mathematical model of the phenomena under study.

The model. We seek to examine changes over time in our measures of supply and abuse and to make comparisons between non-PDMP and PDMP states. Consistent with the preceding discussion we will differentiate between states that are reactive in their approach to prescription monitoring and states that are proactive in their approach to prescription monitoring. In an attempt to identify demographic characteristics likely to be related to the supply and abuse of prescription drugs we will introduce measures derived from United States Census Bureau and United States Bureau of Labor Statistics (BLS) data.

As mentioned earlier, the aggregate model allows us to examine two possible channels by which a PDMP might affect the probability of prescription drug abuse. The first is indirect, operating through the per capita supply of controlled substances. A model for supply might be specified as follows,

$$SUPPLY_{kt} = \alpha_0 + \alpha_1 MALE_{kt} + \alpha_2 WHITE_{kt} + \alpha_3 AGE_{kt} + \alpha_4 UNEMP_{kt} + \alpha_5 HLTHINS_{kt} + \alpha_6 INCOME_{kt} + \alpha_7 TIME_t + \alpha_8 PDMP_{kt} + \alpha_9 XPDMP_{kt} + u_{1k} + e_{1kt} \quad (1)$$

where the subscript for drug is suppressed in the interest of parsimony, $SUPPLY_{kt}$ is the per capita supply of prescription drugs in state k at time t, $MALE_{kt}$ is the proportion male, $WHITE_{kt}$ is the proportion white, AGE_{kt} is the mean age, $UNEMP_{kt}$ is the proportion unemployed, $HLTHINS_{kt}$ is the proportion with health insurance, $INCOME_{kt}$ is the per capita personal income, and $TIME_t$ is measured as year/1000. $PDMP_{kt}$ and $XPDMP_{kt}$ are defined, respectively, as follows,

$$PDMP_{kt} = \begin{cases} 1 & \text{if state } k \text{ is covered by a } PDMP \text{ at time } t \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$XPDMP_{kt} = \begin{cases} 1 & \text{if state } k \text{ is proactively monitoring at time } t \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Finally, u_{1k} represents an unobserved, randomly distributed state effect and e_{1kt} is a randomly distributed error term. We assume

$$E(u_{1k}) = E(e_{1kt}) = 0$$

$$Var(u_{1k}) = \sigma^2_{u1}$$

$$Var(e_{1kt}) = \sigma^2_{e1}$$

$$Cov(e_{1kt}, u_{1k}) = 0$$

The second channel is more direct. The probability of abuse may be related to supply, with the presence of a PDMP having an independent effect. A model for abuse might be specified as follows,

$$\begin{aligned} ABUSE_{kt} = \beta_0 + \beta_1 MALE_{kt} + \beta_2 WHITE_{kt} + \beta_3 AGE_{kt} + \beta_4 UNEMP_{kt} \\ + \beta_5 HLTHINS_{kt} + \beta_6 INCOME_{kt} + \beta_7 TIME_t + \beta_8 PDMP_{kt} + \beta_9 XPDMP_{kt} \\ + \beta_{10} HEROIN_{kt} + \beta_{11} COCAINE_{kt} + \beta_{12} SUPPLY_{kt} + u_{2k} + e_{2kt} \end{aligned} \quad (4)$$

where $ABUSE_{kt}$, $HEROIN_{kt}$, and $COCAINE_{kt}$ are the per capita rates for admissions involving prescription drugs, for admissions with heroin as the primary substance of abuse, and for admissions with cocaine as the primary substance of abuse, respectively, in state k at time t and where we assume

$$E(u_{2k}) = E(e_{2kt}) = 0$$

$$Var(u_{2k}) = \sigma^2_{u2}$$

$$Var(e_{2kt}) = \sigma^2_{e2}$$

$$Cov(e_{2kt}, u_{2k}) = 0$$

Our interest in examining the possible relationship between prescription drug abuse and illicit drug use motivates the inclusion of $HEROIN_{kt}$ and $COCAINE_{kt}$ in Equation (4). It would not be surprising to find per capita admissions for heroin as the primary substance of abuse associated with per capita admissions for pain relievers (which given our operational definition might be the secondary or tertiary substance of abuse). Heroin and prescription pain relievers are both opioid agonists and therefore to some degree substitutable entities. The same reasoning holds true regarding per capita admissions for cocaine as the primary substance of abuse and per capita admissions for stimulants (again as the secondary or tertiary substance of abuse) since both cocaine and prescription stimulants are dopaminergic. Interaction terms will be examined as well but are not represented above.

Equations (1) and (4) together constitute a multi-level simultaneous system which could be solved by ordinary least squares were it not for the random effects terms. But it is not practical to propose a fixed-effects model here due to limited sample size (states are monitored over seven time periods producing only 357 observations). Consistent with arguments by Teachman *et al.* [25] we therefore treat idiosyncratic and unmeasured differences that exist among states as nuisance parameters. The system is estimated *for each of our composite measures* using the SAS GLIMMIX procedure.

Results. Table VII presents information on the final $SUPPLY$ models for pain relievers (PR composite) and stimulants (ST composite). All coefficients are significant at the .0001 level. The equations for pain relievers and stimulants are quite similar. Both indicate positive effects for $TIME$; and both indicate a positive change in intercept and a negative change in slope associated with $XPDMP$ and $TIME * XPDMP$. The latter terms are consistent with the lower grams per capita trajectories for pain reliever and stimulant composites observed in $XPDMP$ states (and depicted in Figures 19-20).

Table VII: Supply Estimates

	Intercept	TIME	XPDMP	TIME*XPDMP
PR composite	-114.8300	57.5336	36.4649	-18.2416
s.e.	2.8216	1.4107	4.7973	2.3985
t Value	-40.70	40.78	7.60	-7.61
pr>t	<.0001	<.0001	<.0001	<.0001
ST composite	-15.7870	7.9265	4.4720	-2.2403
s.e.	0.3592	0.1796	0.6107	0.3053
t Value	-43.95	44.13	7.32	-7.34
pr>t	<.0001	<.0001	<.0001	<.0001

Table VIII presents information on the final $ABUSE$ models for pain relievers and stimulants. Measures involving treatment admissions are rescaled by a factor of 100,000. All coefficients are significant at the .0006 level. The results indicate that $ABUSE$ of pain relievers (PR admissions) is positively related to AGE, $HEROIN$ and $SUPPLY$ (PR composite). The $HEROIN$ finding is consistent with substitution among opioid agonists. Similarly, $ABUSE$ of stimulants (ST admissions) is positively related to $COCAINE$ and $SUPPLY$ (ST composite). The $COCAINE$ finding is consistent with substitution among dopaminergic agents.

Table VIII: Abuse Estimates

	Intercept	AGE	HEROIN	COCAINE	PR composite	ST composite
PR admissions	-201.2607	5.6591	0.1400		54.2018	
s.e.	55.0075	1.5554	0.0150		5.1124	
t Value	-3.66	3.64	9.36		10.60	
pr>t	0.0006	0.0003	<.0001		<.0001	
ST admissions				0.0663		77.0654
s.e.				0.0149		18.5215
t Value				4.44		4.16
pr>t				<.0001		0.0001

Taken together these findings suggest that PDMPs (particularly those which monitor proactively) play a role in reducing supply and in so doing have an indirect effect on abuse. But in order to assess whether variability in supply actually affects the decision to abuse prescription drugs it will be necessary to develop an individual response model. We pursue this task in the following section.

4 A Multilevel Individual Response Model

The aggregate model is informative in that it allows us to examine states as observable units over time, and to assess formally whether there are differences that exist in supply or abuse which may be attributable to the action of a PDMP. But models at this level do not allow us to understand much about individual choice. And one of the things that we are interested in learning more about is whether the presence of a PDMP, either through its effect on supply or directly, affects individual drug-using behavior. For this, we develop a multilevel model that focuses on drug choice as a function of both aggregate and individual factors. The specification of an empirical model to test for the impact of a PDMP draws upon the rational addiction literature. The theory of rational addiction rests on the notion that forward-looking individuals weigh the present value of the benefits of abusing an addictive substance against the present value of its associated costs, where costs and benefits are measured in terms of utility (Becker and Murphy [26]; Becker *et al.* [27]). Empirical results stemming from this research indicate that the demand for addictive substances is sensitive to changes in cost (Saffer and Chaloupka [28]; Grossman *et al.* [29]; Grossman [30]). Phenomena that increase the cost in utility associated with the abuse of a particular substance include an increase in its own price, a reduction in its availability, a decrease in the price of substitute goods, and an increase in the price of complementary goods. All things being equal, the existence of a PDMP can be assumed to reduce the availability of prescription drugs and thereby reduce their demand relative to illicit drugs. The existing literature gives no definitive conclusion as to how addictive substances enter the utility function jointly. Grossman *et al.* [31] cite several studies which tentatively suggest that cigarettes, alcohol, and illegal drugs may be complements. However, to the best of our knowledge, there is no empirical work documenting similarly the relationship between illicit and prescription drugs.

The Model. As before, we assume that a PDMP operates by regulating prescribing and dispensing behavior. Within the context of this model both the presence of a PDMP and supply are regarded as exogenous to abuse. We make use of aggregate measures for PDMP and supply and individual response measures for abuse. The relationships between the aggregate measures and abuse may be mediated by other individual response measures: gender, race, age, employment status, and heroin or cocaine as the primary substance of abuse. Unfortunately, individual response measures for insurance coverage and income are not available for most TEDS cases. But a measure is available for highest grade completed

Let the propensity of the i^{th} individual admitted in state k at time t to exhibit prescription drug abuse be represented by the random variate Y^*_{ikt}, defined over the entire real line. We assume that this propensity depends on X_{ikt}, a matrix of explanatory variables comprising his personal characteristics, the characteristics of his environment, and time. For notational convenience, we partition X_{ikt} into three sets of explanatory variables as follows: let X_{1ikt} represent those variables that vary across individuals as well as across state and time; let X_{2ikt} represent those variables that vary across state and time but not across individuals; and let X_{3ikt} represent those variables designed to capture time-related effects. To simplify notation, we take advantage of the following identities,

$$X_{2ikt} = X_{2lkt} = X_{2kt}$$

$$X_{3ikt} = X_{3lmt} = X_{3t}$$

Thus, we drop the subscript i when referring to state-level variables that do not vary over i for a given state k and a given time t, and we drop the subscripts i and k when referring to time-related variables that do not vary over i and k for a given time t.

The vectors of X_1 are circumscribed by the set of personal characteristics in the TEDS dataset that are relevant to our analysis. As noted above, these include gender, race, age, employment status, and educational attainment; as well as heroin or cocaine as the primary substance of abuse.

The vectors of X_2 include $SUPPLY_{kt}$, $PDMP_{kt}$, and $XPDMP_{kt}$ as defined above in Equation (1). In addition, as an alternative to the hypothesis of state random effects, the large number of observations in the TEDS dataset permits testing for state fixed effects, an option that was unavailable to us in the aggregate analysis.

Allowing X_3 to include a deterministic term is one way of modeling how the probability of admission involving prescription drug abuse has changed over time, all else being equal. Indeed, a preliminary review of estimates of prescription drug abuse derived from a variety of sources, such as the Drug Abuse Warning Network (DAWN), the NSDUH, and TEDS, suggests a strong secular trend during our observation period. Alternatively, changes over time could be modeled using time fixed effects.

The large number of observations in the TEDS dataset also permits inclusion of interactions between the columns of X_1, X_2, and X_3. For example, interactions between appropriate columns of X_1 and X_2 allow us to test for variation in the impact of PDMPs on the probability of admission involving prescription drug abuse by various personal characteristics; while interactions between appropriate columns of X_2 and X_3 allow us to test for variation in the impact of PDMPs on the probability of admission involving prescription drug abuse over time. We can also test for the presence of random variation in slopes across states; or slopes can be allowed to vary deterministically across states.

Thus Y^*_{ikt} is an unobservable response variable that, assuming randomly distributed state effects, has the following three-level linear specification,

$$\left.\begin{aligned} Y^*_{ikt} &= \gamma_{0ikt} + \gamma_{1k}X_{1ikt} + \gamma_{2k}X_{2kt} + \gamma_3 X_{3t} \\ &\quad + \gamma_4 X_{1ikt}X_{2kt} + \gamma_5 X_{1ikt}X_{3t} + \gamma_6 X_{2kt}X_{3t} \\ \gamma_{0i} &= \gamma_0 + u_k + e_{ikt} \\ \gamma_{n2k} &= \gamma_n + \delta_{nk} \end{aligned}\right\} \quad \begin{array}{l} k = 1, ..., 51; \\ t = 1, ..., 7; \\ n = 1, ..., 6 \end{array} \tag{5}$$

where u_k represents an unobserved, randomly distributed state effect, e_{ikt} is a randomly distributed error term, and δ_{nk} captures the random variation in the slopes by state.[3] In addition, we assume

$$\begin{gathered} E(u_k) = E(e_{ikt}) = E(\delta_{nk}) = 0, \forall n \\ Var(u_k) = \sigma^2_u \\ Var(e_{ikt}) = \sigma^2_e \\ Var(\delta_{nk}) = \sigma^2_{\delta n}, \forall n \\ Cov(u_k, \delta_{nk}) = \sigma_{un}, \forall n \\ Cov(e_{ikt}, u_k) = Cov(e_{ikt}, \delta_{nk}) = 0, \forall n \end{gathered} \tag{6}$$

In practice, however, we actually observe a binary response variable, Y_{ikt}, defined by

$$Y_{ikt} = \begin{cases} 1 & \text{if } Y^*_{ikt} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Thus, if $Y^*_{ikt} > 0$, then the ikt^{th} individual admitted for treatment reports that she does indeed abuse a prescription drug and we observe $Y_{ikt} = 1$. If she reports otherwise, then we observe $Y_{ikt} = 0$, an indication that $Y^*_{ikt} \leq 0$.

[3] A fixed effects model with analogous interaction terms will be estimated as well.

Continuing with the example presented in Equation (5), the conditional expectation of Y^*_{ikt}, given particular values for the explanatory variables, can be expressed as follows,

$$E(Y^*_{ikt}|X_{ikt}) = \gamma_0 + \gamma_1 X_{1ikt} + \gamma_2 X_{2kt} + \gamma_3 X_{3kt} + \gamma_4 X_{1ikt}X_{2kt} + \gamma_5 X_{1ikt}X_{3t} + \gamma_6 X_{2kt}X_{3t}$$

Then the probability of observing abuse of a prescription drug by individual ikt is

$$\begin{aligned}
P(Y_{ikt} = 1|X_{ikt}) &= \\
&= P(Y^*_{ikt} > 0 \mid X_{ikt}) \\
&= P(e_{ikt} > -\gamma_0 - (\gamma_1 + \delta_{1k})X_{1ikt} - (\gamma_2 + \delta_{2k})X_{2kt} - (\gamma_3 + \delta_{3k})X_{3kt} \\
&\qquad - (\gamma_4 + \delta_{4k})X_{1ikt}X_{2kt} - (\gamma_5 + \delta_{5k})X_{1ikt}X_{3t} - (\gamma_6 + \delta_{6k})X_{2kt}X_{3t} - u_k) \\
&= F(\gamma_0 + (\gamma_1 + \delta_{1k})X_{1ikt} + (\gamma_2 + \delta_{2k})X_{2kt} + (\gamma_3 + \delta_{3k})X_{3kt} \\
&\qquad + (\gamma_4 + \delta_{4k})X_{1ikt}X_{2kt} + (\gamma_5 + \delta_{5k})X_{1ikt}X_{3t} + (\gamma_6 + \delta_{6k})X_{2kt}X_{3t} + u_k) \\
&= F(\gamma_0 + \gamma_{1k}X_{1ikt} + \gamma_{2k}X_{2kt} + \gamma_3 X_{3t} + \gamma_4 X_{1ikt}X_{2kt} + \gamma_5 X_{1ikt}X_{3t} \\
&\qquad + \gamma_6 X_{2kt}X_{3t} + u_k) \\
&= \pi_{ikt}
\end{aligned} \tag{8}$$

where $F(\cdot)$ is the cumulative distribution function for the random error term, e_{ikt}. The observed values of Y_{ikt} are thus realizations of a binomial process with probability π_{ikt}, such that $Y_{ikt} \sim Bin(1, \pi_{ikt})$ with conditional variance $\pi_{ikt}(1-\pi_{ikt})$, implying the following general form for the likelihood function,

$$L(\gamma \mid X, u, \delta) = \prod_{t=1}^{7} \prod_{k=1}^{51} \prod_{i=1}^{N} \pi_{ikt}^{Y_{ikt}} (1 - \pi_{ikt})^{(1-Y_{ikt})} \tag{9}$$

A more detailed specification of the likelihood requires additional assumptions about the distributions of u_k, δ_{1k}, δ_{2k}, and e_{ikt}. Following convention, we assume that u_k, δ_{1k}, and δ_{2k} are distributed as $N(0, \sigma_u^2)$, $N(0, \sigma_{\delta 1}^2)$, and $N(0, \sigma_{\delta 2}^2)$, respectively. Also following convention, we assume two possible distributions for e_{ikt}: the logistic distribution with σ_e^2 constrained to equal unity, giving rise to the multilevel logit model; and the cumulative standard normal distribution, giving rise to a multilevel probit model. The logit model implies the following functional form for π_{ikt},

$$\pi_{ikt} = \frac{\exp\left(\gamma_0 + \gamma_{1k} X_{1ikt} + \gamma_{2k} X_{2kt} + \gamma_3 X_{3t} + \gamma_4 X_{1ikt} X_{2kt} + \gamma_5 X_{1ikt} X_{3t} + \gamma_6 X_{2kt} X_{3t} + u_k\right)}{1 + \exp\left(\gamma_0 + \gamma_{1k} X_{1ikt} + \gamma_{2k} X_{2kt} + \gamma_3 X_{3t} + \gamma_4 X_{1ikt} X_{2kt} + \gamma_5 X_{1ikt} X_{3t} + \gamma_6 X_{2kt} X_{3t} + u_k\right)} \quad (10)$$

implying in turn the following linear form for the multilevel logit regression model,

$$Y_{ikt} = \pi_{ikt} + e_{ikt} z_{ikt}$$

where $z_{ikt} = \sqrt{\pi_{ikt}(1 - \pi_{ikt})}$ represents the binomial standard deviation. Solving Equation (10) for the exponentiated expression yields,

$$\ln\left(\frac{\pi_{ikt}}{1 - \pi_{ikt}}\right) = \gamma_0 + \gamma_{1k} X_{1ikt} + \gamma_{2k} X_{2kt} + \gamma_3 X_{3t} + \gamma_4 X_{1ikt} X_{2kt} + \gamma_5 X_{1ikt} X_{3t} + \gamma_6 X_{2kt} X_{3t} + u_k$$

which has the familiar interpretation of the log odds of observing $Y_{ikt} = 1$. Alternatively, the probit model implies the following functional form for π_{ikt},

$$\pi_{ikt} = \Phi\left(\gamma_0 + \gamma_{1k} X_{1ikt} + \gamma_{2k} X_{2kt} + \gamma_3 X_{3t} + \gamma_4 X_{1ikt} X_{2kt} + \gamma_5 X_{1ikt} X_{3t} + \gamma_6 X_{2kt} X_{3t} + u_k\right) \quad (11)$$

where $\Phi(\cdot)$ denotes the cumulative standard normal distribution.

The logistic and cumulative standard normal distributions are similar in that both transform a variable defined over the interval between and including 0 and 1 into an interval defined over the entire real line. However, the logistic distribution is thicker in the tails.

Results. We estimate the model described in the previous section with particular interest in the sign and size of the elements of γ_{2k} and γ_6. Indeed, our interest in these parameters supersedes our interest in estimates of Y_{ikt} itself. This prioritization of objectives is not trivial since, as criteria for model selection, the two are not necessarily compatible (Greene [32]).

For samples that are well-balanced between values of Y_{ikt}, the choice is less important since logit and probit models are known to give similar results. But in this case the proportion of individuals admitted to treatment who report prescription drug abuse ($Y_{ikt} = 1$) is relatively small (less than 10 percent). And under these circumstances, the two models can give very different results (see Greene [33]). It will therefore be informative to assess the stability of our estimates relative to alternative distributional assumptions.

Equations (10) and (11) indicate that our coefficients are distribution-dependent; and therefore the results produced by a logit model may not be consistent with the results produced by a comparable probit model. As an aid to assessing stability across models we calculate the marginal effect associated with each explanatory variable following Greene [32]. Thus,

$$\frac{\partial E\left[Y^*\right]}{\partial X} = \left[\frac{dF\left(\gamma' X\right)}{d(\gamma' X)}\right]\gamma$$

where $F(\cdot)$ is the cumulative distribution function referenced in Equation (8).

Model selection is made further problematic by the large size of the dataset. Teachman *et al.* [25] point out that as sample size increases hypothesis tests based on the chi-square statistic may result in rejection of a null hypothesis that is "only trivially false." With this observation in mind, we seek the most parsimonious model in which coefficient estimates are found to be insensitive to marginal changes in specification. Only coefficients statistically different from 0 at the .0001 level are accepted for inclusion.

We begin by presenting the random effects logit model. Estimates for the most parsimonious versions of Equation (5) are provided in Table IX for pain relievers and in Table X for stimulants, along with their standard errors, t-statistics, and marginal effects. The findings indicate that for both classes of drugs, women have higher probabilities of admission involving abuse than men. Again for both classes of drugs, whites have higher probabilities of admission involving abuse than non-whites. While the probability of admission involving pain reliever abuse increases with age, the opposite holds true for the probability of admission involving stimulant abuse. For both classes of drugs, full-time employment reduces the probability of admission involving abuse. Educational attainment increases the probability of admission involving pain reliever abuse and decreases the probability of admission involving stimulant abuse. Heroin abuse increases the probability of admission involving pain reliever abuse, while cocaine abuse appears to have the opposite effect. As suggested earlier by the results of our aggregate analysis, this may indicate substitution among opioid agonists. Both heroin and cocaine abuse reduce the probability of admission involving stimulant abuse. Increasing the $SUPPLY$ of pain relievers (PR composite) increases the probability of admission involving pain reliever abuse; and increasing the $SUPPLY$ of stimulants (ST composite) increases the probability of admission involving stimulant abuse.

Table IX: Pain Reliever Abuse Estimates (Random Effects Logit Model)

	Estimate	s.e.	t Value	pr > t	Marginal Effect
Intercept	-5.3003	0.0952	-55.66	<.0001	-0.1289
Male	-0.5900	0.0033	-179.68	<.0001	-0.0144
White	1.0970	0.0045	244.75	<.0001	0.0267
Age	0.0107	0.0001	75.63	<.0001	0.0003
Employment	-0.1893	0.0040	-47.35	<.0001	-0.0046
Education	0.2156	0.0017	125.87	<.0001	0.0052
Heroin	0.3000	0.0044	68.45	<.0001	0.0073
Cocaine	-1.0215	0.0073	-140.07	<.0001	-0.0248
PR composite	2.4733	0.0136	181.45	<.0001	0.0602
Covariance parameter	0.4580	0.0920			

Table X: Stimulant Abuse Estimates (Random Effects Logit Model)

	Estimate	s.e.	t Value	pr > t	Marginal Effect
Intercept	-3.8337	0.1438	-26.65	<.0001	-0.0410
Male	-0.4707	0.0045	-105.31	<.0001	-0.0050
White	0.9835	0.0061	162.45	<.0001	0.0105
Age	-0.0734	0.0010	-77.21	<.0001	-0.0008
Employment	-0.3991	0.0055	-72.37	<.0001	-0.0043
Education	-0.0678	0.0024	-27.87	<.0001	-0.0007
Heroin	-1.1517	0.0106	-109.00	<.0001	-0.0123
Cocaine	-0.8100	0.0093	-87.55	<.0001	-0.0087
ST composite	2.4943	0.1436	17.37	<.0001	0.0267
Covariance parameter	1.0430	0.2088			

We are particularly interested in the relationship between abuse and $SUPPLY$. Figure 25 depicts the probability of admission involving pain reliever abuse as a function of $SUPPLY$ (PR composite) holding constant the values of all other explanatory variables. The relationship is nonlinear and accelerating thus suggesting the potential for a substantial return on efforts to curtail availability. Figure 26 depicts analogously the probability of admission involving stimulant abuse as a function of $SUPPLY$ (ST composite). This relationship is more linear.

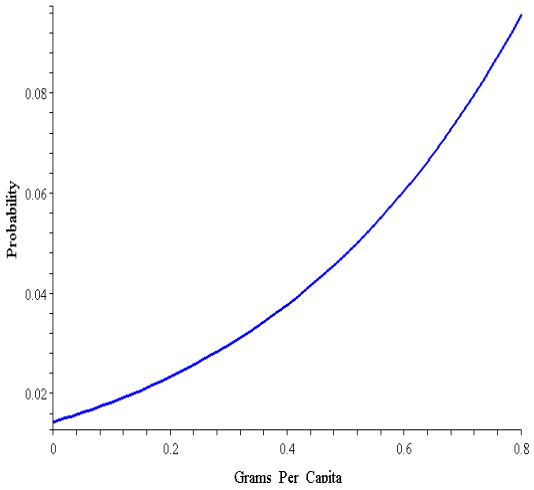

Figure 25: PR Abuse by PR Composite

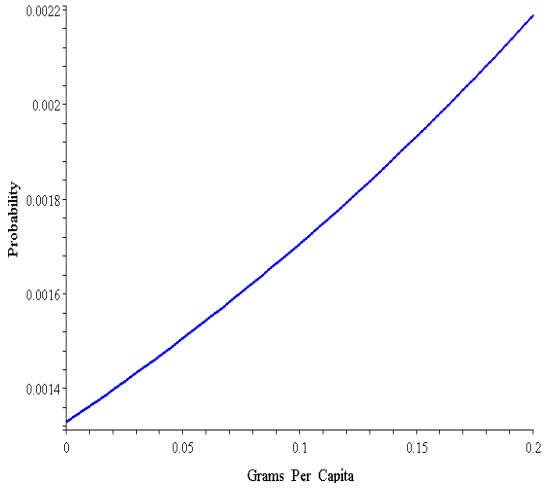

Figure 26: ST Abuse by ST Composite

As noted above it will be useful to examine the effects of alternative model specifications (state fixed effects versus state random effects) and distributional assumptions (logistic versus cumulative standard normal) on the stability of our estimates.

We begin by presenting the results from a logit model with state fixed effects in Table XI for pain relievers and Table XII for stimulants. The coefficients are remarkably similar to those presented in Tables IX and X.

We then re-estimate using a probit model with state fixed effects. With highly unbalanced samples such as this the logit and probit models can give different results. However, comparing the marginal effects in Tables XIII and XIV to those in Tables XI and XII, we see that the models are consistent. They support the hypothesis that the probability of admission involving prescription drug abuse responds positively to increases in drug supply and (by inference) negatively to the presence of a proactively monitoring PDMP.

Table XI: Pain Reliever Abuse Estimates (Fixed Effects Logit Model)

	Estimate	s.e.	t Value	pr > t	Marginal Effect
Intercept	-5.9552	0.0403	-147.61	<.0001	-0.1448
Male	-0.5900	0.0033	-179.68	<.0001	-0.0144
White	1.0970	0.0045	244.74	<.0001	0.0267
Age	0.0107	0.0001	75.63	<.0001	0.0003
Employment	-0.1893	0.0040	-47.35	<.0001	-0.0046
Education	0.2156	0.0017	125.86	<.0001	0.0052
Heroin	0.3000	0.0044	68.44	<.0001	0.0073
Cocaine	-1.0215	0.0073	-140.08	<.0001	-0.0248
PR composite	2.4733	0.0136	181.43	<.0001	0.0602
Alabama	1.6178	0.0411	39.41	<.0001	0.0393
Alaska	-0.2891	0.0541	-5.34	<.0001	-0.0070
Arizona	-0.9918	0.1042	-9.52	<.0001	-0.0241
Arkansas	0.9314	0.0428	21.75	<.0001	0.0227
California	0.4877	0.0400	12.18	<.0001	0.0119
Colorado	-0.2496	0.0421	-5.93	<.0001	-0.0061
Connecticut	0.6641	0.0407	16.33	<.0001	0.0162
Delaware	0.4623	0.0480	9.63	<.0001	0.0112
District of Columbia	-0.1187	0.0750	-1.58	0.1133	-0.0029
Florida	0.9200	0.0402	22.87	<.0001	0.0224
Georgia	1.4196	0.1604	8.85	<.0001	0.0345
Hawaii	0.7331	0.0497	14.76	<.0001	0.0178
Idaho	0.0963	0.0518	1.86	0.0631	0.0023
Illinois	0.1039	0.0425	2.45	0.0144	0.0025
Indiana	1.2222	0.0409	29.88	<.0001	0.0297
Iowa	-0.0321	0.0437	-0.73	0.4631	-0.0008
Kansas	0.1896	0.0462	4.10	<.0001	0.0046
Kentucky	1.2726	0.0414	30.75	<.0001	0.0310
Louisiana	1.7543	0.0409	42.94	<.0001	0.0427
Maine	1.4966	0.0411	36.38	<.0001	0.0364
Maryland	0.7957	0.0404	19.71	<.0001	0.0194
Massachusetts	1.0685	0.0401	26.67	<.0001	0.0260
Michigan	1.1824	0.0402	29.42	<.0001	0.0288
Minnesota	0.6069	0.0412	14.72	<.0001	0.0148
Mississippi	1.9330	0.0463	41.73	<.0001	0.0470
Missouri	-0.1290	0.0422	-3.06	0.0022	-0.0031
Montana	0.8535	0.0446	19.14	<.0001	0.0208
Nebraska	-0.1132	0.0527	-2.15	0.0316	-0.0028
Nevada	-0.4040	0.0476	-8.49	<.0001	-0.0098
New Hampshire	0.3962	0.0474	8.36	<.0001	0.0096
New Jersey	0.6901	0.0407	16.97	<.0001	0.0168
New Mexico	0.3889	0.0561	6.94	<.0001	0.0095
New York	0.7822	0.0399	19.63	<.0001	0.0190
North Carolina	0.8643	0.0413	20.95	<.0001	0.0210
North Dakota	0.8464	0.0574	14.74	<.0001	0.0206
Ohio	0.6425	0.0405	15.85	<.0001	0.0156
Oklahoma	0.8038	0.0425	18.90	<.0001	0.0195
Oregon	-0.5042	0.0417	-12.10	<.0001	-0.0123
Pennsylvania	0.9622	0.0403	23.89	<.0001	0.0234
Rhode Island	1.3893	0.0418	33.22	<.0001	0.0338
South Carolina	0.7090	0.0419	16.92	<.0001	0.0172
South Dakota	-0.5368	0.0610	-8.80	<.0001	-0.0131
Tennessee	1.9650	0.0425	46.20	<.0001	0.0478
Texas	1.6153	0.0409	39.54	<.0001	0.0393
Utah	0.8150	0.0427	19.09	<.0001	0.0198
Vermont	1.1462	0.0453	25.30	<.0001	0.0279
Virginia	1.3499	0.0415	32.51	<.0001	0.0328
Washington	0.5796	0.0406	14.28	<.0001	0.0141
West Virginia	0.9371	0.0497	18.85	<.0001	0.0228
Wisconsin	0.0604	0.0443	1.36	0.1724	0.0015
Wyoming	0.0000 .	.		.	0.0000

Table XII: Stimulant Abuse Estimates (Fixed Effects Logit Model)

	Estimate	s.e.	t Value	pr > t	Marginal Effect
Intercept	-2.4930	0.0254	-97.98	<.0001	-0.0209
Male	-0.4665	0.0045	-104.31	<.0001	-0.0039
White	0.9839	0.0061	162.51	<.0001	0.0082
Age	-0.0180	0.0002	-89.37	<.0001	-0.0002
Employment	-0.4036	0.0055	-73.15	<.0001	-0.0034
Education	-0.0630	0.0024	-26.18	<.0001	-0.0005
Heroin	-1.1518	0.0106	-109.03	<.0001	-0.0097
Cocaine	-0.8138	0.0092	-88.01	<.0001	-0.0068
ST composite	2.5162	0.1437	17.52	<.0001	0.0211
Alabama	-1.0852	0.0308	-35.27	<.0001	-0.0091
Alaska	-0.8956	0.0431	-20.76	<.0001	-0.0075
Arizona	-1.3472	0.0732	-18.41	<.0001	-0.0113
Arkansas	1.8387	0.0236	77.78	<.0001	0.0154
California	-1.2817	0.0241	-53.30	<.0001	-0.0107
Colorado	-2.1101	0.0308	-68.53	<.0001	-0.0177
Connecticut	-2.3080	0.0359	-64.39	<.0001	-0.0194
Delaware	-2.2540	0.0728	-30.95	<.0001	-0.0189
District of Columbia	-0.7688	0.0656	-11.71	<.0001	-0.0064
Florida	-1.9830	0.0280	-70.88	<.0001	-0.0166
Georgia	-1.5129	0.3820	-3.96	<.0001	-0.0127
Hawaii	-1.1833	0.0482	-24.55	<.0001	-0.0099
Idaho	-1.8181	0.0465	-39.13	<.0001	-0.0152
Illinois	-0.4466	0.0244	-18.34	<.0001	-0.0037
Indiana	-1.6279	0.0311	-52.28	<.0001	-0.0136
Iowa	-2.0557	0.0325	-63.31	<.0001	-0.0172
Kansas	-1.2641	0.0328	-38.52	<.0001	-0.0106
Kentucky	-1.4767	0.0341	-43.34	<.0001	-0.0124
Louisiana	-0.7764	0.0285	-27.27	<.0001	-0.0065
Maine	-1.8836	0.0411	-45.85	<.0001	-0.0158
Maryland	-2.4678	0.0334	-73.85	<.0001	-0.0207
Massachusetts	-2.5212	0.0329	-76.73	<.0001	-0.0211
Michigan	-2.2813	0.0297	-76.94	<.0001	-0.0191
Minnesota	-1.3321	0.0271	-49.15	<.0001	-0.0112
Mississippi	-1.1709	0.0618	-18.94	<.0001	-0.0098
Missouri	-1.8028	0.0293	-61.50	<.0001	-0.0151
Montana	-1.3441	0.0410	-32.81	<.0001	-0.0113
Nebraska	-2.0983	0.0525	-39.98	<.0001	-0.0176
Nevada	-0.5407	0.0305	-17.71	<.0001	-0.0045
New Hampshire	-1.5649	0.0475	-32.93	<.0001	-0.0131
New Jersey	-1.9364	0.0323	-60.03	<.0001	-0.0162
New Mexico	-1.0256	0.0481	-21.31	<.0001	-0.0086
New York	-1.8552	0.0243	-76.49	<.0001	-0.0156
North Carolina	-1.8646	0.0328	-56.92	<.0001	-0.0156
North Dakota	-0.1791	0.0421	-4.25	<.0001	-0.0015
Ohio	-1.8905	0.0272	-69.58	<.0001	-0.0159
Oklahoma	0.0523	0.0256	2.04	0.0411	0.0004
Oregon	1.7898	0.0226	79.06	<.0001	0.0150
Pennsylvania	-1.8422	0.0281	-65.47	<.0001	-0.0154
Rhode Island	-2.4572	0.0570	-43.12	<.0001	-0.0206
South Carolina	-2.2875	0.0370	-61.76	<.0001	-0.0192
South Dakota	0.7050	0.0261	26.98	<.0001	0.0059
Tennessee	-0.3887	0.0325	-11.97	<.0001	-0.0033
Texas	0.9459	0.0235	40.21	<.0001	0.0079
Utah	-1.2430	0.0328	-37.85	<.0001	-0.0104
Vermont	-2.1863	0.0678	-32.26	<.0001	-0.0183
Virginia	-1.1377	0.0321	-35.48	<.0001	-0.0095
Washington	-0.8360	0.0247	-33.85	<.0001	-0.0070
West Virginia	-2.0920	0.0797	-26.26	<.0001	-0.0175
Wisconsin	-2.2710	0.0410	-55.42	<.0001	-0.0190
Wyoming	0.0000	.	.	.	0.0000

Table XIII: Pain Reliever Abuse Estimates (Fixed Effects Probit Model)

	Estimate	s.e.	t Value	pr > t	Marginal Effect
Intercept	-2.9986	0.0168	-178.40	<.0001	-0.1805
Male	-0.2756	0.0015	-179.89	<.0001	-0.0166
White	0.4731	0.0019	251.90	<.0001	0.0285
Age	0.0056	0.0001	84.66	<.0001	0.0003
Employment	-0.0841	0.0018	-46.35	<.0001	-0.0051
Education	0.0993	0.0008	125.64	<.0001	0.0060
Heroin	0.1443	0.0020	71.06	<.0001	0.0087
Cocaine	-0.4427	0.0030	-147.48	<.0001	-0.0267
PR composite	1.1573	0.0064	181.06	<.0001	0.0697
Alabama	0.7394	0.0173	42.69	<.0001	0.0445
Alaska	-0.1427	0.0227	-6.28	<.0001	-0.0086
Arizona	-0.4005	0.0398	-10.07	<.0001	-0.0241
Arkansas	0.3997	0.0181	22.06	<.0001	0.0241
California	0.2146	0.0166	12.90	<.0001	0.0129
Colorado	-0.0982	0.0174	-5.65	<.0001	-0.0059
Connecticut	0.2877	0.0170	16.96	<.0001	0.0173
Delaware	0.1955	0.0204	9.56	<.0001	0.0118
District of Columbia	-0.0070	0.0285	-0.25	0.8051	-0.0004
Florida	0.4060	0.0168	24.20	<.0001	0.0244
Georgia	0.6419	0.0792	8.11	<.0001	0.0386
Hawaii	0.3165	0.0211	15.00	<.0001	0.0191
Idaho	0.0438	0.0215	2.04	0.0416	0.0026
Illinois	0.0748	0.0175	4.28	<.0001	0.0045
Indiana	0.5497	0.0172	32.02	<.0001	0.0331
Iowa	-0.0047	0.0181	-0.26	0.7945	-0.0003
Kansas	0.0905	0.0192	4.72	<.0001	0.0054
Kentucky	0.5828	0.0175	33.27	<.0001	0.0351
Louisiana	0.8025	0.0172	46.62	<.0001	0.0483
Maine	0.7228	0.0175	41.36	<.0001	0.0435
Maryland	0.3379	0.0168	20.07	<.0001	0.0203
Massachusetts	0.4785	0.0167	28.65	<.0001	0.0288
Michigan	0.5259	0.0168	31.40	<.0001	0.0317
Minnesota	0.2664	0.0172	15.49	<.0001	0.0160
Mississippi	0.8911	0.0207	43.00	<.0001	0.0536
Missouri	-0.0637	0.0175	-3.64	0.0003	-0.0038
Montana	0.3806	0.0191	19.93	<.0001	0.0229
Nebraska	-0.0257	0.0214	-1.20	0.2311	-0.0015
Nevada	-0.1796	0.0199	-9.04	<.0001	-0.0108
New Hampshire	0.1667	0.0203	8.20	<.0001	0.0100
New Jersey	0.3005	0.0170	17.73	<.0001	0.0181
New Mexico	0.1791	0.0234	7.66	<.0001	0.0108
New York	0.3451	0.0166	20.84	<.0001	0.0208
North Carolina	0.3682	0.0173	21.33	<.0001	0.0222
North Dakota	0.3820	0.0249	15.33	<.0001	0.0230
Ohio	0.2805	0.0169	16.62	<.0001	0.0169
Oklahoma	0.3522	0.0179	19.67	<.0001	0.0212
Oregon	-0.2265	0.0173	-13.09	<.0001	-0.0136
Pennsylvania	0.4255	0.0168	25.32	<.0001	0.0256
Rhode Island	0.6338	0.0177	35.75	<.0001	0.0382
South Carolina	0.2997	0.0175	17.11	<.0001	0.0180
South Dakota	-0.1901	0.0240	-7.94	<.0001	-0.0114
Tennessee	0.9124	0.0183	49.81	<.0001	0.0549
Texas	0.7255	0.0171	42.38	<.0001	0.0437
Utah	0.3597	0.0181	19.93	<.0001	0.0217
Vermont	0.5192	0.0197	26.31	<.0001	0.0313
Virginia	0.5990	0.0175	34.15	<.0001	0.0361
Washington	0.2539	0.0169	14.99	<.0001	0.0153
West Virginia	0.4307	0.0219	19.67	<.0001	0.0259
Wisconsin	0.0228	0.0184	1.24	0.2146	0.0014
Wyoming	0.0000 .	.		.	0.0000

Table XIV: Stimulant Abuse Estimates (Fixed Effects Probit Model)

	Estimate	s.e.	t Value	pr > t	Marginal Effect
Intercept	-1.3961	0.0121	-115.67	<.0001	-0.0337
Male	-0.2018	0.0020	-98.52	<.0001	-0.0049
White	0.3992	0.0025	158.37	<.0001	0.0096
Age	-0.0085	0.0001	-92.33	<.0001	-0.0002
Employment	-0.1591	0.0025	-63.99	<.0001	-0.0038
Education	-0.0216	0.0011	-19.68	<.0001	-0.0005
Heroin	-0.4617	0.0043	-108.44	<.0001	-0.0111
Cocaine	-0.3282	0.0038	-86.65	<.0001	-0.0079
ST composite	1.0332	0.0657	15.73	<.0001	0.0249
Alabama	-0.4982	0.0139	-35.74	<.0001	-0.0120
Alaska	-0.4096	0.0187	-21.94	<.0001	-0.0099
Arizona	-0.5934	0.0297	-19.98	<.0001	-0.0143
Arkansas	0.9580	0.0117	81.61	<.0001	0.0231
California	-0.5507	0.0114	-48.32	<.0001	-0.0133
Colorado	-0.8746	0.0132	-66.15	<.0001	-0.0211
Connecticut	-0.9347	0.0145	-64.30	<.0001	-0.0226
Delaware	-0.9262	0.0268	-34.59	<.0001	-0.0223
District of Columbia	-0.2940	0.0245	-12.02	<.0001	-0.0071
Florida	-0.8431	0.0125	-67.46	<.0001	-0.0203
Georgia	-0.6561	0.1486	-4.41	<.0001	-0.0158
Hawaii	-0.5207	0.0199	-26.17	<.0001	-0.0126
Idaho	-0.7868	0.0192	-41.10	<.0001	-0.0190
Illinois	-0.2033	0.0116	-17.50	<.0001	-0.0049
Indiana	-0.7067	0.0137	-51.42	<.0001	-0.0171
Iowa	-0.8762	0.0140	-62.62	<.0001	-0.0211
Kansas	-0.5633	0.0146	-38.59	<.0001	-0.0136
Kentucky	-0.6461	0.0149	-43.30	<.0001	-0.0156
Louisiana	-0.3637	0.0132	-27.52	<.0001	-0.0088
Maine	-0.8140	0.0171	-47.66	<.0001	-0.0196
Maryland	-1.0105	0.0139	-72.82	<.0001	-0.0244
Massachusetts	-1.0215	0.0137	-74.83	<.0001	-0.0247
Michigan	-0.9529	0.0129	-73.81	<.0001	-0.0230
Minnesota	-0.5934	0.0125	-47.58	<.0001	-0.0143
Mississippi	-0.5276	0.0256	-20.59	<.0001	-0.0127
Missouri	-0.7772	0.0130	-59.60	<.0001	-0.0188
Montana	-0.5901	0.0176	-33.56	<.0001	-0.0142
Nebraska	-0.8790	0.0204	-43.03	<.0001	-0.0212
Nevada	-0.2553	0.0142	-17.94	<.0001	-0.0062
New Hampshire	-0.6934	0.0200	-34.64	<.0001	-0.0167
New Jersey	-0.8064	0.0137	-58.92	<.0001	-0.0195
New Mexico	-0.4634	0.0205	-22.57	<.0001	-0.0112
New York	-0.7708	0.0114	-67.80	<.0001	-0.0186
North Carolina	-0.7887	0.0140	-56.30	<.0001	-0.0190
North Dakota	-0.0823	0.0199	-4.14	<.0001	-0.0020
Ohio	-0.8046	0.0123	-65.48	<.0001	-0.0194
Oklahoma	0.0244	0.0124	1.97	0.0485	0.0006
Oregon	0.9538	0.0111	86.31	<.0001	0.0230
Pennsylvania	-0.7878	0.0126	-62.52	<.0001	-0.0190
Rhode Island	-1.0125	0.0214	-47.23	<.0001	-0.0244
South Carolina	-0.9534	0.0152	-62.75	<.0001	-0.0230
South Dakota	0.3589	0.0129	27.73	<.0001	0.0087
Tennessee	-0.1952	0.0152	-12.81	<.0001	-0.0047
Texas	0.4184	0.0115	36.43	<.0001	0.0101
Utah	-0.5477	0.0146	-37.41	<.0001	-0.0132
Vermont	-0.9284	0.0260	-35.73	<.0001	-0.0224
Virginia	-0.4942	0.0143	-34.61	<.0001	-0.0119
Washington	-0.3772	0.0117	-32.16	<.0001	-0.0091
West Virginia	-0.8897	0.0306	-29.12	<.0001	-0.0215
Wisconsin	-0.9548	0.0165	-57.72	<.0001	-0.0230
Wyoming	0.0000	.	.	.	0.0000

5 Discussion

This work examines the direct and indirect effects of PDMPs on the abuse of prescription drugs. Within this context we focus on the impact that PDMPs have on the supply of prescription drugs; and on the impact that PDMPs and supply together have on abuse. Methodological considerations lead us to focus on Schedule II pain relievers and stimulants, and composite measures for these two classes of drugs are developed for use in our analysis. Our approach involves estimation of both aggregate and individual response models.

The aggregate model suggests that the presence of a PDMP reduces per capita supply of prescription pain relievers and stimulants, and that this in turn reduces the probability of abuse for such drugs (the probability of prescription pain reliever abuse is a function of the per capita supply of prescription pain relievers, and the probability of prescription stimulant abuse is a function of the per capita supply of prescription stimulants). The evidence also suggests that states which are proactive in their approach to regulation may be more effective in reducing the per capita supply of prescription pain relievers and stimulants than states which are reactive in their approach to regulation.

The individual response model assesses the effects of aggregate characteristics (such as the presence of a PDMP and the supply of prescription pain relievers and stimulants) and personal characteristics (such as gender, race, age, employment status, educational attainment, and heroin or cocaine abuse) on the probability of prescription drug abuse. The findings are consistent with those provided by the aggregate model, suggesting that the probability of prescription pain reliever abuse is a function of the per capita supply of pain relievers, and that the probability of prescription stimulant abuse is a function of the per capita supply of stimulants.

We noted earlier that the probability of prescription pain reliever abuse is actually higher in states that have monitoring programs than in states that do not. On the surface this appears difficult to explain since these states have been effective in reducing the per capita supply of pain relievers. And we know from our individual response model that the decision to abuse pain relievers is sensitive to supply. We are thus drawn to return to our aggregate model in an effort to explain this paradox and to quantify the impact of PDMPs.

Taking the coefficients from Table VII we project values for per capita supply in states that monitor proactively as though no programs existed there. The coefficients from Table VIII are then used with these projected values for supply, as well as with population means for age and the per capita rates at which individuals report heroin and cocaine abuse on admission to treatment, to produce "synthetic estimates" of the probability of abuse in the absence of program intervention.

The results of this simulation are expressed as admissions per 100,000 and presented in Figures 27-28. They indicate that by 2003 the rate of pain reliever abuse would have been 10.1 percent higher and the rate of stimulant abuse would have been 4.1 percent higher in the absence of proactive regulatory control.

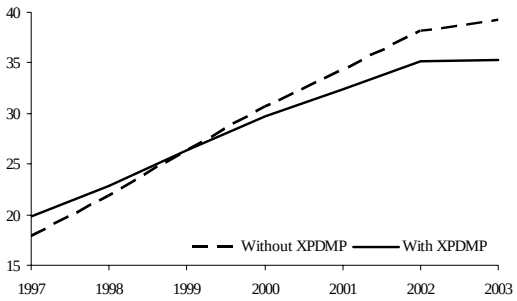

Figure 27. Pain Reliever Admissions in XPDMP States

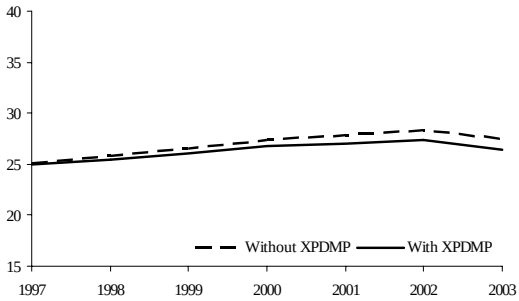

Figure 28: Stimulant Admissions in XPDMP States

In summary, the results from our aggregate and individual response models indicate that PDMPs which monitor proactively have inhibited growth in prescription sales (for pain relievers and stimulants) and in so doing exerted an indirect effect on the probability of abuse for these drugs.

Directions for future research. The rational addiction model suggests the importance of illicit drug prices in the decision to abuse prescription drugs. It is well known that illicit drug users often compensate for reduced supply by substituting licit drugs that have similar effects. We might therefore reasonably expect prescription pain relievers to become popular in areas, and during times when, the price of heroin is relatively high. It may thus be instructive to introduce measures of price per gram pure for heroin, cocaine, crack, and methamphetamine into our model and to examine possible substitution effects in greater detail.

In 2004 the RAND corporation received a contract from the Office of National Drug Control Policy (ONDCP) to develop a consistent series of estimates for price and purity (Arkes *et al.* [21]). The System to Retrieve Information from Drug Evidence (STRIDE) provided the basis for these efforts.[4] Data availability allowed price and purity estimates to be made for 29 cities, quarterly, for each drug identified above, and these exist over the duration of our study period. ONDCP has made the RAND estimates available to SAI for use in its analysis. We propose to develop a model that draws upon this information in subsequent work.

[4]STRIDE is a DEA database that retains information on seizures, purchases, and other drug acquisition events that occur during the course of law enforcement activity. It is designed primarily to control forensic inventory and to provide scientific evidence in support of prosecution. Because STRIDE data are not intended to support research of the kind being conducted here, they do not constitute a random sample of all drug transactions that occur within any geographic area. This limits the consistency with which places are represented over time, the statistical techniques that can be used to analyze the data, and the inferences that can be drawn based upon the results of such analyses (see Manski *et al.* [34]; and Horowitz [35]). The system nonetheless remains the best available source of information on illicit drug prices and purity (Saffer and Chaloupka [28]**;** Manski *et al.* [34]; DeSimone [36]).

6 References

1. Robinson W. Ecological correlations and the behavior of individuals, *American Sociological Review* 1950; **15**: 351–357.

2. Freedman D, Klein S, Sacks J, Smyth C, Everett C. Ecological regression and voting rights, *Evaluation Review* 1991: **15**: 659–817.

3. Greenland S, Robins J. Invited commentary: ecologic studies—biases, misconceptions, and counterexamples, *American Journal of Epidemiology* 1994; **139**: 747–760.

4. Freedman D, Klein S, Ostland M, Roberts M. Review of a solution to the ecological inference problem, *Journal of the American Statistical Association* 1998; **93**: 1518–1522.

5. Neeleman J, Lewis G. Suicide, religion, and socieconomic conditions: an ecological study in 26 countries, *Journal of Epidemiology and Community Health* 1999; **53**: 204–210.

6. Gordon D, Stevenson K, Griffie J, Muchka S, Rapp C, Ford-Roberts K. Opioid equianalgesic calculations, *Journal of Palliative Medicine* 1999; **2**: 209-218.

7. Anderson R, Saiers J, Abram S, Schlict C. Accuracy in equianalgesic dosing: conversion dilemmas, *Journal of Pain and Symptom Management* 2001; **21**: 397-406.

8. Pereira J, Lawlor P, Vigano A, Dorgan M, Bruera E. Equianalgesic dose ratios for opioids: a critical review and proposals for long-term dosing, *Journal of Pain and Symptom Management* 2001; **22**: 672-687.

9. Paix A, Coleman A, Lees, J, Grigson J, Brooksbank M, Thorne D, Ashby M. Subcutaneous fentanyl and sufentanyl infusion substitution for morphine intolerance in cancer pain management, *Pain* 1995; **63**: 263-269.

10. Watanabe S, Pereira J, Hanson J, Bruera E. Fentanyl by continuous subcutaneous infusion for the management of cancer pain: a retrospective study, *Journal of Pain Symptom Management* 1998; **16**: 323-326.

11. Hunt R, Fazekas B, Thorne D, Brooksbank M. A comparison of subcutaneous morphine and fentanyl in hospice cancer patients, *Journal of Pain Symptom Management* 1999; **18**:111-119.

12. Bruera E, Pereira J, Watanabe S, Belzile M, Kuehn N, Hanson J. Opioid rotation in patients with cancer pain, *Cancer* 1996; **78**: 852-857.

13. Lawler P, Turner K, Hanson J, Bruera E. Dose ratio between morphine and hydromorphone in patients with cancer pain: a retrospective study, *Pain* 1997; **72**:79-85.

14. Dunbar PJ, Chapman CR, Buckley FP, Garvin JR. Clinical analgesic equivalence for morphine and hydromorphone with prolonged PCA, *Pain* 1996; **68**: 265-270.

15. Lawler PG, Turner KS, Hanson J, Bruera ED. Dose ratio between morphine and methadone in patients with cancer pain: a retrospective study, *Cancer* 1998; **82**:1167-1173.

16. Ripamonti C, Groff L, Brunelli C, Polastri D, Stravakis A, DeConno F. Switching from morphine to oral methadone in treating cancer pain: what is the equianalgesic dose ratio?, *Journal of Clinical Oncology* 1998; **16**: 3216-3221.

17. Beaver WT, Wallerstein SL, Rogers A, Houde HW. Analgesic studies of codeine and oxycodone in patients with cancer II: comparisons of intramuscular oxycodone with intramuscular morphine and codeine, *Journal of Pharmacology and Experimental Therapeutics* 1978; **207**:101-108.

18. Heiskanen T, Kalso E. Controlled-release oxycodone and morphine in cancer-related pain, *Pain* 1997; **73**: 37-45.

19. Kalso E, Vainio A. Morphine and oxycodone hydrochloride in the management of cancer pain, *Journal of Clinical Pharmacy and Therapeutics* 1990; **47**: 639-646.

20. Bruera E, Belzile M, Pitushkin E, Fainsinger R, Darke A, Harsanyi Z, Babul N, Ford I. Randomized, double blind, cross-over trial comparing safety and efficacy of oral controlled-release oxycodone with controlled release morphine in patients with cancer pain, *Journal of Clinical Oncology* 1998; **16**: 3222-3229.

21. Arkes J, Pacula R, Paddock S, Caulkins J, Reuter P. *Technical Report For The Price and Purity of Illicit Drugs: 1981 Through the Second Quarter of 2003.* Office of National Drug Control Policy: Washington DC, 2004.

22. Bokhari F, Mayes R, Scheffler R. An analysis of the significant variation in psychostimulant use across the US, *Pharmacoepidemiology and Drug Safety* 2005; **14**: 267-275.

23. Simeone R, Rhodes W, Hunt D, Truitt L. *A Plan for Estimating the Number of "Hardcore" Drug Users in the United States.* Office of National Control Policy: Washington DC, 1997.

24. Simeone R, Holland L, Viveros-Aguelara R. Estimating the size of an illicit drug-using population, *Statistics in Medicine* 2003; **29**: 2969-2993.

25. Teachman J, Duncan G, Yeung W, Levy D. Covariance structure models for fixed and random effects, *Sociological Methods and Research* 2001; **30**: 271-288.

26. Becker G, Murphy K. A theory of rational addiction, *The Journal of Political Economy* 1988; **96**: 675-700.

27. Becker G, Grossman M, Murphy K. An empirical analysis of cigarette addiction, *The American Economic Review* 1994; **84**: 396-418.

28. Saffer H, Chaloupka F. *The Demand for Illicit Drugs (NBER Working Paper No. 5238).* National Bureau of Economic Review: Cambridge, 1995.

29. Grossman M, Chaloupka F, Brown C. The demand for cocaine by young adults: a rational addiction approach, *Journal of Health Economics* 1998; **17**: 427–474.

30. Grossman M. *Individual Behaviors and Substance Use: The Role of Price (NBER Working Paper No. 10948).* National Bureau of Economic Review: Cambridge, 2004.

31. Grossman M, Chaloupka F, Shim K. Illegal drug use and public policy, *Health Affairs* 2002; **21**: 134-144.

32. Greene W. *Econometric Analysis.* McMillan: New York, 1993.

33. Greene W. *Estimating Econometric Models with Fixed Effects (Department of Economics Working Paper No. 01-10).* New York University: New York, 2001.

34. Manski C, Pepper J, Petrie C. *Informing America's Policy on Illegal Drugs: What We Don't Know Keeps Hurting Us.* National Academy Press: Washington DC, 2001.

35. Horowitz J. Should the DEA's STRIDE data be used for economic analysis of markets for illegal drugs, *Journal of the American Statistical Association* 2001; **96**:1254–1271.

36. DeSimone J. Illegal drug use and employment, *Journal of Labor Economics* 2002; **20**: 952–977.