# ESSAYS IN HEALTH ECONOMICS

Zahra Mohammadi

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Supervisor of Dissertation

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Petra Todd, Edmund J. and Louise W. Kahn Term Professor of Economics

Graduate Group Chairperson

---

Jesus Fernandez-Villaverde, Professor of Economics

Dissertation Committee

Petra Todd, Professor of Economics

Andrew Shephard, Assistant Professor of Economics

Robert Town, Professor of Economics

ESSAYS IN HEALTH ECONOMICS

*Dedicated to my parents*

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# ABSTRACT


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Zahra Mohammadi

Petra Todd

Opioid abuse is currently the most significant public health problem in the US. Many US states have implemented prescription drug monitoring programs (PDMPs) in response. In the first paper, I use a new micro-level medical claims database to exploit state-level and time-series variations in PDMP implementation and shed light on the impacts of these programs. My results show that PDMPs have led to an overall 14% reduction in the odds ratio of abuse/addiction. Also, there is evidence of substantial heterogeneity in impacts, with larger impacts for females and minorities. Another finding is that at least 23% of opioid abuse is a result of drug diversion to nonmedical opioid users. PDMPs were not successful in decreasing the rate of abuse for this group, and, in fact, there is some evidence that they increased the diversion to heroin. Finally, I show that PDMPs' effectiveness varies by type of insurance and that they are more effective in reducing abuse rates in the general population as compared with Medicare Part D recipients. I use my estimates to analyze the potential effects of modifying PDMPs to include giving insurance providers access to electronic databases, providing educational programs for less-educated people, and expanding their "must access" requirement. In the second chapter, I estimate different models for opioid demand and compare their performance. My results suggest that the NB2 and Poisson FE models best match the data. Using these models for calculating the marginal effect of insurance characteristics provides suggestive evidence of the best insurance design to reduce the demand for opioids.

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# CHAPTER 1 : The Effects of Prescription Drug Monitoring Programs on the Opioid Abuse Epidemic

**Abstract:** Opioid abuse is currently the most significant public health problem in the U.S. Many U.S. states have implemented prescription drug monitoring programs (PDMPs) in response. In this paper, I use a new micro-level medical claims database to exploit state-level and time-series variations in PDMP implementation and shed light on the impacts of these programs. My results show that PDMPs have led to an overall 14% reduction in the odds ratio of abuse/addiction. Also, there is evidence of substantial heterogeneity in impacts, with larger impacts for females and minorities. Another finding is that at least 23% of opioid abuse is a result of drug diversion to nonmedical opioid users. PDMPs were not successful in decreasing the rate of abuse for this group, and, in fact, there is some evidence that they increased the diversion to heroin. Finally, I show that PDMPs' effectiveness varies by type of insurance and that they are more effective in reducing abuse rates in the general population as compared with Medicare Part D recipients. I use my estimates to analyze the potential effects of modifying PDMPs to include giving insurance providers access to electronic databases, providing educational programs for less-educated people, and expanding their "must access" requirement.

## 1.1. Introduction

Prescription drug abuse has been described by the Centers for Disease Control as an epidemic in the United States. The rate of drug overdose deaths in the United States in 2015 was more than 2.5 times the rate in 1999, with the greatest percentage increase among adults aged 55-64 (from 4.2 per 100,000 in 1999 to 21.8 in 2015) (Hedegaard et al. (2017)). Based on the National Survey of Drug Use and Health, nearly all prescription drugs involved in overdoses are originally prescribed by a physician, rather than, for example, being stolen from pharmacies. Thus, policy makers are increasingly focusing attention on preventing the overprescription of drugs and their subsequent diversion to people other than the patient.

The main policy response to this prescription drug epidemic is the introduction of Prescription Drug Monitoring Programs (PDMPs), which are in place in all states as of 2017. As part of these programs, statewide electronic databases have been set up to track prescriptions dispensed for controlled substances. Information collected can be used to identify diverted drugs as well as to facilitate the identification of prescription drug-addicted individuals (Finklea et al. (2014)). There are a variety of studies examining the effectiveness of PDMPs as implemented in different states. Haegerich et al. (2014) summarize studies relevant to PDMPs until 2012 and suggest that "PDMP evaluations have detected some positive changes in prescribing patterns, decreased use of multiple providers and pharmacies, and decreased substance abuse treatment admissions and poison center report rates (although findings are mixed)."

In this paper, I evaluate the effects of PDMPs using a new micro-level medical claim dataset, the Clinformatics Data Mart, consisting of 19 million people in 25 states from 2001-2012. First, I perform a descriptive analysis of the trends in substance abuse/addiction during 2001-2012 for different substances including opioids, cocaine, cannabis, and amphetamines. I study the correlation between opioid abuse and different substances and possible implications for the characteristics of the abuser population. Second, I use the time and state variation in the implementation of PDMPs to perform a difference-in-difference analysis of

the effects of PDMPs on abuse/addiction reduction, after controlling for time, state, and demographic effects. Further, I study the heterogeneous impact of the program on different subsamples. I measure how program effectiveness varies by demographic groups and by type of insurance. Third, I combine medical claims with pharmacy claims to identify possible cases of nonmedical opioid abuse, which sheds light on the extent of diversion of opioids from patients to nonmedical abusers. I evaluate the effectiveness of the PDMPs for medical versus nonmedical opioid users by looking at the medical history of each patient. Finally, I study the effectiveness of the program in changing the patterns of prescriptions among providers and the overall probability of taking opioids in the study population. In this section, I perform an analysis similar to Buchmueller and Carey (2017) and Kilby (2016) and compare the results of my study to that of the latest studies conducted on different population groups including Medicare and employer-sponsored individuals.

The Clinformatics Data Mart dataset includes individuals from diverse backgrounds representative of the U.S. population, which enables me to generalize my results to the entire U.S. population. Also, the large sample sizes allow for rich subgroup analysis. Another difference between my study and previous studies is the long time span of data coverage, which makes it possible to test the difference-in-difference assumption of parallel trends and to only include comparison group states that are similar to states that implemented PDMPs. Finally, as individuals' access to prescription drugs also depends to a large extent on their health insurance policies, having detailed information about insurance providers gives me the opportunity to study one of the factors that has not been considered in previous research.

Another novel feature of my analysis is to use the medical claims data as a basis for understanding the problem of drug diversion. Some studies only include people observed to have at least one opioid prescription, but my results show that, among the abuser population, at least 23% did not fill any opioid prescriptions during the year of treatment. My results show that there is not necessarily a close correspondence between dose of medication prescribed

and propensity for abuse.

My results show an overall 14% reduction in odds of abuse/addiction. The effect is slightly higher for females compared with males, and for blacks compared with whites. The effect is seen most clearly in the low-income population and also in highly educated people. PDMPs decreased the odds of abuse by 17% among low-income families, and 12% for middle-income families; there was no significant effect for high-income families. These programs also decreased the odds of abuse by 16% among bachelor degree holders, while no significant effect was evident for people with less than a high school education. PDMPs' effectiveness varies significantly by type of insurance: The odds of abuse reduced 19% for those with HMOs and 11% for those with EPOs, and there was no significant effect for those with PPOs or POS plans. This is intuitive given that insurance policies lead to different patient-provider matches due to in-network and out-of-network provisions. I can see that, although PDMPs provide similar information to all providers, the insurance structure matters for the effectiveness of these programs for each demographic subgroup analyzed. A caveat is that it could be possible that people who have an opioid abuse problem would choose insurances that are more generous and more lenient when it comes to getting access to providers that give prescriptions.

Prescription claim histories show that at least 23% of opioid abusers do not have any insurance claims for opioid purchases, which means at least 23% of abuse/addiction cases are the result of opioid diversion. There is no significant effect from PDMPs in abuse/addiction reduction among individuals without opioid prescription claims. Finally, PDMPs have affected other outcomes, including the number of pharmacies and providers visited by patients and quantities of prescribed medications.

## 1.2. Background

### *1.2.1. Opioid for pain management*

Opium has been used for pain management for centuries. The opioid family of drugs continues to be a major part of pain management in medical practice today (Ballantyne and Mao (2003)). Despite its pervasive use, there is little certainty on opioid therapy's risks and benefits.

The first opioid epidemic occurred in the late 19th century, which resulted in the first legal attempts to restrict access to these drugs. In addition to these legal attempts, the introduction of other pain medications limited the use of opioids.

In the late 1980s, however, there was a shift in the discussion of chronic noncancer pain management. Portenoy and Foley (1986) studied 38 cases of long-term opioid therapy, asserting that it was a "humane alternative" to other forms of pain management (e.g., surgery). Similarly, Zenz et al. (1992) observed 100 patients taking opioid therapy lasting 224 days on average and found no cases of addiction. They thus declared opioid therapy as an effective treatment for long-term pain management without addiction being an important concern. Papers with similar conclusions emerged in subsequent medical literature (Fink (2000), Portenoy (1996)). On the ground, the introduction of OxyContin in 1995 shifted the treatment of pain drastically. Purdo Pharma funded more than 20,000 pain-related educational programs to alter physicians' and medical professionals' perceptions of opioid therapy. Although there were no clinical trials to assess the safety of long-term opioid treatment for noncancer patients, the company cited some methodologically flawed papers claiming that the risk of addiction was as low as 1% (Kolodny et al. (2015)). By 1998, "[k]ey organizations that strongly support[ed] the use of opioids to treat chronic pain [...] published consensus statements to guide physicians in prescribing these drugs" (Ballantyne and Mao (2003)).

With these developments, in 1996, the rate of opioid use started to increase. This was

followed by an increase in the rate of mortality and morbidity by opioids, but it took policy makers some time to realize that it was not only the nonmedical users who were at risk of overdose. Pain patients who were addicted to opioids were a group that was very likely to overdose on these drugs (Kolodny et al. (2015)). Furlan et al. (2006), in a meta-analysis of opioid therapy studies, inferred that, despite common belief, "[a]ddiction or opioid abuse in patients with chronic pain cannot be assumed not to exist" because the length of trials are too short for development of addictive behaviors. Martell et al. (2007) investigated the case of patients with chronic back pain and found that, although the effectiveness of these drugs for long-term pain management was unclear, abusive behavior developed in around 25% of the patients. Another review by Højsted and Sjøgren (2007) suggested that the risk of addiction could be as high as 50% in noncancer pain patients. Furthermore, Dunn et al. (2010) investigated the relationship between prescribed doses of opioids and abusive behavior and concluded that "[p]atients receiving higher doses of prescribed opioids are at increased risk of opioid overdose, underscoring the need for close supervision of these patients."

In response to this growing public health risk, policy makers first targeted illegal access, but as inappropriate use among patients became more clear by 2005, different policies focusing on this segment emerged. The Prescription Drug Monitoring Programs, which are described in the following section, are the most important of these policies.

### *1.2.2. Prescription Drug Monitoring Programs*

Prescription Drug Monitoring Programs (PDMPs) are state-administered databases that contain information on the prescribing and dispensing of controlled substances. Information contained in the PDMPs may be used by doctors and pharmacists to identify patients who may be doctor shopping (seeing multiple doctors to obtain prescriptions), need substance abuse treatment, or are at risk for overdose. In accordance with state laws, PDMP information may also be used by state regulatory and law enforcement officials to pursue cases involving inappropriate prescribing or dispensing, so-called "pill mills," or other

sources of diversion.

The first PDMP was established in California in 1939, and as the need to collect data on prescription drugs for law enforcement and monitoring purposes grew, eight more states established this program by 1989. In this period, which is called the "Paper Era" of the PDMPs, the information was mainly used by law enforcement agencies to curtail diversion. By 1990, the "Electronic Era" of the PDMPs began, which made the sharing of data easier between providers, pharmacists, and drug agencies. In the next decade, the steady rise in the abuse and diversion of controlled substances further increased the importance of PDMPs, and eventually there was a drive to align and consolidate the programs in different states, which so far differed vastly in regulations and implementation. Thus started the "Federal Era" of the PDMPs in 2002, when the the National Alliance for Model State Drug Laws (NAMSDL) drafted a model program outlining common goals that should be shared among existing and new PDMPs (Blumenschein et al. (2010)). As a result, PDMPs that were enacted in states after 2003 were very similar, and their enactment can be viewed as a natural experiment in contrast to the early PDMPs that were started in states with high abuse rates.

The impact of PDMPs has been studied in three main areas: effects on provider behavior, patient behavior, and health outcomes. PDMPs resulted in a decrease in the number of prescriptions for schedule II narcotics such as oxycodone but resulted in an increase in prescriptions for schedule III pain killers such as hydrocodone, which are easier to prescribe. Overall, however, these programs decreased inappropriate prescription behaviors. For patients, PDMPs decreased patients' visits to multiple pharmacies and discouraged doctor shopping. A survey of Ohio, California, and Kentucky prescribers shows that access to new information on patient history through PDMPs has changed their prescription behavior. Results from Wyoming, Nevada, Massachusetts, and Maine show that mandatory access to the PDMPs has decreased both doctor shopping and prescribed doses by doctors (PMP

Center of Excellence (2012), Haegerich et al. (2014)).[1]

The effects of PDMPs on health outcomes are less clear. Simeone and Holland (2006), found a significant reduction in substance abuse treatment admission, and Reifler et al. (2012), show a significant decline in the rate of growth of abuse. On the other hand, while Reifler et al. (2012), and **?** found a decline in abuse-related admissions, it was statistically insignificant, and Paulozzi et al. (2011) found no significant change in drug overdose mortality (Haegerich et al. (2014)). Meara et al. (2016) studied disabled Medicare beneficiaries as a high-risk group and concluded that "[a]doption of controlled-substance laws was not associated with reductions in potentially hazardous use of opioids or overdose."

Some studies suggest the primary factor behind insignificant health benefits from PDMPs is low or infrequent access of the database by prescribers. A 2015 study of primary care prescribers found that, while a majority reported having obtained data from their PDMP at some point in time, where participation in the PDMP was voluntary prescribers checked the patient history only 14% of the time before prescribing an opioid (Rutkow et al. (2015), PMP Center of Excellence). In line with this finding, most recent studies focusing on the attributes of the program show a higher degree of success. Buchmueller and Carey (2017) provide evidence that "must access" PDMPs significantly reduce measures of misuse in Medicare Part D. In contrast, PDMPs without such provisions have no effect.

As far as I know, the effectiveness of PDMPs for people with different individual characteristics is not studied in the literature. Although it is known that the risk hazard of opioid abuse is different among different population groups. For example, Paulozzi (2012) summarizes the literature on prescription drug use through 2011 and concludes that demographic characteristics most likely associated with abuse include being male, middle aged, white, low income, and suffering from mental health issues. African Americans and Hispanics are less likely to be prescribed any drugs (Gu et al. (2010)), including controlled prescription

[1]Haegerich et al. (2014) summarize studies relevant to PDMPs, including Pletcher et al. (2008), Curtis et al. (2006), Simoni-Wastila and Qian (2012), Wastila and Bishop (1996), Reisman et al. (2009), Simeone and Holland (2006), Dormuth et al. (2012), Ross-Degnan et al. (2004), Pearson et al. (2006).

drugs (National Center for Health Statistics (2006)), and are less likely to report nonmedical use of prescription pain relievers (SAMHSA (2014a)).

## 1.3. Data

My primary dataset is the medical and prescription drug claims dataset, Clinformatics Data Mart (CDM) for years 2001-2012. CDM contains administrative health claims for members of a large national managed-care company affiliated with OptumInsight. It includes individuals with both medical and prescription drug coverage, and collects data for approximately 15 million people annually, for a total of more than 40 million unique individuals over a 10-year period. CDM largely consists of commercial health plan data but also contains historic claims for Managed Medicaid and Medicare.[2] The population is geographically diverse, spanning all 50 states. CDM includes demographic and geographic information relating to gender, age, and state of residence, in addition to medical and pharmacy claims.

I include the states that implemented the PDMP for the first time between 2003 and 2012.[3] Prescription drug monitoring programs that were implemented during this period belong to the "Federal Era" of the PDMP and have generally similar characteristics. Because the implementation of the policies can happen anytime during a year, I will consider PDMPs being active in a year if the user access date began before July of that year.

The PDMP Training and Technical Assistance Center (TTAC) and the National Alliance for Model State Drug Laws (NAMSDL) are the main sources providing information on the date of operation for PDMP programs, with some disparities for a couple of states. NAMSDL reflects the date that prescribers and/or dispensers were allowed to have access to PDMP information, whether electronic or hard copy, while TTAC's category reflects the date that the programs began receiving and storing data electronically.[4] Table 1 reports

[2]Medicare Choice after 2006 and Medicaid after 2011 are not included, so I removed these individuals from my analysis.

[3]No state started its program in 2001 or 2002.

[4]This information is provided by Heather Gray, the legislative director of National Alliance for Model State Drug Laws.

the implementation date provided by NAMSDL.[5] In addition, I use the Prescription Drug Abuse Policy System, which provides detailed data of variation in state laws regarding implementation of PDMPs up until 2016 using the relevant legislative documentation to examine the similarities and disparities among the states in my study.[6] States that I include in my analysis provide access to prescribers, dispensers, and the regulatory board. Dispensers have to report data to PDMPs; however, access to PDMPs before prescribing is not mandatory, and PDMPs are not allowed to share the data with private insurers. PDMPs differ in their permission or requirement to identify suspicious activity and take any action, such as reporting suspicious activities to law enforcement or the provider/dispenser. By restricting the data to these 25 states, and to people 11 to 65 years of age, my final sample includes around 6 million people annually, which is approximately 19 million unique individuals total.

#### *1.3.1. Trends in prescription drug abuse/dependence, co-occurrence with other substance use disorders*

There have been some controversies about the underlying factors for opioid abuse or dependence, as these drugs differ from other street drugs in that they are the only ones that can be accessed for legitimate medical reasons but lead to dependence. At first, policy makers assumed that abuse or dependence on these products occurs only among people who do not have a medical prescription for opioids; however, they later found that there is such a thing as accidental dependence. The possibility of opioid abuse/dependence among medical users shifted the focus of drug control from solely the distribution level to the patient level.

Incidence of abuse/dependence among pain patients suggests that long-term opioid therapy may lead to dependence and abuse. At the same time, nonmedical abuse is also prevalent. Surveys show that the main source for nonmedical use of opioids is prescriptions written for friends or family members, which suggest over-prescription of these drugs. Understanding

[5] Accessed on June 2015: http://www.pdmpassist.org/pdf/PPTs/LE2012/1_Giglio_HistoryofPDMPs.pdf
[6] Data accessed on Oct 2016 at www.pdaps.org.

the inherent differences between these two groups of people, medical and nonmedical users, is important for effective policy making.

Surveys on nonmedical users of opioids suggest that these people are also more likely to abuse other drugs (McCabe et al. (2008)); therefore, studying the demographics of abusers with multiple substance problems, in combination with their medical history, should provide a picture of these types of abusers and how they differ from patients on opioid therapy who ended up as abusers. At first, I look at the trend of abuse or dependence for different substances. I identify substance abuse, addiction or poisoning by applying the ICD-9[7] codes listed in Table 2 to the five provided diagnoses codes in each medical record. Descriptions associated with each ICD-9 code are provided in the documentation for the CDM data.[8]Similar diagnoses in a given day, or as part of one insurance claim, counts as one visit. Figure 1 provides the number of visits during 2001-2012 for each substance. A visit to an inpatient or outpatient facility can be the result of abuse of multiple drugs, each one recorded with a different diagnosis code. I count the substance reported first as the primary substance.

The total cases of substance abuse/dependence more than doubled during these 10 years, but the growth has been fastest for the opioid drug family. The total number of admissions in this group more than quadrupled. Further, the rates and trends in admissions by each cause, especially for alcohol and opioids, are similar to those reported by SAMHSA (2014b), which confirms that this dataset closely represents the United States population. Table 3 shows that more than 99% of opioids reported in cases of abuse/dependence are prescription opioids. The share of these drugs is constantly increasing, while the percentage of heroin-related cases decreased from 0.53% to 0.36%, and methadone-related cases decreased from

[7]International Classification of Diseases, Ninth Revision.

[8]I use ICD-9 codes provided by the Centers for Disease Control and Prevention to identify poisoning cases: https://www.cdc.gov/drugoverdose/pdf/pdo_guide_to_icd9cm_and_icd10_codesa.pdf; I use the description provided for each code to identify the cases of addiction for each substance. My list is similar to other studies with slight differences; for example, Meara et al. (2016) use similar codes to identify nonfatal opioid-related abuse cases, but they also include E950.0, which is associated with suicide. In addition to that, my list includes dependence to opioid cases.

0.29% to 0.09%.[9]

The studies based on the treatment admission data without specific individual identifiers may provide biased information about the characteristics of the population under study. I estimate the average number of visits for each type of drug abuse/dependence by dividing the total number of visits in each category by the total number of unique individuals in each one. Table 4 shows these multiple visits during a year are common for all type of substances. A person with an opioid abuse or dependence problem on average visits inpatient or outpatient facilities seven times a year. So instead of studying the population characteristics of admitted people, it is more informative to investigate the effect of policies to the number of unique individuals with a treatment record for abuse or addiction.[10]

To study the population characteristics of the abusers, I aggregated the data annually, indicating if each individual had cases of abuse/dependence for alcohol, opioids, cocaine, amphetamines, or cannabis. Figure 2 shows the number of people who visited medical providers for any substance misuse during 2001-2012. The trends are similar to those reported by SAMHSA (2014a), which comes from the National Survey on Drug Use and Health. In 2001, the number of people with cannabis abuse problems was about 20% higher than those with opioid abuse/addiction. But opioid cases have grown much faster, and by 2012, there were twice as many cases of opioid abuse. Fortunately, the total number of individuals with cocaine abuse problems declined, and the number has stayed almost constant since 2005 for those with cannabis and amphetamine abuse problems. Table 5 shows that there is a high correlation between the abuse of different types of substances, with the highest being 0.35 for the correlation between opioid and other medications abuse. The correlation between abuse of opioids and other substances, including cocaine, cannabis, and amphetamines is 0.18, 0.14, and 0.10, respectively. For the rest of the data summary,

[9]Cases of methadone abuse/dependence are identified with ICD-9 codes that are different from other prescription opioids as reported in Table 2. For the rest of the analysis, I consider methadone as part of prescription opioid cases.

[10]SAMHSA (2014b) and other studies using the TED dataset used these types of analyses because of the lack of identifiers for individuals.

I focus on individuals with a prescription opioid abuse/dependence history.

Table 6 shows that people who visit medical providers for only opioid misuse are on average 3.5 years older than people who get admitted for a combination of drugs, including opioids. This provides some suggestive evidence that the older population uses opioids for medical reasons rather than for recreational purposes. Figure 3 shows the percentage of the people abusing opioids in each age group during 2001-2012. The probability of abuse is almost the same, 0.1%, among those 18-54 years of age in 2001, but it is increasing with a different rate among different age groups. The probability goes to 0.79% for those 18-23 years of age (620% rate of growth) and 0.55% for those 24-33 years of age (399% rate of growth). The rate of growth is drastic among the elderly as well, it goes from 0.06% to 0.26% (376% increase).

Providers prescribe opioids differently for different demographics based on age, gender, and income or race/ethnicity. Pletcher et al. (2008) argue that white people are more likely to get opioids for pain-related admissions to emergency rooms in comparison with other races, and even the "national quality improvement initiatives" of the 1990s did not reduce this gap. PDMPs aim to provide information about the medical history of patients to improve the practice of prescribing controlled drugs, but it is not clear how these programs affect the already existing biases. I will investigate this using regression analysis in the next section.

## 1.4. Econometric Analysis

### *1.4.1. Effect of PDMPs on prescription opioid and heroin abuse/dependence*

I first consider the effect of PDMP implementation on the abuse/dependence of prescription opioids and heroin in the whole population. I estimate the following regression models:

$$y_{it} = \alpha + \gamma_i + \lambda_t + \tau(pdmp_{st}) + \epsilon_{ist} \tag{1.1}$$

$$y_{it} = \alpha + \gamma_i + \lambda_t + \sum_{l=-4}^{l=+4} \tau_l(pdmp_{s,t+l}) + \epsilon_{ist} \tag{1.2}$$

Here, $y_{it}$ is an indicator for patient $i$ abusing either heroin or prescription opioids in year $t$, $\gamma_i$ is the individual fixed effect, $\lambda_t$ is the time fixed effect, $pdmp_{st}$ is an indicator for active PDMP in state $s$ during year $t$, and $pdmp_{s,t+l}$ is an indicator for active PDMP in year $t+l$. The event study analysis in the second equation is necessary to test the validity of the parallel trend assumption in difference-in-difference analysis; it confirms that the implementation of PDMPs for the set of states included in my analysis qualifies as a natural experiment. Figure 4 shows the estimation results of equation 1.2. It is clear that after controlling for individual and year fixed effects, there is no significant trend in the abuse of prescription opioids or heroin before implementation of PDMPs among states included in my data. Figure 4 shows that the implementation of PDMPs reduced the probability of prescription drug abuse/dependence but gradually increased the probability of heroin abuse/dependence. The increase becomes significant two years after the program.

*1.4.2. Effect of PDMPs on prescription opioid abuse/dependence in subsamples*

In this section, I study the individual characteristics that determine the effectiveness of the programs in reducing prescription opioid abuse/dependence for each subsample. I first estimate the model including individual characteristics and the interaction between characteristics and PDMP implementation instead of individual fixed effects:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + X_{it}\beta_0 + pdmp \times X_{it}\beta_1 + \epsilon_{it}$$

In which $X_{it}$ is a vector including age, gender, race, income, education, and type of insurance. I use the logistic regression in order to accommodate the smaller sample size in some of the subgroups. In Table 7, I report the results of this estimation in comparison to the model without individual controls and the model without the interaction of individual characteristics and PDMP implementation. The interaction terms, although not reported here, are significant and different among different demographic groups. To investigate this heterogeneity more closely, I divide people by their income, race, gender, education, and

type of insurance. Then I estimate a similar logistic regression for each group:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + X_{it}\beta_0 + \epsilon_{it}$$

$X_{it}$ includes all individual characteristics not used in categorizing people in subsamples. Although the type of insurance seems to be an endogenous variable, it is unlikely that it will be affected by the event of abuse or addiction. In Table 9, I show that the effectiveness of the program decreases by family income even after controlling for education level. The odds of opioid abuse decreases by around 18% for individuals from low-income families (less than $40,000), 10 to 13% for individuals from middle-income families ($40,000-$75,000), while having no significant effect for people from higher-income families. Table 10 shows that the effectiveness increases by individuals' education level; people with a higher education are less likely to abuse prescription opioids after implementation of PDMPs. The reduction in the odds ratio is the highest for those with bachelor degrees (17%). PDMPs subsequently decrease the odds ratio of those with bachelor degree by 16% and those with high-school diploma by 11%. It is important to notice that these effects are estimated after controlling for family income level, age, and gender, which suggest one mechanism for effectiveness of these programs is informing individuals about the risks of opioid use.

Table 11 reports the results by the type of insurance. It suggests that HMO insurance holders benefit the most from PDMPs, followed by those with EPOs. PDMPs resulted in a 20% reduction of the odds of abuse for those with HMOs, a 12% reduction for those with EPOs and no significant effect for people with PPOs or POSs. This is intuitive given that insurance policies lead to different patient-provider matches due to in-network and out-of-network provisions. I can see that, although PDMPs provide similar information to all providers, the insurance structure matters for the effectiveness of PDMPs for each demographic subgroup analyzed. A caveat is that it could be possible that people who have an opioid abuse problem would choose insurances that are more generous and more lenient when it comes to getting access to providers that give prescriptions.

*1.4.3. Relationship between the abuse/dependence and prescription*

The next step in analyzing the abuse/dependence of prescription opioids is to understand the relationship between abuse and prescriptions for opioids. To investigate the relationship between abuse and prescription. I assign an indicator $rx = 1$ to each individual-year if a person has an opioid prescription filled during that year. I identify narcotic in prescription claims data using universal standard classification codes (usc-id) provided by the CDM for each drug. '022**' is the usc-id code for any form of narcotics, tablet, capsule, patch, etc., at any strength, including less controlled and more easily prescribed narcotics such as acetaminophen-codeine. There are hundreds of different opioids in the data with the highest frequency being for oxycodone, hydrocodone, codeine, and propoxyphene. To have a valid measure to compare different prescriptions over time, I use the morphine equivalent of each prescription by multiplying the quantity of the drug being prescribed by the milligram morphine equivalent (mme) factor for each drug and then aggregating the data for each individual for each year to find the total mme of prescribed medication. In addition, I find the total days of supply, the number of distinct pharmacies, and the providers that each patient visited to get prescriptions for opioids, which I will use in the next section. Then, I combine medical history with prescription claims data to investigate the effects of being prescribed any type of narcotics in opioid abuse/dependence.

Information from Table 12 shows that 69.3% of the people did not fill any prescription for a narcotic during their coverage period in my data. Among the 30.7% of the people who have been prescribed opioids, only 0.92% have records of abuse/addiction. On the other hand, among the narcotic abusers/addicts, we can see that 22.98% never filled a prescription. This table shows that the problem of diversion of drugs is serious. It is important to notice that this table overestimates the number of prescriptions for narcotics. I include all the prescriptions filled for any type of narcotics at any dose and quantity. The morphine content of some prescriptions is very small, which makes it impossible to cause any sort of abuse or addiction.

In Table 5, I look at the population that has ever been prescribed any narcotics and the population of abusers separately throughout the years from 2001 to 2012. In the sample of people who have abused opioids in each year, around 37% had not been prescribed any opioids in 2001, and this number increased throughout the years, which means that abuse of narcotics without prescriptions prevails over these years. These numbers are just a rough estimate, since patients could save prescriptions in a given year and abuse them in the future. But as we saw in Table 12, even after pooling the data over the years, the number of abusers/addicts with no prescriptions is at least as high as 23%, so the actual number may be somewhere in between. In the subsample of people who received opioid medication, 0.49% abused opioids in 2001, and this number constantly increased and reached 1.25% in 2012. As we saw in Table 12, even if we include all the prescription claims throughout the coverage, only 1% of total individuals filling a prescription ended up abusing it themselves.

Although different surveys show that friends and family are the main sources of opioids among nonmedical users (McCabe et al. (2007)), it is not possible to find the source of these drugs in my data. It is only possible to study the demographic of this population to provide a more accurate guideline for providers. In Figure 6, it is clear that the distribution of the age of nonmedical abusers is tilted to the left, suggesting that the younger population uses these drugs for recreational purposes, especially people younger than 24 years of age. On the other hand, among those 54-64 years of age, it is twice as likely for abusers to be getting the drugs through prescription rather than other sources. I similarly look at the patterns by other demographics. Although not as clear as in the case of age, it seems that whites and females who abuse opioids are more likely to get them through prescriptions. I estimate the effectiveness of PDMPs in preventing diversion by estimating a regression model similar to that of the previous section for two groups of people—those who filled any prescription for opioids and those who have not:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + X_{it}\beta_0 + \epsilon_{it}$$

$X_{it}$ includes total mme and days of supply of medication for people who filled any prescription for opioids. Table 13 shows that, after controlling for mme and days of supply, implementation of PDMPs reduced the odds of opioid abuse by 10% among patients, but they did not have any significant effect on the abuse of opioids among nonmedical users. One of the goals of PDMPs was to reduce the diversion of opioids by restricting the access to these drugs among patients, but my results suggest that these programs did not provide any benefit of this sort.

*1.4.4. Patterns of opioid prescription*

One of the more studied aspects of PDMPs is the effect they have in the patterns of prescriptions. I perform a series of analyses similar to Kilby (2016) and Buchmueller and Carey (2017). I estimate the model:

$$y_{it} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + \epsilon_{it}$$

In which $y_{it}$ measures total mme for each patient $i$ at year $t$. The results in Table 16 show a reduction in prescribed opioids similar to the finding in Kilby (2016) from analyzing Automated Reports and Consolidated Orders System (ARCOS) data. But none of the specifications resulted in a significant estimation.

I follow the Buchmueller and Carey (2017) method in constructing some proxy measures of misuse consisting of quantity-based outcomes and shopping outcomes. The first measure is the share of enrollees who took any opioids at all. The other quantity-based outcomes are intended to capture patterns that are indicative of misuse or dangerous for individuals' health. It includes an indicator for higher than 391 days of supply in a year (more than thirteen thirty-day prescriptions), having a daily average of opioid use higher than 120 milligram morphine equivalent (mme). The shopping outcomes include an indicator for patients who visited more than 10 prescribers in a year to get prescriptions for opioids and more than 10 pharmacies to fill their prescriptions for opioids. I report the summary

statistics of these variables in Table 14. To evaluate the PDMP effect on these variables, I use the aggregate level difference-in-difference analysis:

$$y_{st} = \alpha + \gamma_s + \lambda_t + \tau pdmp_{st} + \epsilon_{it}$$

Here, $y_{st}$ is the frequency of outcome in each state year divided by the total number of population with at least one prescription for an opioid. $\gamma_s$ and $\lambda_t$ represent state and year fixed effects and standard errors clustered at the state level. I weighted each observation with the value of the denominator. I report the results of these estimations in Table 17. These results can be compared with the results of Buchmueller and Carey (2017) for the states without the "must access" PDMP requirement. Buchmueller and Carey (2017) do not find any significant effect for similar variables and conclude that without the "must access" specification, PDMPs are not effective. My estimation shows that PDMPs effectively reduce the cases of +391 days of supply among prescription holders. The rate of visiting more than 10 pharmacies decreased by 0.034%. Similar to the individual-level analysis in the previous section, the rate of opioid abuse significantly decreases among people with prescriptions. The discrepancy among the results of the two studies are likely to be the result of the difference between the subsample population in each study. Buchmueller and Carey (2017) study the Medicare Part D beneficiaries, while my analysis represents the whole population, which means that PDMPs are more effective in reducing opioid misuse among the general population in comparison to reducing opioid misuse among Medicare Part D beneficiaries.

### *1.4.5. Limitation*

Some limitations arise from the use of the ICD-9 codes in identifying abusers. There are similar to those mentioned in other studies that use this method (White et al. (2009)). This way of identification is likely to underestimate the number of cases for two reasons. Individuals experiencing nonfatal overdoses also might be less likely to seek care because they expect disapproval or legal consequences (Paulozzi (2012)). Also, if patients don't use insurance for payment of medical treatment, I won't be able to observe them in this dataset.

## 1.5. Conclusion

Despite the strong emphasis of the role of Prescription Drug Monitoring Programs on the war on prescription drug abuse, there has not been much conclusive evidence in the literature that these programs actually reduce the abuse of these drugs. In this study, I analyze opioid addiction in addition to opioid poisoning to measure the health benefits of the PDMPs. Using a nationally representative dataset, including 25 states from 2001-2012, I show that PDMPs have been effective in reducing the probability of abuse/addiction of opioids. The effect is heterogeneous among different groups based on their income, education, and ethnicity, but more important, the effect is heterogeneous for people holding different insurance policies. This suggests that some practices among HMO insurance providers, including a close network of providers and referral requirements for visits to specialists, may prove to be valuable when it comes to fighting the opioid abuse epidemic, or at least in improving the effectiveness of PDMPs.

## 1.6. Tables and Figures

Table 1: Year of PDMP implementation

| State | Year | State | Year |
|---|---|---|---|
| Alabama | 2008 | Massachusetts | 2011 |
| Alaska | 2012 | Minnesota | 2010 |
| Arizona | 2009 | Mississippi | 2006 |
| Arkansas | 2013 | New Jersey | 2012 |
| Colorado | 2008 | New Mexico | 2006 |
| Connecticut | 2009 | North Carolina | 2008 |
| Delaware | 2013 | North Dakota | 2007 |
| Florida | 2012 | Ohio | 2007 |
| Georgia | 2013 | Oregon | 2012 |
| Indiana | 2007 | South Carolina | 2008 |
| Iowa | 2009 | South Dakota | 2012 |
| Kansas | 2011 | Vermont | 2009 |
| Louisiana | 2009 | Washington | 2012 |
| Maine | 2005 | Wyoming | 2004 |

**Notes:** The implementation years are user access dates reported by NAMSDL. PDMPs are considered active in a year if providers have access to the PDMP before July of the implementation year.

Table 2: ICD-9 codes of abuse or addiction

| ICD-9 code | Description |
|---|---|
| 303 | alcohol dependence syndrome |
| 3050 | nondependent alcohol abuse |
| 980 | toxic effect of alcohol |
| 3040 | opioid type dependence |
| 3055 | nondependent opioid abuse |
| 9650 | poisoning opiates & related narcotics |
| E850 | accidental poisoning-analgesic |
| 96501 | poisoning by heroin |
| E8500 | accidental poisoning by heroin |
| 96500 | poisoning by opium, unspecified |
| E8502 | accidental poisoning other opiates & related narcotics |
| 96509 | poison opiates & related narcotics oth |
| 3047 | comb opioid rx w/any other rx depend |
| 96502 | poisoning by methadone |
| E8501 | accidental poisoning by methadone |
| 3042 | cocaine dependence |
| 3056 | nondependent cocaine abuse |
| 3043 | cannabis dependence |
| 3052 | nondependent cannabis abuse |
| 3044 | amphetamines & other psychostimulant depend |
| 3057 | nondependent amphetamine |
| 3059 | other mixed/unspecified nondependence drug abs |
| E8589 | accidental poisoning unspec drug |
| 97*** | poisoning by other prescription drugs |
| 98*** | toxic effects of other prescription drugs |

**Notes:** The codes for opioid and other drugs abuse/dependence. For the cases of opioid abuse, the codes that are reported here are similar to those used in recent papers, including Meara et al. (2016) and Buchmueller and Carey (2017).

Table 3: Number of visits for abuse/dependence by opioid categories

| | Year (frequency) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| Heroin | 284 | 397 | 398 | 414 | 320 | 340 | 294 | 427 | 501 | 456 | 566 | 812 |
| Methadone | 153 | 276 | 254 | 462 | 418 | 374 | 385 | 536 | 389 | 205 | 187 | 203 |
| Rx opioid | 52954 | 58022 | 66346 | 62011 | 75412 | 77409 | 96589 | 128188 | 168355 | 163431 | 167587 | 225410 |
| Total | 53391 | 58695 | 66998 | 62887 | 76150 | 78123 | 97268 | 129151 | 169245 | 164092 | 168340 | 226425 |

| | Year (percentage) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
| Heroin | 0.53 | 0.68 | 0.59 | 0.66 | 0.42 | 0.44 | 0.3 | 0.33 | 0.3 | 0.28 | 0.34 | 0.36 |
| Methadone | 0.29 | 0.47 | 0.38 | 0.73 | 0.55 | 0.48 | 0.4 | 0.42 | 0.23 | 0.12 | 0.11 | 0.09 |
| Rx opioid | 99.18 | 98.85 | 99.03 | 98.61 | 99.03 | 99.09 | 99.3 | 99.25 | 99.47 | 99.6 | 99.55 | 99.55 |
| Total | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Notes:** Cases of methadone abuse/dependence are identified with ICD-9 codes that are different from other prescription opioids as reported in Table 2. For the rest of the analysis, I consider methadone as part of prescription opioid cases.

Table 4: Average number of visits per person to inpatient or outpatient facilities for each substance

| Substance | Average number of visits |
|---|---|
| Alcohol | 4.2 |
| Opioids | 6.6 |
| Cocaine | 3.9 |
| Cannabis | 3.9 |
| Amphetamines | 3.2 |

**Notes:** In this table, I report the average number of visits for each substance in all 50 states during 2001-2012.

Table 5: Correlation between admission for different types of substances

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
|---|---|---|---|---|---|---|
| *(1) Alcohol* | 1 | | | | | |
| *(2) Opioids* | 0.158 | 1 | | | | |
| *(3) Cocaine* | 0.184 | 0.181 | 1 | | | |
| *(4) Cannabis* | 0.205 | 0.140 | 0.194 | 1 | | |
| *(5) Amphetamines* | 0.103 | 0.105 | 0.118 | 0.160 | 1 | |
| *(6) Other meds* | 0.185 | 0.354 | 0.182 | 0.170 | 0.122 | 1 |

**Notes:** Pairwise correlations for abuse/dependence among different substances incidents. All the numbers are significant in 0.001 level.

Table 6: Age difference among different types of abusers

| | Mean age |
|---|---|
| Only opioids | 38.519 |
| | (1.896) |
| Opioid with other substances | 35.057 |
| | (2.402) |
| Diff(1-2) | 3.462*** |
| | (2.146) |

**Note:** This table reports the mean age of the individuals who only abuse opioids and compares them with people who abuse opioids in combination with other substances.

Table 7: Effect of PDMPs on probability of abuse/addiction

| | (1) | (2) | (3) |
|---|---|---|---|
| PDMP | $-0.186^{***}$ | $-0.154^{***}$ | $-0.085^{**}$ |
| | (0.010) | (0.010) | (0.043) |
| **Controls:** | | | |
| State FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Ind. Controls | No | Yes | Yes |
| PDMP × Ind. Controls | No | No | Yes |
| R−Square | 0.019 | 0.040 | 0.041 |
| Observations | 62,708,948 | 56,719,688 | 56,719,688 |

**Notes:** Coefficients of logit regression for probability of an individual diagnosed with abuse/addiction of a prescription opioid. Individual controls include age, gender, education, income, and type of insurance. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 8: Effect of PDMPs on probability of abuse by gender, race category

| | *Black* | | *White* | |
|---|---|---|---|---|
| | *Female* | *Male* | *Female* | *Male* |
| PDMP | -0.198*** | -0.178*** | -0.151*** | -0.149*** |
| | (0.052) | (0.052) | (0.017) | (0.015) |
| **Controls:** | | | | |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Ind. Controls | Yes | Yes | Yes | Yes |
| R-Square | 0.054 | 0.056 | 0.036 | 0.045 |
| Observations | 2,749,701 | 2,261,260 | 21,113,962 | 20,594,947 |

**Notes:** Coefficients of logit regression for probability of an individual diagnosed with abuse/addiction of a prescription opioid. Individual controls include age, gender, education, income, and type of insurance. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 9: Effect of PDMP on probability of abuse by income category

| | *Income* | | | | | |
|---|---|---|---|---|---|---|
| | *(1) Less than 40K* | *(2) 40-49K* | *(3) 50-59K* | *(4) 60-75K* | *(5) 75-99K* | *(6) 100K+* |
| PDMP | -0.185** | -0.102 | -0.129** | -0.107 | -0.069 | -0.062 |
| | (0.074) | (0.077) | (0.064) | (0.066) | (0.071) | (0.041) |
| **Controls:** | | | | | | |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Ind. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| R-Square | 0.043 | 0.030 | 0.031 | 0.032 | 0.038 | 0.047 |
| Observations | 7,389,628 | 5,292,648 | 5,313,836 | 6,727,332 | 8,994,455 | 15,026,741 |

**Notes:** Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of a prescription opioid for different income groups. Individual controls include age, education, gender, and type of insurance. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 10: PDMP effect on probability of abuse by education level

| | *Education* | | | |
|---|---|---|---|---|
| | *(1) Less than 12th grade* | *(2) High school diploma* | *(3) Less than bachelor degree* | *(4) Bachelor degree plus* |
| PDMP | -0.011 | -0.119* | -0.158* | -0.175** |
| | (0.277) | (0.069) | (0.086) | (0.088) |
| **Controls:** | | | | |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Ind. Controls | Yes | Yes | Yes | Yes |
| R-Square | 0.055 | 0.042 | 0.040 | 0.041 |
| Observations | 347,537 | 17,141,161 | 29,477,892 | 9,337,854 |

**Notes:** Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of a prescription opioid for different education levels. All specifications control for other individual characteristics including age, gender,income, and type of insurance in addition to state and year fixed effects. Robust standard errors, clustered at the state level are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 11: Effect of PDMP on probability of abuse by type of insurance

| | *Insurance* | | | | |
|---|---|---|---|---|---|
| | *EPO* | *HMO* | *IND* | *POS* | *PPO* |
| PDMP | -0.120** | -0.209*** | -0.391 | -0.036 | 0.026 |
| | (0.047) | (0.053) | (0.321) | (0.029) | (0.149) |
| **Controls:** | | | | | |
| State FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Ind. Controls | Yes | Yes | Yes | Yes | Yes |
| R-Square | 0.044 | 0.057 | 0.109 | 0.036 | 0.036 |
| Observations | 6,931,178 | 16,550,381 | 159,186 | 34,051,197 | 4,888,403 |

**Notes:** Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of a prescription opioid for different types of insurance. All specifications control for individual characteristics including age, gender, income, and education in addition to state and year fixed effects. Robust standard errors, clustered at the state level, in parentheses. * p <0.10, ** p <0.05, *** p<0.01

Table 12: Relationship between narcotic prescription and event of opioid abuse/dependence

| | | *Ever abused opioids?* | |
|---|---|---|---|
| | | *No* | *Yes* |
| *Ever been prescribed opioids?* | *No* | 69.22 | 0.08 |
| | *Yes* | 30.42 | 0.28 |
| Pr(abuse \| prescribed)= | | 0.92% | |
| Pr(abuse \| not prescribed)= | | 0.12% | |
| Pr(not prescribed \| abuser)= | | 22.98% | |

**Notes:** Dataset includes the medical and prescription claims of around 19 million people in 25 states between 2001-2012. The abuse indicator is Yes if they have ever been diagnosed with any prescription opioid abuse/addiction, and the narcotic indicator is Yes if they have ever been prescribed any form of narcotics.

Table 13: Effectiveness of the PDMP for patients with prescription vs. patients without prescription

| | *(1) w prescription* | *(2) w/o prescription* |
|---|---|---|
| PDMP | -0.105** | -0.077 |
| | (0.048) | (0.079) |
| ln(mme+1) | -0.036** | |
| | (0.014) | |
| ln(day_sup+1) | 0.684*** | |
| | (0.023) | |
| **Controls:** | | |
| State FE | Yes | Yes |
| Year FE | Yes | Yes |
| Ind. Controls | No | No |
| R-Square | 0.132 | 0.025 |
| Observations | 18,936,921 | 42,830,641 |
| Percent Mean | 0.378 | 0.059 |

**Notes:** Coefficients of logit regression for probability of an individual diagnosed with abuse or addiction of a prescription opioid with state and year fixed effects. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01.

Table 14: Summary statistics: Outcomes among opioid takers

| | Mean | Median | 99th Percentile |
|---|---|---|---|
| Mean Daily MME | 6.67 | 0.62 | 129.15 |
| Mean MME per Prescription | 60.75 | 36 | 800 |
| Total Days of supply | 32.55 | 6 | 462 |
| Number of Prescriptions | 2.75 | 1 | 24 |
| Number of Prescribers | 1.34 | 1 | 5 |
| Number of Pharmacies | 1.24 | 1 | 4 |

**Note:** Summary statistics of misuse proxy measures, constructed similar to Buchmueller and Carey (2017).

Table 15: Correlation of outcomes among whole population

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
|---|---|---|---|---|---|
| *(1) 391+ Days Supply* | 1 | | | | |
| *(2) 120+ Daily MME* | 0.585 | 1 | | | |
| *(3) 10+ Pharmacy* | 0.093 | 0.065 | 1 | | |
| *(4) 10+ Provider* | 0.089 | 0.050 | 0.382 | 1 | |
| *(5) Opioid abuse* | 0.094 | 0.093 | 0.061 | 0.080 | 1 |

**Notes:** Pairwise correlations for measures of misuse. All the numbers are significant in 0.001 level.

Table 16: The effect of PDMPs on prescribed opioids

| | (1) *mme* | (2) *ln(mme+1)* | (3) *Sch2 mme* | (4) *ln(Sch2 mme+1)* | (5) *Sch3 mme* | (6) *ln(Sch3 mme+1)* |
|---|---|---|---|---|---|---|
| PDMP | -41.307 | 0.016 | -41.326 | 0.016 | -0.649*** | -0.005* |
| | (30.687) | (0.016) | (31.257) | (0.015) | (0.193) | (0.003) |
| R-Square | 0.000 | 0.004 | 0.000 | 0.006 | 0.000 | 0.002 |
| Observations | 61,767,467 | 61,767,467 | 61,767,491 | 61,767,475 | 61,767,491 | 61,767,487 |
| Mean | 426 | 0.934 | 407 | 0.800 | 5.625 | 0.096 |

**Notes:** The dependent variable in (1) is the total mme in each year for each individual. The dependent variable in (2) is the log transformation of the mme+1. The dependent variable in (3) is schedule 2 share of total mme, the dependent variable in (4) is the log transformation of schedule 2 (mme+1). Similarly, dependent variables in (4) and (5) are the schedule 3 mme and its log transformation. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 17: Effectiveness of PDMPs on opioid misuse

| | *P(taking opioids)* | *120+ daily mme* | *391+ days' supply* | *10+ pharmacy* | *10+ providers* | *Opioid abuse* |
|---|---|---|---|---|---|---|
| PDMP | 0.167 | -0.298 | -0.186* | -0.034* | -0.090 | -0.183* |
| | (0.391) | (0.177) | (0.094) | (0.017) | (0.066) | (0.104) |
| R-Square | 0.910 | 0.906 | 0.928 | 0.764 | 0.868 | 0.862 |
| Observations | 300 | 300 | 300 | 300 | 300 | 300 |
| Weighted Mean | 16.204 | 1.246 | 1.663 | 0.069 | 0.189 | 0.826 |

**Notes:** Dependent variables are constructed similar to Buchmueller and Carey (2017). All regressions have year and state fixed effects with the number of observations in each state-year. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p <0.05, *** p<0.01

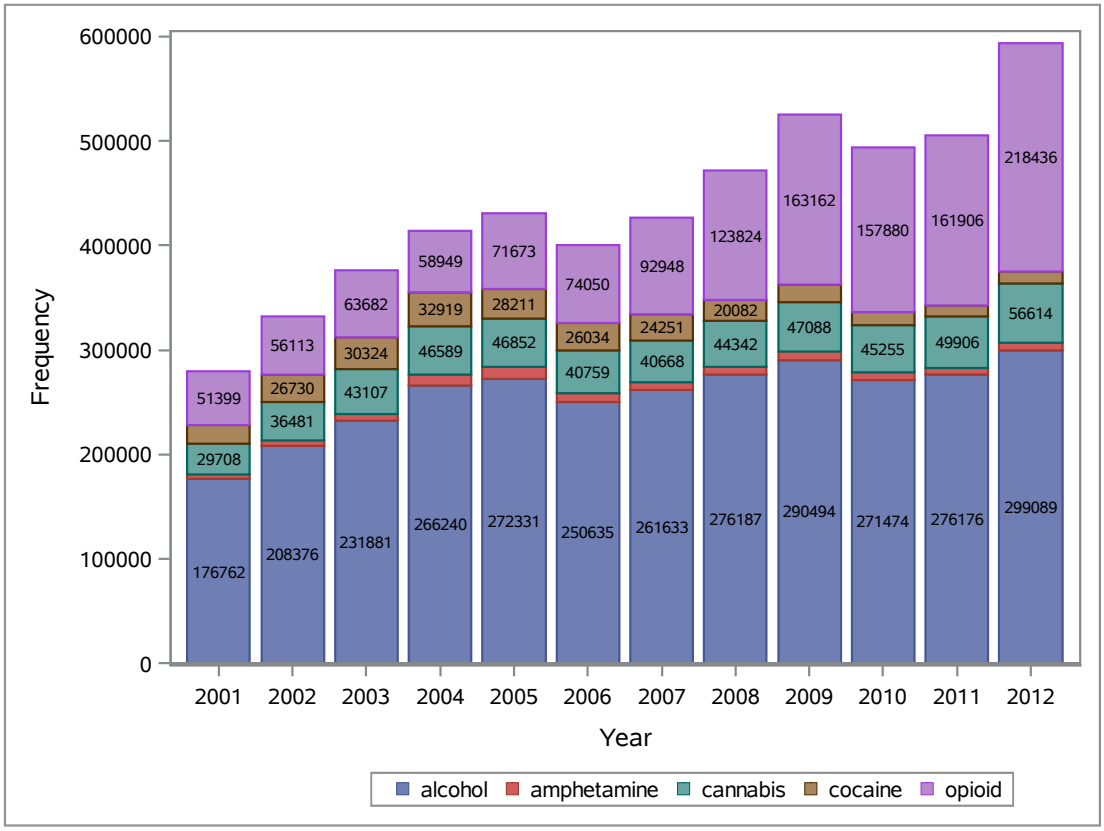
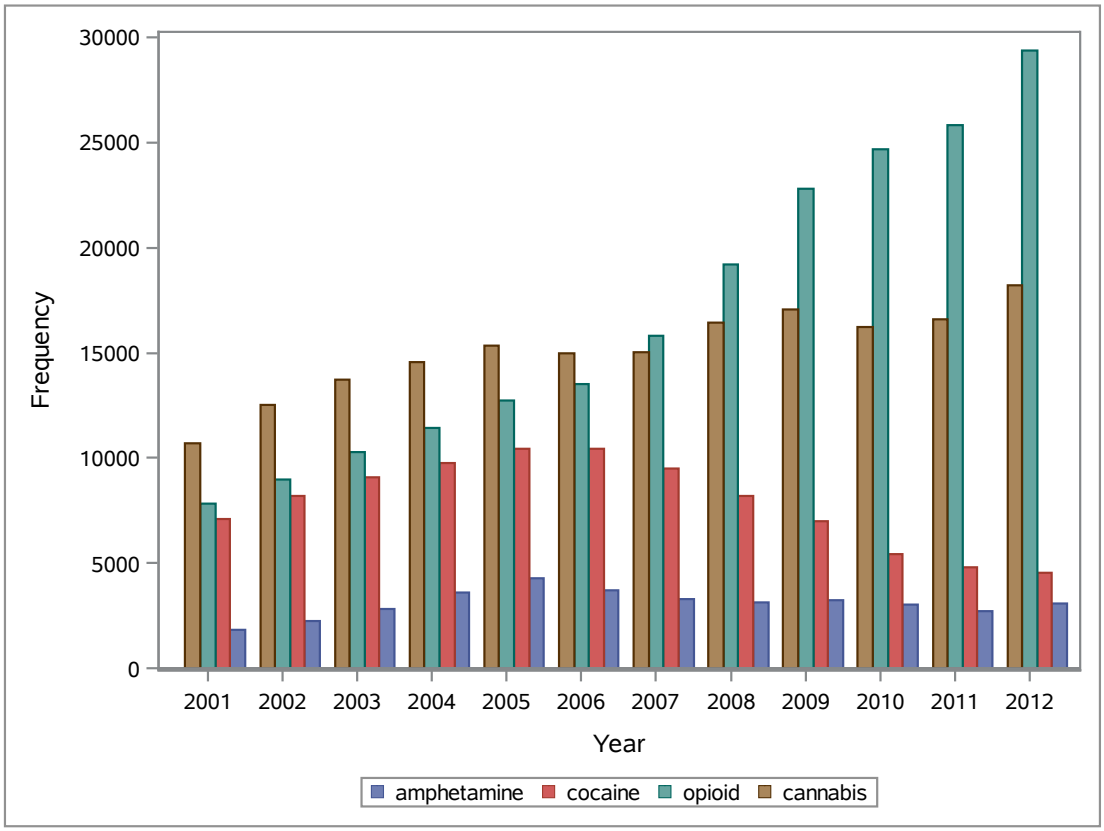
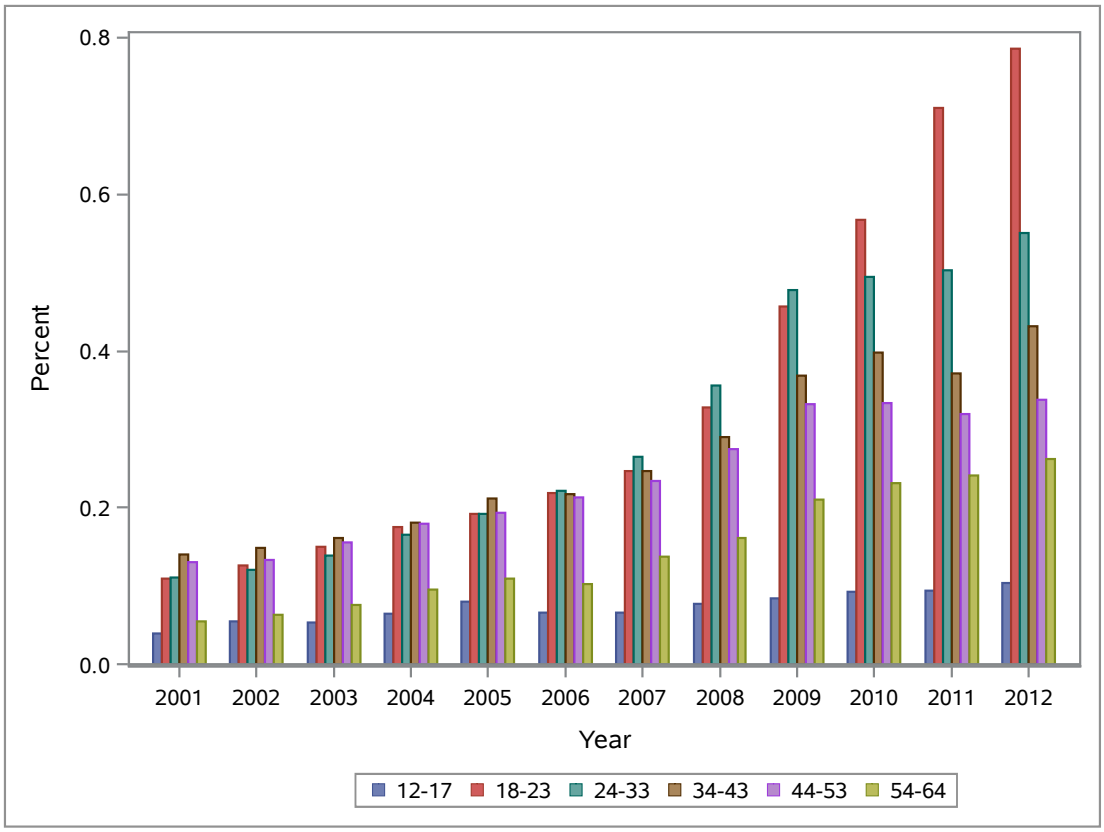



Figure 1: Number of visits for abuse/dependence by substance category




**Note:** The numbers show the frequency of visits related to each substance abuse/dependence during 2001-2012 over 50 states.

Figure 2: Total number of people who visit any inpatient/outpatient facilities for each substance




**Note:** Each bar represents the percentage of people in each age-year category that abused prescription opioids.

Figure 3: Trend in abuse of prescription opioids by age category in 25 states

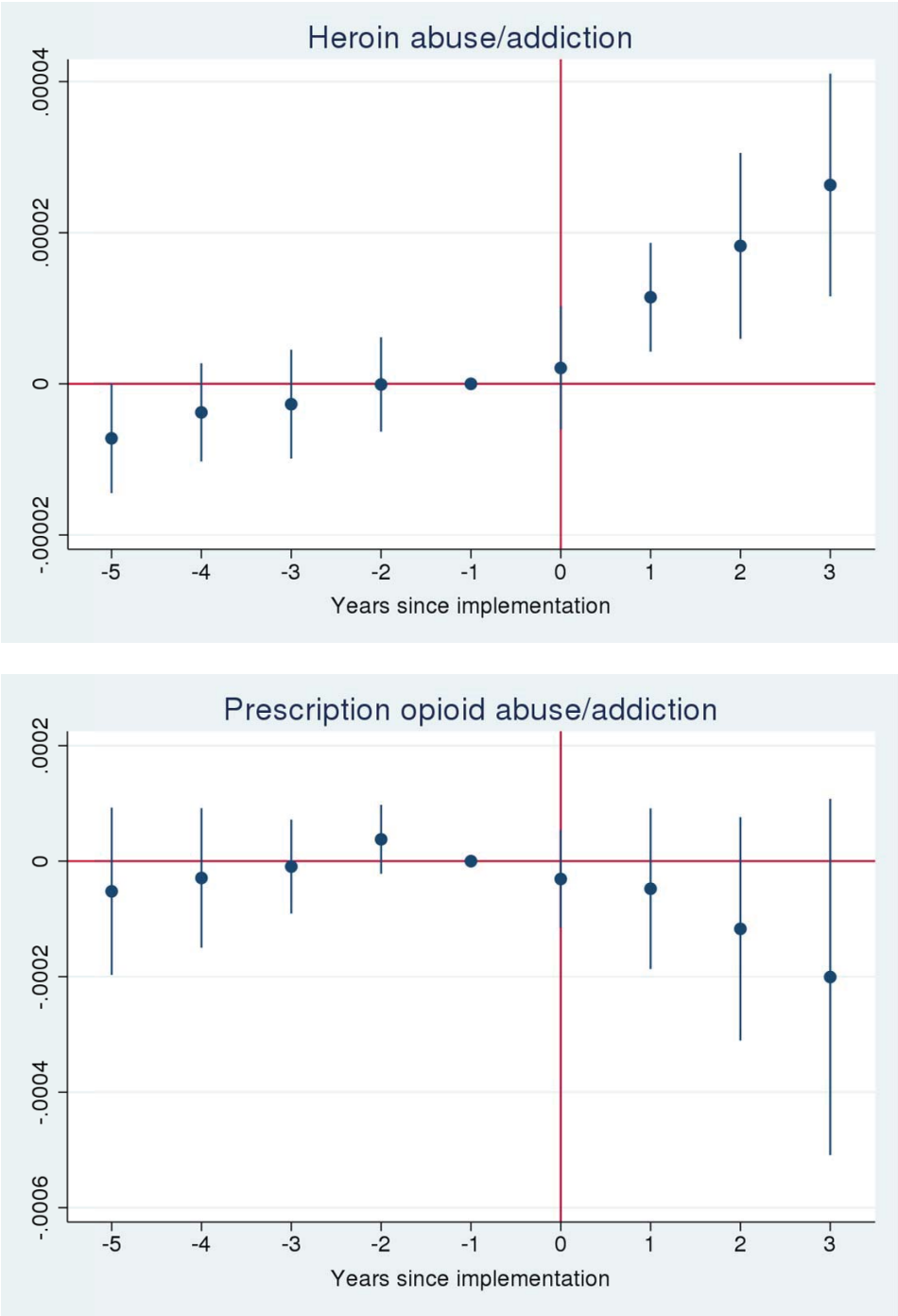
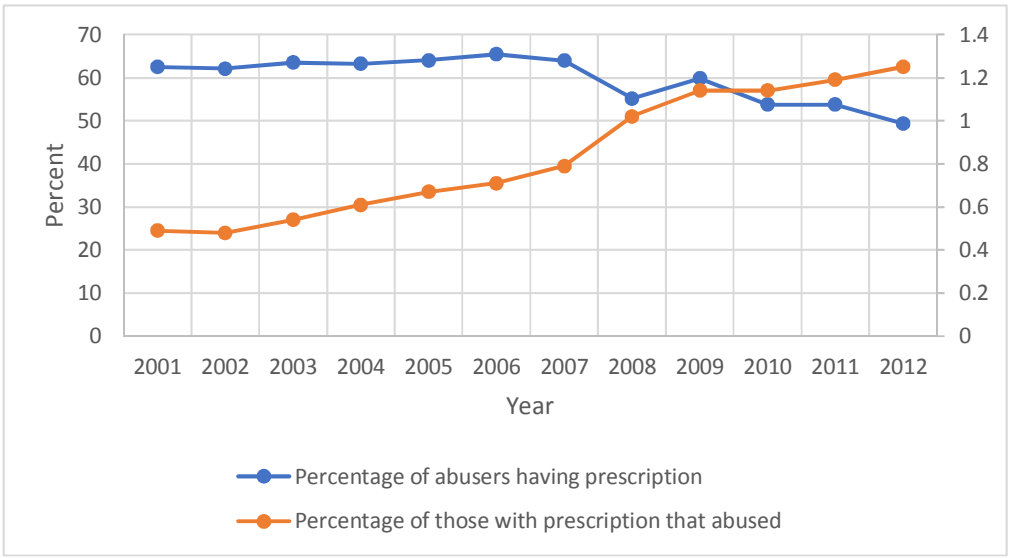



Figure 4: Probability of prescription opioid abuse/dependence 4 years after and before the implementation of PDMPs




**Notes:** Left axis and blue line show the percentage of abusers that filled any prescription for opioids.
Right axis and orange line show the percentage of patients with an opioid prescription that have a record of abuse/addiction of opioids in that year.

Figure 5: Relationship between narcotic prescription and event of abuse/dependence from 2001-2012

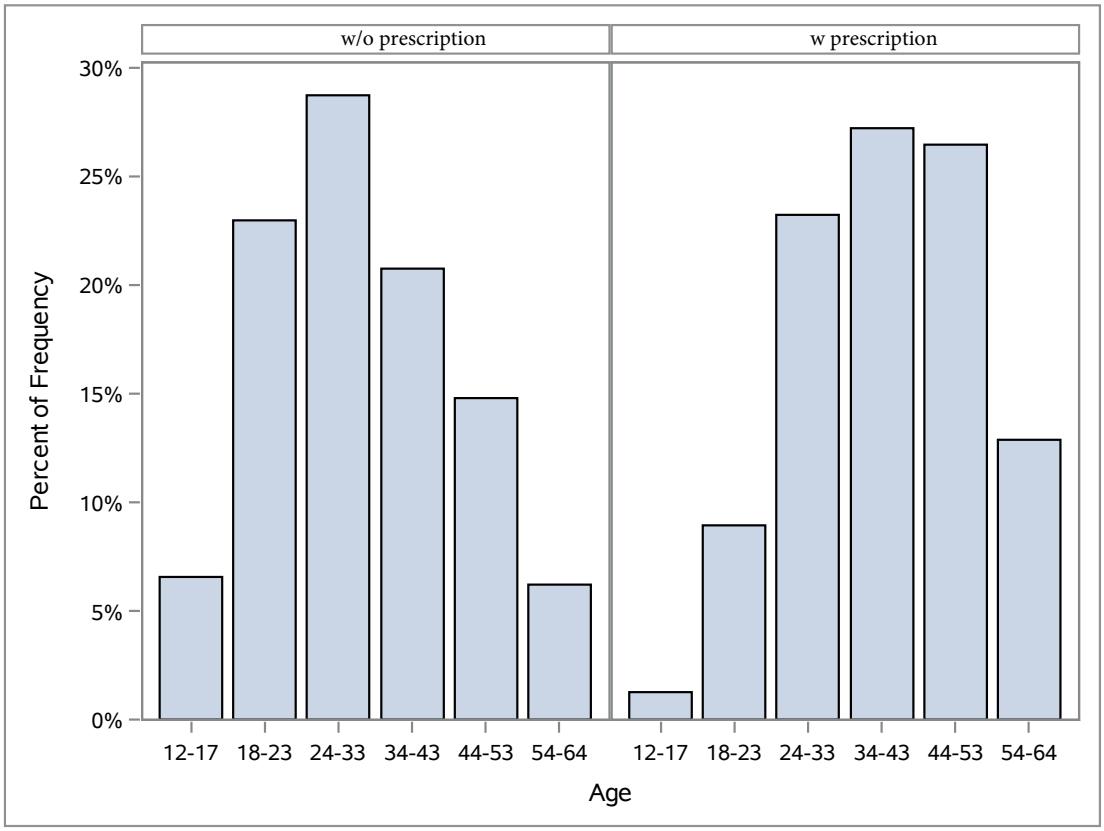



Figure 6: Age distribution of abuser population by source of drug

# CHAPTER 2 : Demand Estimation of Opioid Treatment

**Abstract:** In this paper, I develop, estimate, and compare different count models of the demand for opioid treatment. I use medical and prescription claims data for around 20 million people. I compare the explanatory power of these models with those of the Neural Network algorithm from machine learning. My results show that NB2 estimations perform better in explaining the variations of the data in comparison with other models including, Poisson, NB1, and OLS in pooled models, while a fixed effect Poisson model provides the best fit in panel data regression. As long as we use the aggregated level data with similar variables, the performance of classification algorithms in a complicated method such as Neural Network is similar to regression analysis. Finally, estimating the marginal effects of each insurance plan characteristics in the demand for opioids indicates that demand is lower in Exclusive Provider Organization (EPO) with an Administrative Service Only (ASO) and Health Reimbursement Arrangement (HRA) structure. It suggests implementing similar structures in reimbursement, and the providers' network would reduce demand significantly.

## 2.1. Introduction

Count models are extensively used for modeling healthcare utilization (Cameron and Trivedi (2013)). In this paper, I analyze the patterns and factors contributing to the demand for opioid medications using the medical and prescription history of patients.

The data include around 2 million people per year for 10 years. Each individual is observed in the data for at least 3 years and is covered by some form of insurance. I measure the demand for opioids for each person by using the number of prescriptions written in each year for them. I combine this information with demographic information and medical record data to account for conditions inducing pain. First, I perform pooled OLS regression analysis and then compare the outcome with a variety of cross-sectional and longitudinal count data models. Finally, I train a Neural Network and use a test sample to compare the performance of this algorithm with regression methods.

The most common count data models include Poisson models and the negative binomial models. The negative binomial models are a generalized version of Poisson models that allow for variance dispersion, $Var(y_i|z_i) = \mu_i + \alpha\mu_i^p$. I use the two most commonly used penalized model selection criteria, the Bayesian information criterion (BIC) and Akaike's information criterion (AIC), to compare the performances of different models in addition to $R^2$. My results show that NB2, the negative binomial with $p = 2$, estimations perform better in explaining the data variations in comparison with other models including, Poisson, NB1, which is the negative binomial with p=1, and OLS in cross-sectional form. However, a fixed effect Poisson model provides the best fit in the panel data regression. And, as long as we are using the aggregated level data with similar variables, the performance of classification algorithms in a complicated method such as the Neural Network is similar to regression analysis. Estimating marginal effects from the NB2 regression suggests that HMOs and PPOs significantly increase the number of visits by 0.22 and 0.61 in comparison with EPS. Access service only plans reduce visits by 0.47. HRA plan holders visit doctors 0.44 and 0.66 less compared with HSA and people with no consumer access. This estimation suggests that we could reduce the number of visits and consequently total consumption of opioids by intervening in the insurance market and providing similar structure to that of EPO, ASO and HRA in the market for opioid medications.

## 2.2. Data

The data are an administrative panel of medical and prescription records of around 20 million people provided by Optum. This is a subsample of Clinformatics Data Mart (CDM) that include individuals age 11-65 who were covered by United Health Group for at least 3 years during 2001-2011 in 25 states. I aggregate the prescription data yearly to measure the demand for opioids at each individual year. I measure demand for opioids by the number of prescriptions written for each patient in each year. I combine these data with demographic information and the medical records of each patient.

Opioids are prescribed for a large set of health conditions associated with pain, and prescribing practices vary widely among different providers. Each provider reports his diagnosis using up to 5 ICD-9 diagnosis codes. Although opioids are used for pain management, pain is not clearly stated in the description of their ICD-9 codes. The issue of how to indicate the presence of a condition that might require opioid treatment does not have a clear solution. Kilby (2016) uses a subset of data to identify pain-related conditions based on the use of opioids as the treatment method. This might raise the endogeneity concern, given that opioids are not the only possible treatment for pain. To address this problem, I review the medical literature and guidelines on pain management in addition to two pain specialists' opinions to provide a list of 397 diagnosis codes that often involve narcotic prescriptions as a method for pain management.[1] These are the diagnosis codes for conditions that are medically justified to be treated with an opioid. I further nest these 5 digit codes into 69 categories based on the first 3 digits that nest conditions together based on the underlying general disease and a manifestation of a particular organ or site (World Health Organization (2006)). Table 18 reports a sample of these conditions. I create a set of dummy variables to indicate diagnosis with any of these conditions in each year.

Table 19 shows the frequency of prescriptions written; on average, 76% of the population in each year does not fill any prescription, 13.4% fills only one prescription, 4.1% fills two prescriptions, 1.7% fills three prescriptions, and only 4% fill more than three prescriptions. The summary in table 20 shows that the standard deviation of the number of prescriptions is almost 4 times higher than the average. This suggests that the distribution of this observation is more likely to fit a more dispersed distribution such as the negative binomial rather than a Poisson distribution.

Opioid consumption in the U.S. is the highest among industrial countries. I show in the last chapter

[1] The main list is downloaded from http://www.aceanesthesiapain.com/ResourceCenter/IndexofDiagnosisCodes.aspx.

that Prescription Drugs Monitoring Programs (PDMPs), which are the most important public policy response, did not decrease the overall milligram morphine prescribed for patients. So it is important to study the demand for opioids in more detail to understand what type of policies would be relevant. Table 21 shows the average milligram morphine content of the prescription significantly increases by the number of prescriptions, so decreasing the number of doctor visits might decrease the overall consumption. In particular, it is interesting to investigate if the effect of observable characteristics of individuals or their insurance provider can explain any variation in the prescription data.

## 2.3. Econometric Analysis

### *2.3.1. Regression analysis*

I start the analysis by estimating an OLS regression for count data as the baseline model including alternative sets of control variables:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \sum_{j=1}^{J} \beta_{2j} D_{ijt} + \beta_3 pdmp_{st} + \gamma_s + \lambda_t + \epsilon_{it} \tag{2.1}$$

$y_{it}$ is the number of prescriptions per year, $x_{it}$ is the set of individual demographics and insurance type, $D_j$ is the set of diagnosis codes associated with opioid therapy, $\gamma_s$ is state fixed effect, $\lambda_t$ is year fixed effect, and $pdmp_{st}$ is an indicator for the implementation of Prescription Drug Monitoring Programs(PDMPs) in state $s$ at year $t$. PDMPs are the most important policy initiative in response to the opioid abuse epidemic, and I studied their effect on different health outcomes in my previous chapter. My results indicated the effectiveness of these programs on different health outcomes; however, these programs did not reduce the total morphine prescribed per person per year significantly. So, I study the demand for opioids in more detail in this chapter and determine what is the best model to explain the variation in the data and how that can provide policy advice. I compare the performance of this estimation in fitting the data with common count models, which are Poisson and the negative binomials (NB1, NB2). I use the AIC and BIC in addition to $R^2$ to choose the model that best describes the data and can be used for further exploration of policy effectiveness.

The Poisson regression model specifies $y_i$ given $z_i$ as Poisson distributed with density:

$$f(y_i|z_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} \quad y_i = 0, 1, 2, ..$$

and the mean parameter

$$E(y_i|z_i) = \mu_i = exp(z_i'\beta)$$

In these analyses $z_i = \{x_{it}, D_{ijt}, \gamma_s, \lambda_t, pdmp_{st}\}$, similar to the parameters of equation 2.1. Given the observations, the maximum likelihood estimator used for parameter estimations is:

$$\ln L(\beta) = \sum_{i=1}^{n} y_i z_i'\beta - exp(z_i'\beta) - \ln(y_i!)$$

In the Poisson distribution, the mean and the variance of the random variable are the same. This restriction does not match with the summary of the number of prescriptions per year in Table 20, so we consider less restrictive models that provide a more flexible structure for the variance.

$$Var(y_i|z_i) = \mu_i + \alpha\mu_i^p,$$

Poisson is a special case of this model with $\alpha = 0$. The NB1 variance function sets $p = 1$, then the variance is:

$$Var(y_i|x_i) = \mu_i + \alpha\mu_i$$

where $\alpha > 0$ is an overdispersion parameter. The NB2 variance function sets $p = 2$:

$$Var(y_i|x_i) = \mu_i + \alpha\mu_i^2$$

By expanding these models to longitudinal form, we can use the panel structure of the data and estimate fixed effect models. A key benefit of using panel data instead of cross-sectional data is that it allows for a more general individual heterogeneity, in addition to what can be observed through individual observables (Cameron and Trivedi (2013)). Individual demographics do not change over time, so these models will not be helpful to study the effect of individual demographics on the outcome. But they can be used to measure the importance of variables that change over time, mainly insurance characteristics. So , the outcomes of these models avoid the potential bias of individual selection into different types of insurance.

### *2.3.2. The Neural Network*

Data mining is widely used in different disciplines. The healthcare environment is one of the areas with a huge amount of data and a lack of effective tools for analysis of relationships and trends in the data (Srinivas et al. (2010)). In this set of analyses, I estimate the parameters of different Neural Networks to find the one that performs best in fitting the data. Similar to the biological neuron structure, Neural Networks define neuron as a central processing unit and generate output (dependent variables) from the set of inputs (independent variables). The independent variables form the input layer; the middle layer, which performs the processing, is called the hidden layer; and the dependent variable forms the output layer. The hidden layer converts the input to the desired output. Figure 7 shows the structure of a simple Neural Network with 4 input variables, a hidden layer of 5 nodes with a single outcome (Müller et al. (2012)).

In a regression analysis model, we use the whole data to estimate the parameters of the model, but to avoid overfitting the data in a Neural Network, we first train the model with a random subset of the data to estimate the vector of parameters. Then we use these estimates to measure the performance of the model on test data. I measure the performance by comparing AIC, BIC, and $R^2$ of the model with regression outcomes. Regression models assume a restrictive relation between the explanatory variables, while data mining algorithms provide more flexibility in terms of interaction between the variables. Specifically, in the regression analysis, most of the explanatory power results from including the diagnosis codes of pain-related conditions. It seems reasonable to expect a more complicated relationship between this set of variables and the outcome observed in the data. I train a Neural Network using 70% of the data and compare the $R^2$ of the fitted model on the test sample with $R^2$ calculated in regression estimations. In the next section, I report the estimation parameters of each model and compare their performance using AIC, BIC, and $R^2$.

## 2.4. Results

Table 22 provides the results of OLS and Poisson estimations with and without controls for diagnosis codes. It is clear that including the diagnosis codes significantly improves the explanatory power of both models. After controlling for diagnosis codes, gender is not significant in determining the number of prescriptions that patients receive each year. The number of prescriptions increases with age, but decreases with income and education level. White people get more prescription

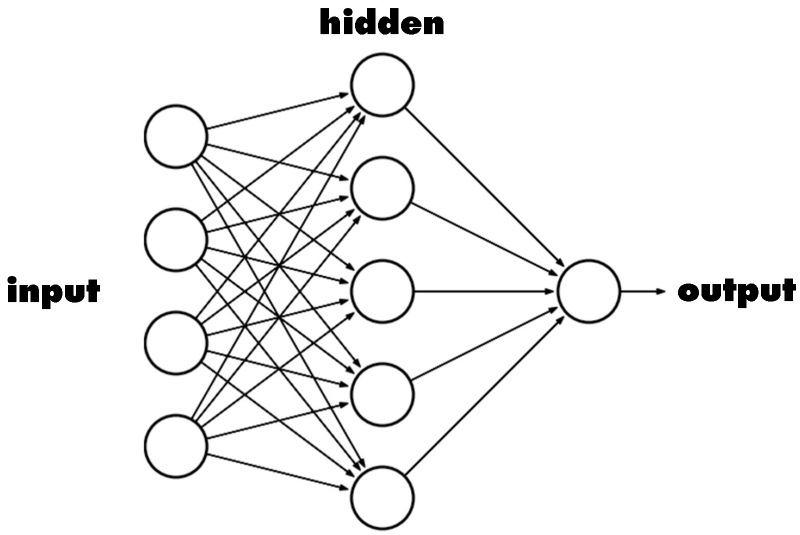



Figure 7: A simple Neural Network structure

than any other race group. People with Health Maintenance Organization (HMO) insurance have the most number of prescription followed by the Prefered Provider Organization (PPO) holders. Exclusive Provider Organization (EPO) holders, which I used as the base group, have the lowest average number of visits. Table 22 shows that Poisson regression fits the data better with pseudo-$R^2 = 17.7\%$ in comparison with $R^2 = 12.5\%$ of the OLS regression. It also has a higher value for likelihood function. PDMPs increase the number of visits, although not significantly.

Table 23 provides the results of NB1 and NB2 estimations. These two models mostly suggest similar patterns to those shown in Table 22; the main difference arises in the NB1 model. The NB1 model indicates that men significantly get fewer prescriptions and that the type of insurance does not change the access to prescriptions among patients. These are big discrepancies and make the choice of correct model important.

These are nonnested models, so the best criteria to compare their fitness to data are the use of AIC and BIC. Table 24 provides these information criteria for the OLS, Poisson, NB1, and NB2 models. The values of both AIC and BIC are lowest for the NB2 model, which suggests the distribution of the number of prescriptions follows a negative binomial distribution with parameter p=1. However, the Poisson regression has the highest value for $R^2$.

In these regression estimations, I model the number of visits as depending on the number of the

type of insurance. Insurance variables are treated as exogenous, but health insurance is frequently a choice variable rather than being assigned. It raises the concern of selection bias and invalidates the causal interpretation of insurance effect on the outcome in the next part. To address this concern, I estimate the model including fixed effects which controls for the unobservable characteristics of the individual.

The panel data format allows estimation of regressions with random and fixed effects. The random effect estimator assumes that random effects are iid distributed over time and are uncorrelated with regressors, which means unobservable individual effects are not correlated with individuals' observables. This assumption does not seem justifiable for patients given that the unobservable characteristics of a diagnosis would be highly correlated with the type of diagnosis for each patient. The outcomes of these regressions are reported in Table 25. The coefficients are not significant in random effect models. Further, the Hausman test rejects the null hypothesis of uncorrelated individual observables and unobservables. AIC and BIC values reported in Table 26 confirm that the Poisson FE model is the model that fits the data most closely.[2]

To make the estimation of the Neural Network model computationally feasible, I restrict the sample to individuals with 9 years of coverage. Then, I randomly select 70% of the observations to train three Neural Networks. The number of input variables significantly reduces the speed of convergence in the estimation of Neural Networks, so I reduce the number of inputs. To reduce the number of independent variables without losing much of the information, I impose the principal component analysis method to the set of diagnosis codes. The estimation indicates that 95% of the variation in diagnosis codes can be explained by 15 principal components. I use these 15 vectors in addition to demographic information as input variables of the Neural Network. I utilize the estimation parameters to predict the dependent variable in the test sample and compare the prediction values with actual observations in the data to calculate pseudo-$R^2$. Figure 7 shows the two sets of estimated models with AIC, BIC, and $R^2$ parameters reported in Table 27. The Neural Network with 15 nodes in hidden layer performs slightly better in terms of $R^2$, but it has higher AIC and BIC. So, the Neural Network with 10 nodes in the hidden layer is the best Neural Network to fit the variation in these data but it still doesn't improve the estimation compare with the NB2 model.

Comparison of the different plans indicates the importance of the insurance plans in the demand

[2] The likelihood functions are not concave for fixed effect and random effect negative binomial models, so the parameters of these models cannot be estimated.

for opioids. I estimate pooled data OLS and pooled data NB2 regression, including more control variables for characteristics of each prescription. Including more variables reduces the sample to individuals who received opioid treatment during the data but allows for a richer set of control variables, including the average morphine equivalent of each prescription, average days of supply in each prescription, and average copay for each prescription. Including these controls ensures that the differences in the number of prescriptions are not a result of variation in the quantity of opioids prescribed for each visit.

Table 28 reports the marginal effects of these characteristics. OLS estimation suggests that the HMO enrollees receive 0.06 more prescriptions compared with EPO enrollees. PPO enrollees get 0.2 more prescriptions per year compare with EPO enrollees. Administrative Service Only (ASO) is another characteristic of insurance plans. In insurance plans with ASO, employers have more freedom in managing claims and benefits, which results in 0.12 fewer prescriptions for patients. Consumer Driven Health Plan (CDHP) is a code that defines different payment arrangments. It can be a Health Reimbursement Arrangement (HRA) or a health saving arrangement (HSA) or neither. In the HRA plans, the employers' fund does not accumulate in a separate fund, and the employer only pays after the employee incurs expenses. Insurance plans with HRA reduce the number of prescriptions by about 0.15 compared with HSA or not having any payment plans. Calculation of marginal effects from NB2 model results in larger effects. The first column in the table shows that HMO and PPO significantly increase the number of visits by 0.22 and 0.61 in comparison with EPO. Indemnity (IND), Point of Service (POS) and other plans also increase the number of visits, but not significantly. Access service only plans reduce visits by 0.47. HRA plan holders visit doctors 0.44 and 0.66 less compared with HSA and people with no consumer access. This estimation suggests that we could significantly reduce the number of visits and consequently total consumption of opioids by intervening in the insurance market. A plan that leads to lower demand for opioids should provide a structure similar to EPS, ASO, and HRA in the market for opioid medications.

## 2.5. Conclusion and Discussion

There is a large set of count models that might seem appropriate for this type of data, including zero-inflated models, finite mixture models, and zero-truncated models, but the estimation of these models was not possible. Most of the variables in these data are categorical variables, which turn the likelihood functions to a nonconcave function, over a reasonable set of starting values.

This paper compares the performance of a set of regression models in predicting the number of prescriptions for patients and compares the results with the outcome of a Neural Network model. The NB2 model proves the best in describing the data in the cross-sectional form, while the Poisson FE model is the most appropriate one using the panel structure of the data. PDMPs slightly, but not significantly, increase the number of the prescriptions written in a year. Age is the most significant explanatory variable. Demand for opioids increases by age, higher education and income lead to lower demand, while whites are the racial group with the highest demand for opioids. Finally, estimating the marginal effects of each insurance plans' characteristics in the demand for opioids indicates that demand is lower in EPOs with ASO and HRA structure, so implementing similar structures in reimbursement and providers network would reduce demand significantly.

Table 18: ICD-9 Codes for a sample of pain-related conditions

| ICD-9 Code | Condition |
|---|---|
| 053.2 | HERPES ZOSTER DERMAT |
| 053.21 | HERPES ZOSTER KERATO |
| 053.22 | HERPES ZOSTER IRIDOC |
| 053.29 | HERPES ZOSTER WITH O |
| 053.71 | OTITIS EXTERNA DUE T |
| 053.79 | HERPES ZOSTER WITH O |
| 250.6 | DIABETES WITH NEUROL |
| 250.61 | DIABETES WITH NEUROL |
| 250.62 | DIABETES WITH NEUROL |
| 250.63 | DIABETES WITH NEUROL |
| 346 | MIGRAINE WITH AURA, |
| 346.01 | MIGRAINE WITH AURA |
| 346.02 | MIGRAINE WITH AURA |
| 346.03 | MIGRAINE WITH AURA |

**Notes:** The table provides an example of codes reported in the list of ICD-9 pain-related conditions.

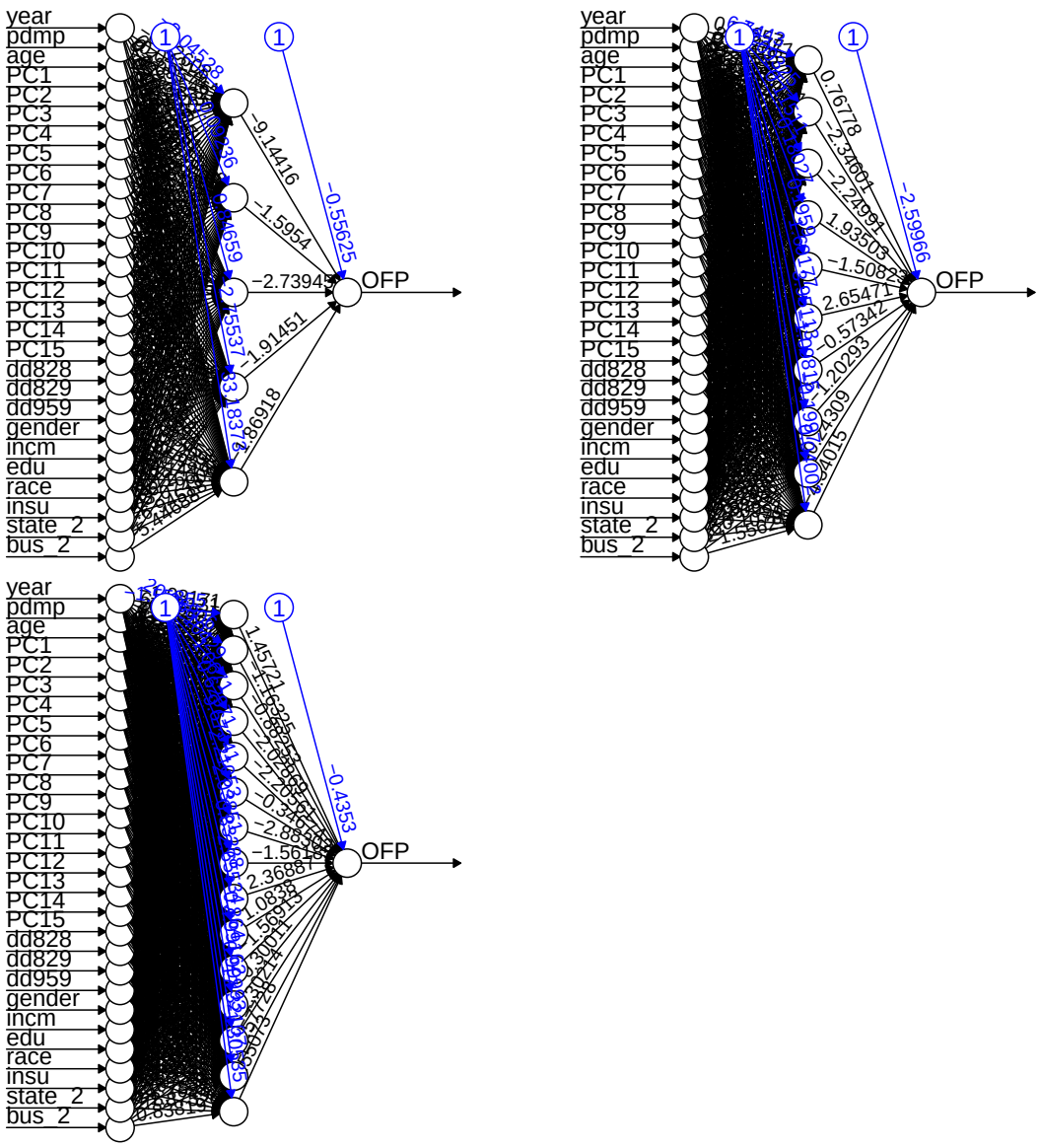



Figure 8: Neural Network with 5, 10, and 15 nodes in the hidden layer

Table 19: Frequency distribution of number of prescriptions

| Number of prescriptions | Count | Percent % |
|---|---|---|
| 0 | 14,796,379 | 76.8 |
| 1 | 2,588,495 | 13.4 |
| 2 | 787,441 | 4.1 |
| 3 | 320,451 | 1.7 |
| 4 | 166,398 | 0.9 |
| 5 | 100,855 | 0.5 |
| +6 | 497,341 | 2.6 |
| Total | 19,257,360 | 100.0 |

**Notes:** The data include aggregated total number of prescriptions received by each patient for around 20 million people in 25 states from 2001-2012.

Table 20: Summary of number of prescriptions

| Variable | Obs | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| Number of prescriptions | 19,257,360 | 0.653567 | 2.394603 | 0 | 266 |

Table 21: Summary of MME per prescription

| Number of prescriptions | Mean MME |
|---|---|
| 1 | 264.3086 |
| 2 | 316.0151 |
| 3 | 375.9809 |
| 4 | 474.0938 |
| 5 | 558.5545 |
| +6 | 1467.712 |
| Total | 430.1026 |

**Notes:** The table reports the average milligram morphine equivalent of each prescription. Data include around 20 million people in 25 states from 2001-2011.

Table 22: OLS and Poisson estimation results

| Variables | (1) Poisson | (2) Poisson | (3) OLS | (4) OLS |
|---|---|---|---|---|
| PDMP | 0.00419 | 0.0115 | 0.00996 | 0.0137 |
| | (0.0134) | (0.0144) | (0.00798) | (0.00995) |
| Gender | -0.110*** | 0.00483 | -0.0710*** | -0.00464 |
| | (0.0237) | (0.0161) | (0.0142) | (0.00994) |
| Age = 18-23 | 0.842*** | 0.817*** | 0.181*** | 0.157*** |
| | (0.0229) | (0.0217) | (0.00655) | (0.00483) |
| Age = 24-33 | 1.239*** | 1.150*** | 0.353*** | 0.278*** |
| | (0.0386) | (0.0367) | (0.0207) | (0.0169) |
| Age = 34-43 | 1.503*** | 1.331*** | 0.513*** | 0.377*** |
| | (0.0422) | (0.0387) | (0.0271) | (0.0208) |
| Age = 44-53 | 1.708*** | 1.461*** | 0.668*** | 0.471*** |
| | (0.0427) | (0.0392) | (0.0336) | (0.0249) |
| Age = 54-64 | 1.670*** | 1.357*** | 0.643*** | 0.380*** |
| | (0.0332) | (0.0301) | (0.0267) | (0.0182) |
| Income = 1 | 0.0351* | 0.0276* | 0.0512*** | 0.0436*** |
| | (0.0197) | (0.0164) | (0.0141) | (0.0121) |
| Income = 2 | -0.00584 | 0.00190 | 0.0156 | 0.0181 |
| | (0.0262) | (0.0194) | (0.0199) | (0.0155) |
| Income = 3 | -0.0665** | -0.0471** | -0.0336* | -0.0217 |
| | (0.0271) | (0.0215) | (0.0195) | (0.0156) |
| Income = 4 | -0.111*** | -0.0799*** | -0.0671*** | -0.0493*** |
| | (0.0281) | (0.0209) | (0.0185) | (0.0144) |
| Income = 5 | -0.201*** | -0.159*** | -0.127*** | -0.0981*** |
| | (0.0310) | (0.0232) | (0.0183) | (0.0139) |
| Income = 6 | -0.322*** | -0.262*** | -0.196*** | -0.155*** |
| | (0.0286) | (0.0201) | (0.0166) | (0.0124) |
| Education = B | 0.0989* | 0.0811* | 0.0922** | 0.0824** |
| | (0.0556) | (0.0487) | (0.0357) | (0.0316) |
| Education = C | -0.0181 | -0.00896 | 0.00275 | 0.0126 |
| | (0.0645) | (0.0540) | (0.0434) | (0.0362) |
| Education = D | -0.269*** | -0.219*** | -0.124*** | -0.0874** |
| | (0.0657) | (0.0535) | (0.0428) | (0.0340) |
| Race = B | 0.509*** | 0.436*** | 0.173*** | 0.116*** |
| | (0.0475) | (0.0438) | (0.0232) | (0.0168) |
| Race = H | 0.252** | 0.173 | 0.0423 | -0.0178 |
| | (0.113) | (0.106) | (0.0450) | (0.0401) |
| Race = W | 0.692*** | 0.591*** | 0.301*** | 0.228*** |
| | (0.0377) | (0.0395) | (0.0226) | (0.0211) |
| Insurance = HMO | 0.102*** | 0.0740*** | 0.0661*** | 0.0457*** |
| | (0.0197) | (0.0159) | (0.0128) | (0.0113) |
| Insurance = IND | 0.151** | 0.0554 | 0.138** | 0.0636 |
| | (0.0646) | (0.0430) | (0.0567) | (0.0423) |
| Insurance = OTH | 0.283*** | 0.145*** | 0.186** | 0.135*** |
| | (0.0644) | (0.0559) | (0.0692) | (0.0375) |
| Insurance = POS | -0.00428 | 0.0147 | -0.00130 | 0.00927 |
| | (0.0304) | (0.0224) | (0.0199) | (0.0151) |
| Insurance = PPO | 0.0685 | 0.0623** | 0.0493 | 0.0450* |
| | (0.0462) | (0.0293) | (0.0318) | (0.0219) |
| Constant | -2.451*** | -2.643*** | -0.0550 | -0.196*** |
| | (0.154) | (0.111) | (0.102) | (0.0697) |
| Observations | 18,871,999 | 18,871,999 | 18,871,999 | 18,871,999 |
| R-squared | 0.0500 | 0.177 | 0.016 | 0.125 |
| Ind. FE | No | No | No | No |
| Year FE | Yes | Yes | Yes | Yes |
| Sate FE | Yes | Yes | Yes | Yes |
| Diag Controls | No | Yes | No | Yes |
| Ln L | -2.940e+07 | -2.540e+07 | -4.310e+07 | -4.200e+07 |

**Notes:** Coefficients of the Poisson and OLS regressions for the number of prescription for opioids per individual year. Diagnosis controls include 69 3-digit ICD-9 codes related to pain. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 23: NB1 and NB2 estimation results

| VARIABLES | (1) NB1 | (2) NB2 |
|---|---|---|
| PDMP | 0.0135 | 0.0168 |
| | (0.0112) | (0.0124) |
| Gender | -0.0294*** | -0.0202 |
| | (0.00605) | (0.0147) |
| Age= 18-23 | 0.671*** | 0.818*** |
| | (0.0199) | (0.0225) |
| Age= 24-33 | 0.793*** | 1.076*** |
| | (0.0290) | (0.0405) |
| Age= 34-43 | 0.813*** | 1.238*** |
| | (0.0314) | (0.0419) |
| Age= 44-53 | 0.829*** | 1.394*** |
| | (0.0316) | (0.0406) |
| Age= 54-64 | 0.771*** | 1.336*** |
| | (0.0256) | (0.0299) |
| Income= 1 | 0.0117 | 0.0416*** |
| | (0.0117) | (0.0143) |
| Income= 2 | -0.00667 | 0.00782 |
| | (0.0141) | (0.0203) |
| Income= 3 | -0.0361** | -0.0389* |
| | (0.0149) | (0.0223) |
| Income= 4 | -0.0594*** | -0.0796*** |
| | (0.0136) | (0.0229) |
| Income= 5 | -0.106*** | -0.152*** |
| | (0.0135) | (0.0244) |
| Income= 6 | -0.157*** | -0.255*** |
| | (0.0113) | (0.0208) |
| Education = B | 0.0634* | 0.113** |
| | (0.0353) | (0.0470) |
| Education = C | 0.00137 | 0.0184 |
| | (0.0418) | (0.0565) |
| Education = D | -0.131*** | -0.176*** |
| | (0.0439) | (0.0591) |
| Race = B | 0.321*** | 0.447*** |
| | (0.0287) | (0.0415) |
| Race = H | 0.146** | 0.202** |
| | (0.0671) | (0.0998) |
| Race = W | 0.388*** | 0.586*** |
| | (0.0282) | (0.0402) |
| Insurance = HMO | 0.00708 | 0.0622*** |
| | (0.00871) | (0.0150) |
| Insurance = IND | -0.0126 | 0.0771 |
| | (0.0295) | (0.0520) |
| Insurance = OTH | -0.0354 | 0.161*** |
| | (0.0716) | (0.0275) |
| Insurance = POS | -0.00708 | 0.0104 |
| | (0.0185) | (0.0256) |
| Insurance = PPO | 0.0156 | 0.0584* |
| | (0.0218) | (0.0310) |
| Constant | -1.825*** | -2.724*** |
| | (0.0799) | (0.113) |
| Observations | 18,871,999 | 18,871,999 |
| R-squared | 0.0560 | 0.0614 |
| Ind. FE | No | No |
| Year FE | Yes | Yes |
| Sate FE | Yes | Yes |
| Ind. Controls | Yes | Yes |
| Diag Controls | Yes | Yes |
| Ln L | -1.660e+07 | -1.650e+07 |

**Notes:** Coefficients of the NB1 and NB2 regressions for the number of prescription for opioids per individual year. Diagnosis controls include 69 3-digit ICD-9 codes related to pain. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 24: Cross-sectional data: Model comparison

| Model | Obs | Ln L null | Ln L | df | AIC | BIC |
|---|---|---|---|---|---|---|
| OLS | 18,871,999 | -4.32E+07 | -4.20E+07 | 24 | 8.39E+07 | 8.39E+07 |
| Poisson | 18,871,999 | -3.09E+07 | -2.54E+07 | 25 | 5.09E+07 | 5.09E+07 |
| NB1 | 18,871,999 | -1.76E+07 | -1.66E+07 | 24 | 3.32E+07 | 3.32E+07 |
| NB2 | 18,871,999 | -1.76E+07 | -1.65E+07 | 25 | 3.30E+07 | 3.30E+07 |

Table 25: Panel data models

| Variables | (1) OLS RE | (2) OLS FE | (3) Poisson RE | (4) Poisson FE |
|---|---|---|---|---|
| PDMP | 0.0734*** | 0.0960*** | 0.108 | 0.148*** |
| | (0.0172) | (0.0182) | (0.203) | (0.000931) |
| Insurance = HMO | -0.0212 | -0.0964*** | -0.0349 | -0.132*** |
| | (0.0418) | (0.0175) | (0.445) | (0.00609) |
| Insurance = IND | 0.175*** | -0.185** | 0.227 | -0.194*** |
| | (0.0442) | (0.0869) | (0.696) | (0.0382) |
| Insurance = OTH | -0.00509 | -0.266 | -0.00156 | -0.374*** |
| | (0.0719) | (0.236) | (0.954) | (0.0351) |
| Insurance = POS | -0.000407 | 0.0194* | -0.000345 | 0.0399*** |
| | (0.0203) | (0.0106) | (0.268) | (0.00578) |
| Insurance = PPO | 0.0304 | -0.0530*** | 0.0228 | -0.0827*** |
| | (0.0285) | (0.0122) | (0.484) | (0.00834) |
| /lnalpha | | | 0.987 | |
| | | | (4.164) | |
| Constant | 0.444*** | 0.492*** | -0.843* | |
| | (0.0146) | (0.00713) | (0.490) | |
| Observations | 19,257,360 | 19,257,360 | 21,913,723 | 12,745,615 |
| R-squared | | 0.049 | | |
| Number of patid | 3,953,438 | 3,953,438 | 5,542,282 | 2,623,263 |
| Year FE | No | No | No | No |
| State FE | No | No | No | No |
| Diag Controls | Yes | Yes | Yes | Yes |
| Ln L | | | -1.910e+07 | -9.663e+06 |

**Notes:** Coefficients of the Poisson and OLS regressions with individual random effect and individual fixed effect for the number of prescriptions for opioids per individual year. Diagnosis controls include 69 3-digit ICD-9 codes related to pain. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

Table 26: Panel data: Model comparison

| Model | Obs | Ln L | df | AIC | BIC |
|---|---|---|---|---|---|
| OLS RE | 19,257,360 | . | 24 | . | . |
| OLS FE | 19,257,360 | -3.15E+07 | 24 | 6.30E+07 | 6.30E+07 |
| Poisson RE | 21,913,723 | -1.91E+07 | 76 | 3.82E+07 | 3.82E+07 |
| Poisson FE | 12,745,615 | -9663393 | 74 | 1.93E+07 | 1.93E+07 |

Table 27: Neural Network: Model comparison

| Model | Hidden | Error | AIC | BIC | $R^2$ |
|---|---|---|---|---|---|
| Neural Network | 10 | 83.11444 | 768.2289 | 4549.522 | 0.129 |
| Neural Network | 15 | 82.53771 | 1067.07541 | 6732.7335 | 0.133 |

Table 28: Marginal effect of insurance characteristics on number of prescriptions

| Variables | (1) NB2 | (2) OLS |
|---|---|---|
| Insurance = HMO | 0.218* | 0.0668 |
| | (0.113) | (0.0451) |
| Insurance = IND | 0.701 | 0.219 |
| | (0.428) | (0.158) |
| Insurance = OTH | 0.777*** | 0.297*** |
| | (0.129) | (0.0496) |
| Insurance = POS | 0.0728 | 0.0159 |
| | (0.136) | (0.0318) |
| Insurance = PPO | 0.613*** | 0.209*** |
| | (0.197) | (0.0565) |
| ASO | -0.467*** | -0.126*** |
| | (0.140) | (0.0445) |
| CDHP = HSA | 0.440* | 0.155* |
| | (0.250) | (0.0835) |
| CDHP = NO HRA/HSA | 0.663*** | 0.180*** |
| | (0.174) | (0.0472) |
| Observations | 729,191 | 729,191 |
| R-squared | | 0.287 |
| Year FE | Yes | Yes |
| State FE | Yes | Yes |
| Ind. Controls | Yes | Yes |
| Diag Controls | Yes | Yes |

**Notes:** Marginal effects of the NB2 and OLS regressions for the number of prescriptions for opioids per individual year. Diagnosis controls include 69 3-digit ICD-9 codes related to pain. Individual controls include age, age square, education, gender, and race. Robust standard errors, clustered at the state level, are in parentheses. * p <0.10, ** p < 0.05, *** p <0.01

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