Essays on the Economics of Drug Abuse

ABSTRACT

ESSAYS ON THE ECONOMICS OF DRUG ABUSE

BY

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This dissertation consists of three essays on substance abuse. The first essay examines whether restricting access to legal prescription opioids has an impact on substance abuse behavior. Following the increase in people taking hydrocodone combination products (HCPs) in dangerous amounts, the Drug Enforcement Administration (DEA) requested the Department of Health and Human Services (DHHS) to conduct thorough research on HCPs. After evaluating the medical evidence, the DHHS recommended that all HCPs be transferred from a Schedule III to a Schedule II controlled substance. In 2014, the Drug Enforcement Administration (DEA) implemented the rescheduling of HCPs. The total number of HCPs prescriptions in the U.S fell from 136.7 million in 2013 to 83.6 million in 2017**.** Subsequently, the number of persons misusing HCPs also declined from 7.2 million in 2015 to about 5.5 million in 2018 (National Survey on Drug Use and Health, 2020). Using data from the 2005 to 2019 Treatment Episode Data Set (TEDS) survey, I analyze the effect of the policy on substance abuse behavior. I employ a difference-in-differences strategy that explores the cross-state variation in the pre-implementation hydrocodone prescription rate. I find evidence that suggests that the rescheduling

led to a reduction in the utilization of hydrocodone combination medications. Given this evidence of a "first-stage" effect, I also assess whether the decline in legally-obtained opioid prescriptions affects the misuse of other substances. I find that a one percentage point increase in the mean hydrocodone prescription (i.e., 13kg per 100,000 residents) increases alcohol abuse treatments by 63 treatments per 100,000 adults, marijuana abuse treatments by 40 treatments per 100,000 adults, and cocaine abuse treatments by 13.2 treatments per 100,000 adults.

The second essay investigates whether the rescheduling of HCPs could potentially have a spillover effect on crime. By reducing the supply of HCPs through the rescheduling, the policy may have had an unintended consequence on the cost of obtaining illegal prescription opioids. To explore this question, I use arrest data from 2006 to 2019 from the Uniform Crime Reporting (UCR) program provided by the Federal Bureau of Investigation (FBI) combined with a difference-in-differences strategy. I find evidence that the rescheduling of HCPs led to an increase in violent crimes. I estimate that violent crimes increased by 23.9 offenses per 100,000. The increase in violent crimes is driven by an increase in aggravated assault crimes.

The final essay in my dissertation investigates the impact of the Affordable Care Act's (ACAs) Medicaid expansion on the access and the utilization of substance use disorder (SUD) treatment. After the implementation of the Affordable Care Act, individuals with SUD have greater access to treatment through various programs and policy changes. To estimate the effect of the policy, I exploit the variation in the timing of the Medicaid expansion across states. I find that the ACA's Medicaid expansion led to a 36% decrease in the number of uninsured substance abuse patients and a 90% increase in Medicaid insurance coverage among the same group. Following the gains in insurance coverage among substance abuse patients, one would expect an increase in the utilization of substance abuse treatment. I measure the utilization of substance abuse treatment using the number of admissions per 100,000 non-elderly adults and treatment completion status. The results show that the ACA's Medicaid expansion had no statistically significant effect on substance abuse treatment admissions. A potential explanation for this is that access to health insurance coverage alone may not impose a substantial barrier to seeking substance abuse treatment.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Chapter 1

Hydrocodone Combination Products and the Rescheduling

1.1 Introduction

The Controlled Substance Act (CSA) of 1970 was created under Title II of the Comprehensive Drug Abuse Prevention and Control Act. Its purpose was to classify controlled substances under five schedules according to their potential for abuse and whether they are currently accepted for medical use in the United States. The law gave the Drug Enforcement Administration (DEA) the authority to implement and enforce the provisions of the Controlled Substance Act by coordinating with both states and local governments to prevent the diversion or misuse of controlled substances. The Drug Enforcement Administration could transfer or add a controlled substance to a schedule when evidence suggests that a controlled substance has a high potential for abuse.

After the Drug Enforcement Administration received new evidence from the Department of Health and Human Services (DHHS) that Hydrocodone-containing products (HCPs) have a high potential for abuse, the agency rescheduled hydrocodone-containing products from a Schedule III substance of the Controlled Substance Act to a schedule II substance in 2014[1]. HCPs contain a limited amount of hydrocodone and specified amounts of other controlled substances. Hydrocodone-containing products were initially listed as a Schedule III drug when Congress passed the Controlled Substances Act in 1971. HCPs are the most commonly prescribed opioid in the United States (U.S) (Physician Assistant Board, 2014). Over 136 million hydrocodone-containing prescriptions were dispensed in 2013, and about 70.9 million HCPs

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[1] Schedule II prescriptions prescribed for a legitimate medical purpose must be presented to the pharmacy in written form and signed by the prescriber except in an emergency. In addition, while Schedule III controlled substances may be refilled up to 5 times in a 6-month period, Schedule II medications cannot be refilled, and a new prescription must be written every time.

were dispensed in 2018 (Drug Enforcement Administration, 2019). About 5.5 million individuals above the age of 12 misused hydrocodone-containing products in 2018 (National Survey on Drug Use and Health, 2018).

While economists have not studied the effect of the rescheduling yet, clinicians have found associations with the rescheduling and opioid analgesic prescribing and pain management practices (Jones, Lurie, & Throckmorton, 2016; Fleming et al., 2019; Neuman et al., 2020). This study is motivated by the evidence from the existing literature that the rescheduling of hydrocodone-containing products has led to a reduction in the supply of legally obtained opioids. In this chapter, I estimate the causal effect of placing hydrocodone-containing products into the more restrictive Schedule II category of the Controlled Substance Act on the primary substance abused among substance use disorder (SUD) patients. I explore the cross-state variation in the pre-implementation hydrocodone prescription rates.

Theoretically, the rescheduling of HCPs could induce either substitutionary or cessation behavior among substance abuse patients, making the impact of the rescheduling on the primary drug of addiction ambiguous. The rescheduling of HCPs acts as an adverse supply shock for opioid prescriptions. All else equal, the negative supply shock may lead to an increase in the price of diverted legally-obtained opioids, which could lead HCPs abusers to find a cheaper alternative or pay the higher prices. Using the street prices of cocaine and heroin obtained by undercover law enforcement agents, Dave (2005) studies the impact of the changes in the price of cocaine and heroin price on drug-related emergency department visits in 16 cities in the U.S. Dave (2005) finds that between 1990 and 2002 the price of heroin and cocaine declined 72% and 42% respectively. The decline in the prices of heroin and cocaine coincided with an increase in heroin and cocaine-related emergency department cases. The study also evaluates the responsiveness of heroin and cocaine-related emergency department cases to changes in cocaine and heroin prices. Dave (2005) finds that the elasticity of the probability of cocaine-related emergency department cases with respect to own price is –0.27. Lastly, the increase in street price and limited supply of HCPs could also decrease the number of persons who initiate hydrocodone-containing products. These factors could influence the primary substance abused among SUD patients.

I investigate the impact of the policy on the primary substance abused among substance use disorder patients by leveraging data from the Treatment Episode Dataset. The data contains the demographic and substance use history of individuals seeking SUD treatment. I identify the effect of the policy by using baseline-level differences in the hydrocodone prescription rates across states before the rescheduling. I found evidence that suggests that the rescheduling led to a reduction in the utilization of hydrocodone combination medications. Given this evidence of a "first-stage" effect, I also assess whether the decline in legally-obtained opioid prescriptions affects the misuse of other substances. I found that a one percentage point increase in the mean hydrocodone prescription (i.e., 13kg per 100,000 residents) increases alcohol abuse treatments by 63 treatments per 100,000 adults, marijuana abuse treatments by 40 treatments per 100,000 adults, and cocaine abuse treatments by 13.2 treatments per 100,000 adults.

1.2 Literature Review

1.2.1 Prescription Opioid Abuse

Prescription opioids interact with opioid receptors in the body and brain to produce varying effects. While prescription opioids are safe, particularly when taken for a short time and as prescribed by a doctor, several studies suggest that they can be abused (National Institute on

Drug Abuse, 2020; Brady et al., 2016). The use of opioids for medical and non-medical purposes can lead to physical dependence on the substance. Consequently, prescription opioids are among the most common initiated drugs, with over 5,800 initiates per day in 2015 (SAMHSA, 2015).

The pervasiveness of prescription opioid abuse became popular in the U.S in the 1990s. The opioid epidemic began in the late 1990s when pharmaceutical companies assured both patients and medical professionals that prescription opioids could not be easily abused. As a result, prescription opioids were dispensed in large quantities, leading to an increase in opioid abuse and physical dependence on the substance (Centers for Disease Control and Prevention, 2020).

Opioid addiction carries a high societal and economic cost (McAdam-Marx et al. 2010; McCarty et al. 2010; Leider et al. 2011; Kirson et al. 2017). According to the Council of Economic Advisers (CEA), the economic burden of prescription opioid abuse is estimated to cost $504 billion in 2015 (Council of Economic Advisers, 2017). White et al. (2005) reveals that, on average, the medical expenses of substance abusers are eight times higher than that of normal people. These expenses are primarily driven by the high utilization of hospital services among substance abusers. Chen et al. (2014) use mortality data from the Centers for Disease Control and Prevention to show that between 1999 and 2011, the opioid overdose mortality rate quadrupled in the U.S. Similarly, opioid-overdose emergency room visits accounted for 2.5 million emergency department visits in 2011 alone (SAMHSA, 2013). The increase in healthcare utilization due to opioid abuse exerts an enormous burden on healthcare resources. Leslie et al. (2019) collected Medicaid service utilization data from Medicaid Analytic eXtract to investigate the economic burden of opioid treatment on the Medicaid program. According to their calculations, opioid use disorder increased Medicaid expenses by 72 billion between 1999 and 2013.

1.2.2 Policy Interventions Targeting the Opioid Epidemic

The federal government and several states have implemented various policies aimed at curbing prescription opioid abuse. These policies can be categorized into demand-side and supply-side interventions. Examples of supply-side interventions include Prescription Drug Monitoring Programs (PDMPs), Medicaid Lock-In Programs, pain clinic laws, and abuse-deterrent drug formulations. On the other hand, the demand-side interventions include educating individuals (would-be users) against the harmful effects of opioids and the provision of treatment to current abusers to reduce their demand. Ruhm (2018) acknowledges that while it is unlikely for the demand for opioids to decline in the short run dramatically, supply-side interventions generate a sudden decline in the supply of opioids due to technological advancements.

1.2.3 The Rescheduling of HCPs

The rescheduling of HCPs, which is the identifying variation I use in this study, has changed medical opioid prescription patterns. Using linear regression analysis and data from the IMS Health National Prescription Audit, Zalts et al. (2016) compare the differences between predicted dispensed prescriptions and actual dispensed prescriptions and tablets after rescheduling. Their results indicate that the rescheduling of HCPS led to a 16% decrease in HCPs in the first year of the policy. After examining pain-related prescription data at the emergency department before and after the rescheduling of HCPs, Oehle et al. (2016) find that before the policy change for every ten patients receiving a pain-related prescription, five received an HCP. However, after the implementation of the rescheduling, only one in ten patients received an HCP. Their logistic regression analysis also shows that new patients are more likely to be prescribed other Schedule III and non–Schedule II/III products. Another study conducted on the changes in prescription patterns in Ohio after the rescheduling of hydrocodone combination products suggests that the policy led to a large decline in hydrocodone prescription and an increase in codeine prescription (Liu, Baker, Schuur, & Weiner, 2020).

1.3 Data

The study assumes that the effect of the rescheduling of hydrocodone-containing products should lead to a higher reduction in hydrocodone-containing prescriptions per capita in states with a relatively high hydrocodone prescription rate before 2014. To show this, I obtained hydrocodone sales data in kilograms per 100,000 residents from the Automation of Reports and Consolidated Orders System (ARCOS). The Automation of Reports and Consolidated Orders System is a reporting system that tracks the production and the distribution of controlled substances. The DEA maintains the ARCOS. I used the 2011 hydrocodone sales data as the main treatment variable because it predates the rescheduling.

For the first-stage effect, I showed that the rescheduling of hydrocodone-containing products should affect the total number of hydrocodone combination products dispensed. I used Medicare Provider Utilization and Payment Data: Part D Prescriber Public Use File from the Centers for Medicare & Medicaid Services (CMS) to show that placing hydrocodone-containing products in schedule II of the Controlled Substance Act led to a decrease in the number of hydrocodone-containing products dispensed. The Medicare Part D dataset is a census of prescription claims for enrollees. These individuals include adults above the age of 64 years and the disabled. About 44 million individuals enrolled in the program in 2020. The dataset records the drug name, the total claim count[2], the total 30-day fill count[3], the total daily supply of prescriptions, and the total drug cost made by each prescriber. The Medicare Part D dataset is appealing for this study because of the way hydrocodone-containing prescriptions are reported in the dataset. Unlike the Medicaid prescription dataset, the Medicare Part D dataset does not classify the combination medication into separate groups[4]. I obtained prescription data on Hydrocodone-Acetaminophen, a popular hydrocodone-containing product frequently prescribed for moderate-to-severe pain control, from the Medicare Part D dataset for the years 2013 to 2018. For the analysis, the data was rolled up to the state level.

To investigate the impact of the rescheduling of HCPs on the changes in the primary substance abused among substance use disorder patients, I obtained data from the Treatment Episode Data Set (TEDS-A). The TEDS-A is a compilation of data of admissions into substance abuse treatment centers in the U.S. While the data does not include every admission into treatment facilities in the U.S, it captures a large share of admissions nationwide[5]. The data reported to TEDS-A is obtained from certified state substance abuse agencies that provide substance abuse treatment. Each record in the TEDS-A table represents admission into a treatment facility. The TEDS-A data contains demographic information, date of admission, substance use behavior, and primary substance use at the admission of substance abuse patients. Data from the 2005 to 2019 TEDS-A census were obtained for this study. The data was

[2] The Centers for Medicare and Medicaid Services (CMS) defines the total claim count as the total number of Medicare Part D claims which includes initial prescriptions and refills.
[3] The overall number of Medicare Part D standardized 30-day fills.
[4] While the Medicare Part D dataset labels Hydrocodone-Acetaminophen as one medication, the Medicaid dataset labels Hydrocodone-Acetaminophen as two separate medications (i.e., hydrocodone and acetaminophen). Commercial claims data could also be used for this type of analysis, but I do not have access to the data.
[5] According to SAMHSA, nearly 2 million individuals are admitted into 10,000 publicly and privately funded treatment programs each year.

transformed into state-year counts of the various primary substances abused by substance use disorder patients. Using data from the TEDS-A, I construct several outcome variables that correspond with the various addiction substances. These variables include the count of Alcohol, Cocaine, Cannabis, Heroin, and Methamphetamine per 100,000 adults admitted into a substance use disorder treatment facility in a state.

I controlled for other time-varying and state-specific laws that various studies have identified to be associated with substance abuse (Salomonsen-Sautel et al., 2012; Bachhuber et al., 2014; Hefei, Jason, & Cummings, 2015; McClellan et al., 2018; Alley, Kerr, & Bae, 2020). These laws can be categorized into two main groups. The first set of laws consist of opioid prescription laws. Data on the opioid prescription laws were obtained from Meara et al. (2016). Meara et al. (2016) assembled a database of 81 state controlled-substance laws from 2006 through 2012. After extending the Meara et al. (2016) database from 2016 to 2019, I include the following opioid prescription laws in my model: (1) ID Requirement laws[6], (2) Doctor Shopping laws[7], (3) Prescription Limit laws[8], and (4) Prescription Drug Monitoring Program laws[9]. I also controlled for the 2010 abuse-deterrent reformulation of oxycodone using oxycodone misuse data from Alpert et al. (2018). The second set of laws are marijuana-related laws. They include marijuana decriminalization laws, recreational marijuana laws, and medical marijuana laws. The Marijuana law variables were obtained from Pacula and Smart (2017). Pacula and Smart (2017) constructed a database of such policies, most of which aimed to decriminalize and legalize

[6] ID Requirement laws require pharmacists to request identification (ID) before dispensing a controlled substance.
[7] In some states, it is unlawful to obtain controlled substances from multiple medical practitioners without informing each practitioner about previous prescriptions.
[8] Prescription limit laws regulate the quantity of prescription dispensed and the number of days before a prescription can be refilled.
[9] The PDMP maintains an electronic database on controlled substance prescriptions in a state. Meara et al. (2016) classify a state as having PDMP only when the PDMP is fully operational.

marijuana use. I also obtained the state-level income distribution and unemployment rate from the Bureau of Labor Statistics (BLS). The state-level socioeconomic characteristics such as age, race, gender, education, and marital status were collected from the American Community Survey (ACS), which was downloaded from the Integrated Public Use Microdata Series (IPUMS).

1.4 Empirical Strategy

To identify the effect of the rescheduling of hydrocodone combination products, I explored the cross-state variation in the pre-treatment hydrocodone prescription rate. In theory, the impact of the rescheduling should have more "bite" in states with a higher pre-implementation hydrocodone prescription rate. Alpert et al. (2018) and Evans et al. (2019) use this “bite”- style approach to estimate the impact of the 2010 OxyContin reformulation on heroin and other types of opioid overdoses10. Other studies in economics use the same methodology (Acemoglu et al., 2004; Finkelstein,2007; Courtemanche et al., 2016).

In this study, I used a similar approach. I explored the variation in the hydrocodone prescription rate across states before the implementation of the policy. I used the hydrocodone sales data in 2011 from the ARCOS as the bite variable for this study. I then estimated a two-way fixed-effect model using the Medicare Part D data from 2013 to 2018, and the TED-A data from 2005 to 2019. The model is specified as follows:

$$Y_{st} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}Post_t + \boldsymbol{\beta_2}HPR_s + \boldsymbol{\beta_3}(HPR_s * Post_t) + \boldsymbol{\beta_4 X_{st}} + \boldsymbol{\alpha_s} + \boldsymbol{\delta_t} + \boldsymbol{\gamma_t t} + \boldsymbol{\varepsilon_{st}} \qquad \textbf{(1)}$$

[10] Using the variations in the pre-reformulation OxyContin misuse rates across states as their exposure variable, Alpert et al. (2018) find that heroin overdose deaths were notably greater in states with higher pre-reformulation OxyContin misuse rates.

where Y_{st} is the outcome variable in state s, and year t; $Post_t$ is an indicator for whether the period is either before or after 2014 (the year of the rescheduling). HPR_s is the hydrocodone prescription rate in state s in 2011 obtained from the ARCOs data. X_{st} is a set of dummies for a several drug policies, and economic and demographic control variables. α_s and δ_t are the state and time fixed effect respectively. I also included a state-specific linear time trend, $\gamma_t t$, in the model. Standard errors were clustered at the state level, which is the level at which the bite variable varies. I estimated the outcomes using the state's population as weight.

1.4.1 Event Study

I assess the assumption that in the absence of the rescheduling of the HCPs, the differences in the outcomes would have continued in the same trends. To test whether this assumption holds, I performed an event study analysis. The event study model interacts the hydrocodone prescription rate with the full set of year fixed effects, leaving 2013 as the reference year. The event study equation is specified as:

$$\mathbf{Y_{st}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \sum_{t=start}^{end} (\mathrm{HPR_s} * \mathrm{Year_t}) + \boldsymbol{\beta_2} \boldsymbol{X_{st}} + \boldsymbol{\alpha_s} + \boldsymbol{\gamma_t} + \boldsymbol{\gamma_t t} + \boldsymbol{\varepsilon_{st}} \qquad (\mathbf{2})$$

If the parallel trend assumption holds, I would expect the interaction of the year indicator for 2005, 2007, 2008, 2009, 2010, 2011, 2012, and the hydrocodone prescription rate to be statistically insignificant or very small. In other words, finding a trend in states with lower or higher pre-rescheduling HCP prescribing rates would pose a threat the validity of the identification strategy.

To show that my results are robust to alternative measures of exposure to the hydrocodone combination products, I constructed a new exposure variable using state-level averages of HCP sales data from ARCOS. I used the annual kilograms sold of hydrocodone per 100,000 people data from 2008 to 2011 compared to just the rate in 2011. As a second robustness check, I re-estimated my regressions without population weights. According to Solon et al. (2013), if the variation of the group-mean error term is large, the ordinary least squares regression without weights yields the best-unbiased coefficients.

1.5 Results

Summary statistics for the dependent variables from the Medicare Part D data and the TEDS-A are provided in Table 1.1, stratified by states with a hydrocodone prescription rate above or below the 2011 median hydrocodone prescription rate. In high hydrocodone prescribing states, the average daily supply for Hydrocodone-Acetaminophen among Medicare Part D patients was 1,658.2 pills per 10,000 elderly adults[11], and the 30-day fill count was 82.4 pills per 10,000 elderly adults. In contrast, the average daily supply for Hydrocodone-Acetaminophen was 605.1 pills per 10,000 elderly adults, and the 30-day fill count was 34.7 pills per 10,000 elderly adults in low hydrocodone prescribing states. There were fewer patients per 100,000 residents seeking treatment for alcohol, cocaine, marijuana, and heroin abuse in high hydrocodone prescribing states compared to low hydrocodone prescribing states. On average, 54.7 patients per 100,000 residents were admitted to SUD treatment for methamphetamine abuse in high hydrocodone prescribing states. The state characteristics are reported in Table 1.2. Low hydrocodone prescribing states have a higher proportion of men to women, a lower unemployment rate, and a lower poverty rate.

[11] Individuals above the age of 64 years.

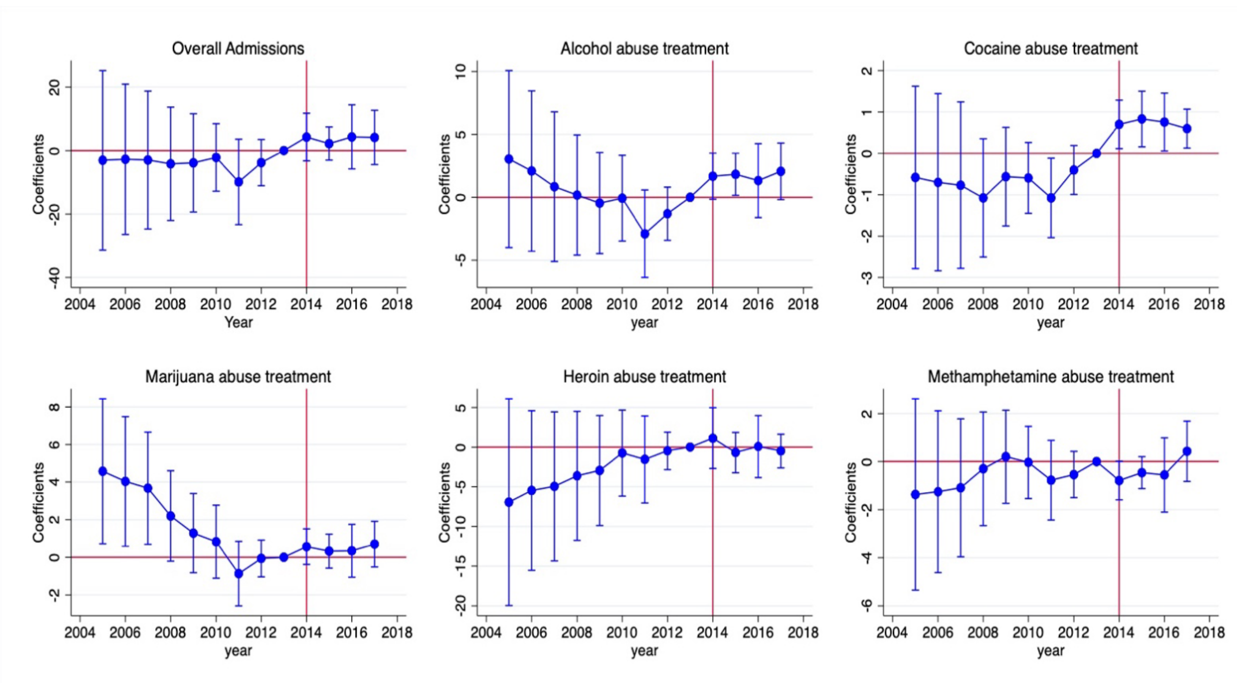
Next, I discuss the results of the impact of the rescheduling of hydrocodone-containing products on hydrocodone/acetaminophen prescription for Medicare Part D patients. I consider the effect of the policy on the various measures of hydrocodone/acetaminophen prescription, including the total daily supply, total 30-day fill count, and total claim count. This investigation aims to provide statistical evidence of the first stage effect of the policy. Table 3 reports the coefficient estimates for the post-rescheduling indicator interacted with the hydrocodone prescribing rate. The coefficient estimates for the hydrocodone prescribing rate and post-rescheduling indicator interaction suggest that the rescheduling of hydrocodone-containing products in 2014 reduces the total daily prescription for hydrocodone/acetaminophen by 15.9 pills per 10,000 elderly residents. In the second column of Table 1.3, I estimate that the policy reduces the total 30-day fill count for hydrocodone/acetaminophen by 0.9 pills per 1,000 residents. Similarly, I find that the rescheduling of hydrocodone-containing products reduces the total claim count for hydrocodone/acetaminophen. Taken together, these results suggest that the rescheduling reduces hydrocodone-acetaminophen, a commonly prescribed hydrocodone-containing product, prescription among Medicare patients.

In Table 1.4, I examine the effect of the rescheduling of hydrocodone combination products on the primary substance use at admission among SUD patients. If the rescheduling of hydrocodone combination products is operating by limiting access to prescription opioids, we would expect more SUD patients to seek treatment for opioid abuse or other substances that are substitutes for opioids. The covariate-adjusted regressions are from the estimation of equation (1). In column 1, I find that the rescheduling of hydrocodone combination products had no statistically significant effect on total admissions into SUD treatment facilities in areas with higher versus lower baseline shares of opioids per capita. Columns 2 to 6 reports results for specific primary substance (e.g., marijuana, heroin, cocaine, alcohol, and methamphetamine) used among SUD patients. In column 2 of Table 1.4, I estimate an effect size of 3 for the coefficient of interest. This implies that a one percentage point higher rate of initial hydrocodone prescription increases the number of persons primarily abusing marijuana by 3 substance use disorder patients per 100,000 residents. At the average pretreatment hydrocodone prescription rate, marijuana abuse treatments increased by 40.4 treatments per 100,000 adults. The result is statistically significant at the one percent level.

Column 3 of Table 1.4 shows the effect of restricting access to hydrocodone-containing products on SUD admissions for alcohol abuse. I consider the direction of the effect as an indicator for the demand for alcohol abuse. Indeed, I find that the number of individuals seeking treatment for alcohol abuse increases by 4.6 treatments per 100,000 residents ($p < 0.01$) after the rescheduling of hydrocodone-containing products is implemented. At the average pretreatment hydrocodone prescription rate, alcohol abuse treatments increased by 62.7 treatments per 100,000 adults. The prevalence of alcohol abuse among SUD patients is consistent with the addiction literature, revealing that the probability of abusing alcohol increases with the decrease in the supply of hydrocodone combination products (Riley and King, 2009; Witkiewitz and Vowles, 2018).

Columns 4 and 5 of Table 1.4 shed light on the impact of the rescheduling on SUD treatment for heroin and cocaine addiction, respectively. I find that following the rescheduling of hydrocodone combination products, the number of persons receiving SUD treatment for heroin abuse declined by 3.1 treatments per 100,000 residents. The rescheduling of hydrocodone-containing products is also associated with an increase in SUD admissions for individuals who primarily abuse cocaine. I find that a one percentage point increase in the initial hydrocodone prescription rate is associated with a 0.9 per 100,000 residents increase in cocaine abusers receiving SUD treatment. Lastly, in column 6 of Table 1.4, I find that the policy has no statistically significant effect on treatment admissions for methamphetamine abuse.

Figure 1.1 Effect of the rescheduling on substance abuse treatment



In Figure 1.1, I show the event study results of the rescheduling of hydrocodone combination products on the several primary substances used by SUD patients. The results of interest are the full set of the interaction of the year indicator for 2006,2007,2008,2009,2010, 2011, 2012, 2014, 2015, 2016, 2017, 2018, and the hydrocodone prescription rate coefficients. Each graph shows the coefficient estimates and 95 percent confidence intervals for every year. In figure 1.1, I observe limited evidence of non-parallel trends for the overall admissions, alcohol abuse admissions, and cocaine abuse admissions. The event study estimates for these outcome variables are close to zero and statistically insignificant nearly every year before the rescheduling of hydrocodone-containing products. As a result, the differences-in-difference estimator reflects a causal effect of the rescheduling of HCP for alcohol abuse and cocaine abuse admissions. The event study result also shows that there was an immediate increase in the number of SUD patients in the year after the policy change that reported abusing alcohol and cocaine. The marijuana abuse admissions event study displays a pre-existing downward trend in states with a higher baseline rate of HCP prescribing that appears to level out a few years before the rescheduling occurs. Similarly, the heroin abuse admissions event study also shows a pre-existing upward trend. Thus, the differences-in-difference estimate for heroin abuse and marijuana abuse admissions may be biased.

In table 1.5, I present results that show the robustness of the model to using as the bite variable the average rate of hydrocodone prescribing between 2008 to 2011. By averaging the exposure variable, I eliminate the likelihood of picking up some effects related to a one-time surge in hydrocodone prescription rate in a particular state before the rescheduling I estimate that an additional percentage point of hydrocodone prescription rate before the rescheduling increases alcohol abuse treatments by 4.8 treatments per 100,000 adults and marijuana abusers receiving treatment by 2.9 treatments per 100,000 adults. These results are comparable to the baseline results in both magnitude and direction[12].

Table 1.6 presents the results when the model is estimated without population weights. After estimating the model without population weight, I find that an additional percentage point of hydrocodone prescription before the rescheduling increases the number of individuals receiving treatment for alcohol abuse by 5.5 treatments per 100,000 adults. The effect size is almost the same as the effect size estimated using population weights (i.e., 4.6 treatments per 100,000

[12] I estimate an effect size of 4.6 SUD patients per 100,000 adults for alcohol abuse treatment and an effect size of 3 SUD patients per 100,000 adults for marijuana abuse treatment using the baseline model.

adults). Similar to the baseline model, the rescheduling had no statistically significant effect on the overall number of persons admitted into SUD treatment facility per 100,000 adults and the number of persons receiving treatment for methamphetamine abuse per 100,000 adults. The other results remain generally comparable to the main results.

1.6 Discussions

The purpose of this study is to investigate the effect of the rescheduling of hydrocodone combination products from a schedule III controlled substance to a schedule II controlled substance on the primary substance abused among SUD patients. By placing hydrocodone combination products in schedule II of the Controlled Substance Act, the DEA imposes regulatory controls and criminal penalties relevant to schedule II controlled substances on individuals who manufacture and distribute hydrocodone combination products. The new regulatory controls imposed on hydrocodone combination products act as a negative supply shock for legally-obtained opioids, which could lead to changes in the primary abuse substance among substance abusers. I find suggestive evidence of this behavior using data from the Treatment Episode Dataset.

The Treatment Episode Dataset is ideally suited to study the impact of the policy on the changes in the primary substance abused because the data, even though self-reported, is collected at a drug treatment facility at the time of client intake. This practice ensures that the data remains accurate since the client has to report the correct information to receive the appropriate treatment. Secondly, the Treatment Episode Dataset reports the primary, secondary, and tertiary substances of use reported by the client. By including the various levels of substance misuse in the data, individuals abusing multiple substances can accurately report their drug abuse habits.

Using the Treatment Episode Dataset to investigate the impact of rescheduling on the primary substance abused among SUD patients, I find that the policy is associated with an increase in the number of persons seeking substance use disorder treatment for marijuana and alcohol abuse. Specifically, I find that following the rescheduling of hydrocodone-containing products, a one percentage point higher rate of initial hydrocodone prescription rate increases alcohol abuse treatments by 62.7 treatments per 100,000 adults and marijuana abuse treatments by 40.4 treatments per 100,000 adults. The policy has no statistically significant effect on Cocaine abusers, Heroin abusers, Methamphetamine, and Other Opiates abusers.

This study makes several significant contributions to the literature on substance abuse. To the best of my knowledge, this is the first empirical work that studies the impact of the rescheduling on the primary substance abused by SUD patients. Many of the prior studies on the rescheduling of hydrocodone combination products have only focused on identifying the causal effect of the policy on the changes in opioid prescribing practices (Oehle et al., 2016; Lui et al., 2020). I extend the literature on the rescheduling by providing empirical evidence of the impact of the policy on pain management and addiction behavior. The results suggest that tackling the opioid crisis by restricting access to prescription opioids may have an unintended consequence on pain management. The first-stage results presuppose that the rescheduling of HCPs has led to an increase in untreated pain. Patients with chronic pain and surgical post-op patients now have limited access to hydrocodone-acetaminophen. Thus, the policy reduces the welfare of people that have a clinical need for pain relief. Lastly, while there has been a 44 percent reduction in opioid prescription across the country as of 2020, substance abuse-related deaths have been on the rise. This research offers a potential explanation for the phenomenon and helps policymakers understand the intricate relationship between substances.

Table 1.1 Summary Statistics of Dependent Variables

	High Hydrocodone Prescribing states	Low Hydrocodone Prescribing States
Medicare Part D: Hydrocodone-Acetaminophen Prescription data (per 10,000 elderly adults)		
Total claim count	80.9 (25.4)	34.06 (14.21)
Total 30-day fill count	82.40 (25.7)	34.71 (14.5)
Total daily supply	1,658.2 (585.16)	605.10 (245.9)
Observations	**52**	**50**
TEDS-A: Substance Use Disorder Admissions data (per 100,000 individuals above the age of 12)		
Total admissions	607.0 (305.7)	1044.6 (515.7)
Alcohol admissions	239.1 (162.2)	500.6 (372.2)
Cocaine admissions	55.7 (41.8)	69.97 (63.1)
Marijuana admissions	116.73 (61.5)	148.94 (76.8)
Heroin admissions	46.8 (54.6)	152.7 (184.8)
Methamphetamine admissions	65.3 (78.9)	48.1 (62.6)
Observations	**247**	**255**

Notes: Standard errors are shown in parentheses. Data were analyzed 2005 to 2014 for the TEDS-A dataset. The Medicaid Part D data were analyzed from 2013 to 2014. States with hydrocodone prescription rate below the median of 11.1 kg per 100,000 persons were classified as low HPR states while states with hydrocodone prescription rate above the median rate were classified as high HPR states. Tennessee, North Dakota, New Mexico, Nebraska, and District of Columbia had missing observations for some years.

Table 1.2 Summary Statistics State Characteristics

	High Hydrocodone Prescribing states	Low Hydrocodone Prescribing States
% Male	48.8	49.1
% Aged below 20	24.3	23.6
% Aged 20 to 40	23.1	23.3
% Aged 40 to 60	26.8	27.6
% White	78.7	78.6
% Black	22.8	15.1
% Single	40.3	41.7
% Married	42.6	43.2
% With zero children	73.2	73.5
% With one child	12.8	12.5
% High School Degree	31.5	29.9
% With No Education	6.3	5.8
% With any health insurance	88.6	92.3
% Living in metro area	60.2	61.2
Poverty rate	16.3	11.8
Unemployment	6.19	5.4
Hydrocodone per 100,000	19.5	7.5
Observations	26	25

Notes: The data was obtained from the American Community Survey dataset. The estimates show the characteristics of high and low hydrocodone prescribing states in 2014.

Table 1.3 Effect of the Rescheduling of HCPs on Hydrocodone-Acetaminophen Prescription

	(1)	(2)	(3)
VARIABLES	Total daily supply	Total 30-day fill count	Total claim count
Post * HPR	-15.9***	-0.9***	-0.84***
	[-20.8, -10.9]	[-1.2, -0.6]	[-1.2, -0.5]
(Implied Effects of the Rescheduling at Mean Pretreatment Hydrocodone Prescription Rate)			
Post * HPR	-216.5*** [-284.2, -148]	-12.1*** [-16.8, -7.7]	-11.6*** [-16.0, -7.3]
Demographic Controls	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes
Opioid laws	Yes	Yes	Yes
Marijuana Laws	Yes	Yes	Yes
R-squared	0.992	0.988	0.989
Observations	306	306	306

Notes: Means and confidence interval are reported. Standard errors are clustered at the state level and are reported in parentheses. The data was from the Medicaid Part D dataset. Data were analyzed 2013 to 2018. *** p<0.01, ** p<0.05, * p<0.1

Table 1.4 Effect of the Rescheduling of HCPs on the Primary Substance Abused

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Admissions	Marijuana Admissions	Alcohol Admissions	Heroin Admissions	Cocaine Admissions	Methamphetamine Admissions
Post* HPR	6.6 [-2.2, 15]	3.0*** [1.4, 4.5]	4.6*** [2.0, 7.2]	-3.1* [-6.3, 0.5]	0.96** [0.1, 1.8]	-0.15 [-1.3, 1.0]
(Implied Effects of the Rescheduling at Mean Pretreatment Hydrocodone Prescription Rate)						
Post * HPR	90.03 [-30, 210]	40.40*** [19.6, 61.1]	62.77*** [27.6, 97.9]	-41.74* [-90.3, 6.8]	13.17** [1.3, 25.0]	-2.07 [-17.9, 13.8]
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Opioid laws	Yes	Yes	Yes	Yes	Yes	Yes
Marijuana Laws	Yes	Yes	Yes	Yes	Yes	Yes
Observations	648	648	648	648	648	698
R-squared	0.931	0.927	0.975	0.943	0.968	0.952

Notes: Means and confidence interval are reported. Standard errors are clustered at the state level and are reported in parentheses. The data source is the Treatment Episode Dataset – Admissions (TEDS – A). Data were analyzed 2005 to 2019. 2014 observations were omitted from the analysis to account for the transition period. *** p<0.01, ** p<0.05, * p<0.1

Table 1.5 Effect of the Rescheduling of HCPs on the Primary Substance Abused (Exposure)

	(1) Total Admissions	(2) Marijuana Admissions	(3) Alcohol Admissions	(4) Heroin Admissions	(5) Cocaine Admissions	(6) Methamphetamine Admissions
Post* HPR	6.8	2.92***	4.83***	-3.1*	0.8	-0.7
	[-3.1, 16.6]	[1.0, 4.9]	[1.4, 8.2]	[-6.7, 0.5]	[-0.2, 1.9]	[-2.3, 1.0]
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Opioid laws	Yes	Yes	Yes	Yes	Yes	Yes
Marijuana Laws	Yes	Yes	Yes	Yes	Yes	Yes
Observations	638	638	638	638	638	638
R-squared	0.932	0.925	0.975	0.94	0.97	0.952

Notes: I use the average hydrocodone prescription data between 2008 to 2011 as exposure variable. Means and confidence interval are reported. Standard errors are clustered at the state level and are reported in parentheses. The data source is the Treatment Episode Dataset – Admissions (TEDS – A) Data were analyzed 2005 to 2019. *** p<0.01, ** p<0.05, * p<0.1

Table 1.6 Effect of the Rescheduling of HCPs on the Primary Substance Abused (No Weights)

	(1) Total Admissions	(2) Marijuana Admissions	(3) Alcohol Admissions	(4) Heroin Admissions	(5) Cocaine Admissions	(6) Methamphetamine Admissions
Post* HPR	6.55	2.7***	5.5***	-3.5**	0.9*	-0.6
	[-1.6, 14.7]	[1.3, 3]	[2.1, 8.8]	[-6.9, -0.1]	[-0.03, 1.8]	[-2.2, 1.0]
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Opioid laws	Yes	Yes	Yes	Yes	Yes	Yes
Marijuana Laws	Yes	Yes	Yes	Yes	Yes	Yes
Observations	648	648	648	648	648	648
R-squared	0.92	0.92	0.97	0.92	0.92	0.95

Notes: For this regression, I drop the population weights. Means and confidence interval are reported. Standard errors are clustered at the state level and are reported in parentheses. The data source is the Treatment Episode Dataset – Admissions (TEDS – A) Data were analyzed 2005 to 2019. *** p<0.01, ** p<0.05, * p<0.1

Chapter 2

The Rescheduling of Hydrocodone Combination Products and Crime

2.1 Introduction

Prescription opioid abuse carries a high societal and economic cost. Between 1999 and 2018, nearly 450,000 individuals lost their lives after overdosing on opioids (Centers for Disease Control and Prevention, 2020). According to the Council of Economic Advisers, the economic burden of prescription opioid abuse exceeds $500 billion annually (Council of Economic Advisors, 2017). As a result, the federal government and several states have implemented various policies aimed at curbing prescription opioid abuse. One of these policies is the rescheduling of hydrocodone combination products (HCPs) from a schedule III to a schedule II controlled substance in 2014. By reducing the supply of HCPs through the rescheduling, the policy may have had an unintended consequence on the street price of other illegally obtained opioids, which could impact the crime rate. In this study, I attempt to answer the question of whether restricting access to hydrocodone combination products could potentially lead to changes in the crime rate.

While the majority of the research on the economic cost of the opioid epidemic focuses mainly on the healthcare costs, a few studies have developed methods that estimate the financial burden of opioid misuse on crime (Birnbaum et al. 2006; Hansen et al. 2011; Florence et al. 2016). The economic burden of prescription opioid abuse on crime includes the cost to the criminal justice system, the cost borne by the victims and other indirect costs (National Drug Intelligence Center, 2011). To arrive at the aggregate economic cost of opioid abuse to the criminal justice system, Birnbaum et al. (2006) compute the cost of opioid abuse to the various criminal justice system components. Their study uses data from National Forensic Laboratory

Information System (NFLIS). Birnbaum et al. (2006) estimated that opioid abuse increased police protection, legal fees and correctional facilities expenses by $438.4 million, $221.2 million, and $771.3 million, respectively, in 2001. Birnbaum et al. (2011) conducted a similar study for 2007 and found that the cost of opioid use disorder to the criminal justice system amounted to $5.1 billion for that year. Unlike Birnbaum et al. (2011) and Birnbaum et al. (2006), Hansen et al. (2011) compute the cost of opioid misuse to crime victims by multiplying the average cost per victim by the share of drug-related crime victims. Their results suggest that in 2006, the cost of drug-related crimes to crime victims amounted to about $23 billion. Moreover, Hansen et al. (2011) also find that drug-related crimes decrease productivity by up to $74 billion per year as a result of incarceration. Another study that assesses the cost of the nonmedical use of opioids to the criminal justice systems is Florence et al. (2016) study. Using reported criminal justice spending in addition to other expenses from the Justice Expenditure and Employment Extracts data, Florence et al. (2016) suggest that opioid prescription abuse increases the criminal justice cost by over $7.6 billion.

2.2 Literature Review

Several studies have shown that changes in drug-related policies have had unintended consequences on crime (Dave, Deza, & Horn, 2021; Szalavitz & Rigg, 2017). One of the earliest pieces of evidence of the association between crime and opioids is from the 1995 disruption of methamphetamine supply by the government. The United States government, through the Drug Enforcement Administration (DEA), closed down two producers that supply more than half of the raw materials used in producing methamphetamine in the entire United States. The intervention raised the price of methamphetamine from $30 to $100 per gram (Dobkin &

Nicosia, 2009). Using a difference-in-differences identification strategy, Dobkin and Nicosia (2009) found that the increase in the price of methamphetamine led to a 50% decline in methamphetamine arrests. They also find that the policy led to an uptick in robberies. Doleac and Mukherjee (2019) investigate whether increasing access to naloxone, a drug that quickly reverses opioid overdose, may affect the crime rate by decreasing the danger of death due to opioid abuse. Their identification strategy exploits the variation in the timing of the implementation of state laws that expand naloxone access. They used data from the National Incident-Based Reporting System, and their study was limited to 33 states. Doleac and Mukherjee (2019) find that the law led to an increase in all opioid-related crimes and opioid-related theft by 6.0 offenses per million and 0.4 offenses per million, respectively.

Another study that examines the relationship between crime and changes in opioid regulation is Mallatt (2018). Mallatt (2018) studies the effect of prescription drug monitoring programs (PMDP) on heroin crime rates. The prescription drug monitoring program (PDMP) was implemented to eliminate doctor-shopping practices and to maintain an electronic record of patients and opioid prescriptions. After exploring the variation in the timing of the implementation of the prescription drug monitoring programs (PDMP), Mallatt (2018) finds that the PDMP law led to 2.1 additional heroin-related crimes per 100,000 residents in a month. A recent study by Dave et al. (2021) also finds that policies that restrict access to opioid prescription may have unintended consequences on crime. Specifically, Dave et al. (2021), using a differences-in-differences identification strategy, maintain that the mandatory-access requirement of the Prescription Drug Monitoring Program has led to a 5% decline in the overall crime rate. Dave et al., (2021) find that the change in the overall crime was especially driven by the decrease in burglary, assault, and motor vehicle theft arrest.

Restricting access to prescription opioids could potentially have a spillover effect on crime. Clinical studies show that opioid misuse stimulates individuals to commit crimes to support their lifestyle, with heavy opioid abusers committing significantly more crimes than moderate abusers (Hammersley et al. 1989). The rescheduling of hydrocodone combination products serves as a negative supply shock for legally obtained opioid prescriptions. The adverse supply shock may lead to an increase in the price of redirected legally-obtained opioids, which could lead HCPs abusers to find a cheaper alternative or pay higher prices. In theory, the rescheduling of the HCPs could lead to an increase in property and violent crimes if substance abusers engage in criminal activities to afford the increase in the price of HCPs, assuming they depend on criminal activities to fund their addiction. On the other hand, if they choose to withdraw from abusing drugs, it could lead to a decrease in the crime rate.

2.2.1 The Rescheduling of Hydrocodone Combination Products

Due to the high potential for abuse, the Controlled Substances Act (CSA) places all substances into one of five schedules. Substances with the highest potential abuse are placed in Schedule I, and substances with relatively less potential for abuse are placed in Schedules V. Hydrocodone Combination Products contain a limited amount of hydrocodone and specified amounts of other substances. According to the United Nations, the United States consumed 99% of the global production of hydrocodone in 2010 (United Nations International Narcotic Control Board, 2012). Following the increase in people taking hydrocodone combination products in dangerous amounts, the Drug Enforcement Administration requested the United States Department of Health and Human Services to conduct thorough research on hydrocodone combination products in 2009.

After evaluating the scientific and medical evidence of the benefits and costs of hydrocodone combination products, the Health and Human Services suggested that all Hydrocodone Combination Products be transferred from a Schedule III substance to a Schedule II controlled substance. The main difference between Schedule III controlled substances and Schedule II substances is that Schedule II substances have a higher potential for abuse. Unlike Schedule III substances, Schedule II prescriptions must be prescribed for a legitimate medical purpose must be presented to the pharmacy in written form and signed by the prescriber except in an emergency. Also, while Schedule III prescriptions can be refilled up to 5 times in a six-month period, Schedule II prescriptions cannot be refilled, and a new prescription must be printed every time.

After the rescheduling of hydrocodone combination products, a few studies have shown that the policy has led to changes in medical opioid prescription (Zalts et al., 2016; Liu, Baker, Schuur, & Weiner, 2020). By comparing the predicted dispensed prescriptions and actual dispensed prescriptions, Zalts et al., (2016) find that the rescheduling of HCPS led to a 16% decrease in hydrocodone combination products in the first year of the policy. Similarly, Oehle et al., (2016) examine pain-related prescription data at the emergency department before and after the rescheduling of HCPs. They find that new patients are less likely to be prescribed hydrocodone combination products.

2.3 Data and Empirical Strategy

To investigate the impact of the rescheduling of HCPs on crime, I obtained crime and law enforcement data from the Uniform Crime Reporting (UCR) program from the Federal Bureau of Investigation. The UCR program provides crime data on all the 50 states and the District of Columbia through the state's UCR program. This data consists of the various arrest counts by state and the number of police and civilian officers per 100,000 residents in a state. Data from the 2006 to 2019 UCR program was collected for this study. The outcome variables I consider are what the FBI classifies as Part I crimes. The FBI uses the reported Part I crimes from each state to calculate the crime rate at any given time. They include violent crimes, robbery, rape, property crimes, larceny, homicide, burglary, motor vehicle theft, aggravated assault per 100,000 in a state.

I identify the effect of the rescheduling of hydrocodone combination products on crime by exploiting the cross-state variation in the pre-treatment hydrocodone prescription rate. Conceptually, the effect of the rescheduling should have more "bite" in states with a larger pre-implementation hydrocodone prescription rate. Several health economists use this approach (Finkelstein, 2007; Courtemanche, Marton, Ukert, Yelowitz, & Zapata, 2016; Alpert, Powell, & Pacula, 2018; Evans, Lieber, & Power, 2019). Alpert et al. (2018) and Evans et al. (2018) use this "bite"-style approach to estimate the impact of the 2010 OxyContin reformulation on heroin and other types of opioid overdoses. By exploiting the variations in the pre-reformulation OxyContin misuse rates across states, Alpert et al. (2018) find that heroin overdose deaths were significantly larger in states with higher pre-reformulation OxyContin misuse rates. I use variations in the hydrocodone prescription rate prior to rescheduling hydrocodone combination products. I obtained hydrocodone prescription data in each state in 2006 from the Automation of Reports and Consolidated Orders System (ARCOS). The Automation of Reports and Consolidated Orders System (ARCOS) maintains a system that tracks the production and distribution of controlled substances in the United States through the Drug Enforcement Administration.

The model that estimates the impact of the rescheduling of hydrocodone combination on crime is as follows:

$$Y_{st} = \beta_0 + \beta_1 Post_t + \beta_2 HPR_s + \beta_3 (HPR_s * Post_t) + \beta_4 X_{st} + \varepsilon_{st} \qquad (1)$$

Y_{st} is the outcome variable, which is the crime rate in state s, and in year t. $Post_t$ is an indicator for whether the period is either before or after 2014 (the year of the rescheduling). HPR_s is the hydrocodone prescription rate in state s in 2006. X_{st} is a set of demographic and economic control variables. I collected data on income distribution and unemployment rate from the Bureau of Labor Statistics (BLS). I obtained state-level socioeconomic characteristics such as age, race, gender, education, marital status from the American Community Survey (ACS), which was downloaded from the Integrated Public Use Microdata Series (IPUMS). I also control for other state-level laws that can affect the supply of opioids by extending the database created by Meara et al. (2016) on the various state-level opioid prescription laws from 2012 to 2019. These policies include doctor-shopping prevention laws, patient identification requirements, tamper-resistant prescription forms regulations, and prescription limit legislations.

To test whether, in the absence of the rescheduling of the hydrocodone combination products, the differences in the outcomes would have continued in the same trends, I employed an event study analysis. The event study interacts the hydrocodone prescription rate with the full set of year fixed effects, leaving 2013 as the reference year. The event study equation is specified as:

$$\mathbf{Y_{st}} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \sum_{t=2006}^{2019} (\mathrm{HPR_s} * \mathrm{Year_t}) + \boldsymbol{\beta}_2 \boldsymbol{X_{st}} + \boldsymbol{\alpha_s} + \boldsymbol{\gamma_t} + \boldsymbol{\varepsilon_{st}} \qquad (2)$$

If the parallel trend assumption holds, I would expect the interaction of the year indicator for 2006, 2007, 2008, 2009, 2010, 2011, 2012, and the hydrocodone prescription rate to be statistically insignificant. Additionally, finding a trend prior to the rescheduling of hydrocodone poses a threat the validity of the identification strategy.

2.4 Results

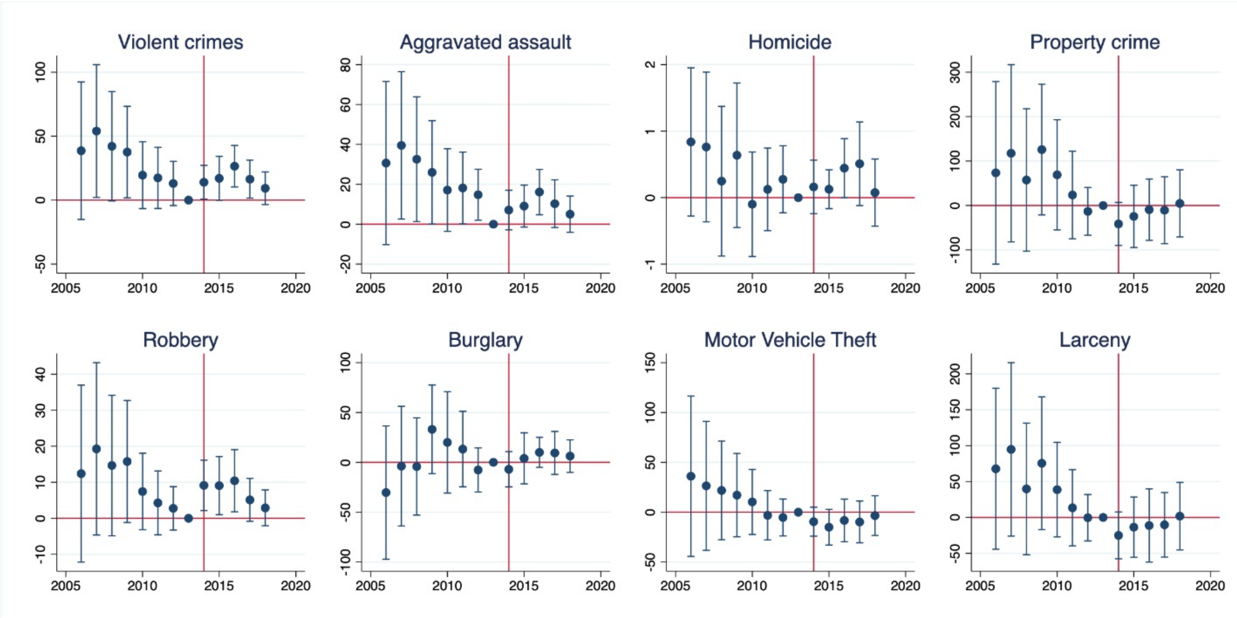
In Table 2.1, I present the summary statistics for the Part I offenses reported to police by various law enforcement agencies. These offenses include violent crimes, robbery, rape, property crimes, larceny, homicide, burglary, aggravated assault per 100,000 adults. The table has four columns. In columns 1 to 2, I report the pre-and post-rescheduling means and standard deviations of all the outcome variables for the states with a low hydrocodone prescription rate. Columns 3 and 4 also report the pre-and post-rescheduling means and standard deviations of all the outcome variables for the states with a high hydrocodone prescription rate.

In terms of the pre-rescheduling crime rates for the low hydrocodone prescribing states, there were about 429.06 violent crimes per 100,000 residents, with 260 (61%) of these constituting aggravated assault crimes and 36 (8%) being rape crimes. The property crime with the highest crime rate is larceny, with 2,280 offenses per 100,000 residents, while the least frequent property crime is robbery with 125.1 offenses per 100,000 residents. In the post-rescheduling period, violent and property crimes declined by approximately 6% and 21%, respectively. I find similar estimates in high hydrocodone prescribing states. On average, aggravated assaults, rape, and homicide offenses were slightly higher in high hydrocodone prescribing states compared to low hydrocodone prescribing states.

I continue with the discussion of the results by presenting the effect of the rescheduling of hydrocodone combination products on crime in Table 2.3. I report the coefficient B1 from Equation (2) using state-year level data from the UCR. Table 2.3 has nine columns representing the nine aggregated crime counts. The regression was weighted using population weights. For each aggregated crime count, I report the regression coefficient, the confidence interval, and statistical significance of the estimated coefficient. I include economic, demographic, and state-specific linear time trends in the estimation of the coefficient to control for potential confounders.

The results in Table 2.3 suggest an important finding. I find evidence that the rescheduling of HCPs significantly increases specific types of crime. Specifically, the rescheduling of HCPs are found to significantly increase violent crimes. The estimate for the violent crime rate implies that a state with the average pre-treatment hydrocodone prescription rate (i.e., 13.6 kg of hydrocodone per 100,000 residents) had 23.9 offenses per 100,000 residents increment in the violent crime rate following the rescheduling of HCPs. The observed increase in violent crimes is purportedly driven by an increase in aggravated assault crimes. I find that the rescheduling of HCPs increases aggravated assaults crimes by 15 offenses per 100,000 residents. Furthermore, there is no evidence to support the claim that the rescheduling of HCPs have had any statistically significant effect on property crimes.

Figure 2.1 Effect of the Rescheduling on Crime



Figures 2.1 present the event study results. The event study results represent the coefficients B2 from Equation (2) which corresponds to the interaction of the year indicator for 2006,2007,2008,2009,2010, 2011, 2012, 2014, 2015, 2016, 2017, 2018, and the hydrocodone prescription rate for violent and property crime rates. In Figure 2.1, the result suggests that the rescheduling of HCPs did not affect crime rates in any statistically significant way for property crimes. I find little to no effects of restricting access to HCPs on larceny, burglary, and motor vehicle theft. The event study result for robbery offenses exhibits limited evidence of parallel trends in the pre-treatment period. I find that the lead pre-policy effects are statistically indistinguishable from zero for aggravated assault offenses. The increase in aggravated assault offenses occurs after the implementation of the rescheduling of HCPs. Put together, the result suggests that the rescheduling of HCPs was not endogenously implemented in response to changes in the crime rate.

2.5 Conclusion

In the United States, prescription opioid abuse remains an urgent public health emergency. Survey data from the Substance Abuse and Mental Health Services Administration (SAMHSA) indicates that over 10 million people misused prescription opioids in 2018. Due to the high economic burden of the opioid epidemic, the DEA has implemented several policies to combat opioid abuse. One of these policies is the rescheduling of HCPs. Upon assessing the medical evidence related to drug products containing hydrocodone, combined with other analgesics, the Department of Health and Human Services recommended that all Hydrocodone Combination Products be transferred from a Schedule III substance to a Schedule II controlled substance. In this study, I examine the effect of the rescheduling of hydrocodone combination products on the changes in crime rate.

The introduction of the rescheduling of HCPs acts as a negative supply shock for opioid prescriptions. While the impact of the rescheduling on crime is not particularly obvious, I believe the main channel through which the policy may affect the crime rate is through the decrease in the supply of HCPs on the illegal market. Individuals who were previously consuming HCPs may now need to use unlawful means to obtain HCPs. One major contribution of this study is that I provide some of the first quantitative evidence of the impact of the rescheduling on crime.

I find suggestive evidence that the rescheduling of HCPs have led to an increase in violent crimes. The estimate suggests that placing HCPs in a more restrictive schedule increased the violent crime rate by about 23.9 offenses per 100,000 residents. The rise in violent crimes was driven by the increase in aggravated assault offenses. The increase in aggravated assaults following the rescheduling of HCPs may reflect the increase in the cost of obtaining illegal substances on the black market, causing substance-using criminals to commit riskier crimes for higher payouts. Secondly, I find no consistent evidence that the rescheduling of HCPs had a significant effect on property crimes. Overall, this study shows that the rescheduling of HCPs may have unintended consequences on crime. Thus, policymakers should understand these broader spillovers of opioid-related interventions.

Table 2.1 Summary Statistics of Outcome Variables

Variables	(1) Pre-treatment means Low OPR	(3) Post-treatment means Low OPR	(2) Pre-treatment means High OPR	(4) Post-treatment means High OPR
Outcomes (per 100,000)				
Violent	429.06	402.3	499.4	488.7
	(274.9)	(239.6)	(166.2)	(153.8)
Property	3167.8	2476.1	3757.9	3003.1
	(870.2)	(849.4)	(671.8)	(592.4)
Homicide	4.8	4.9	6.3	6.9
	(4.7)	(4.5)	(2.5)	(2.6)
Rape	36.4	36.5	38.8	39.5
	(16.5)	(19.7)	(9.7)	(10.6)
Robbery	125.1	91.56	123.1	96.0
	(141.5)	(92.2)	(58.7)	(45.0)
Assault	260.0	252.4	327.9	330.5
	(145.5)	(145.1)	(129.3)	(124)
Larceny	2280.7	1866.5	2527.2	2107.5
	(553.3)	(649.2)	(446.2)	(413.1)
Burglary	611.9	385.1	915.4	603.0
	(189.2)	(138.4)	(254.1)	(179.7)
MV Theft	275.2	224.5	315.3	292.6
	(216.1)	(135)	(141.6)	(64.1)
Observations	234	130	225	125

Notes: Standard errors are shown in parentheses. Data were analyzed 2006 to 2019 for the TEDS-A dataset. The Medicaid Part D data were analyzed from 2013 to 2014. States with hydrocodone prescription rate below the median of 11.1 kg per 100,000 persons were classified as low HPR states while states with hydrocodone prescription rate above the median rate were classified as high HPR states.

Table 2.2 Summary Statistics of State Characteristics

Demography Characteristics		
	Low Hydrocodone Prescribing States	High Hydrocodone Prescribing States
% Male	49.0 (1.2)	48.8 (0.7)
% Below 20 years	23.9 (2.4)	25.0 (2.4)
% 20 – 40 years	23.2 (3.3)	23.3 (1.5)
% 40 – 60 years	28.1 (2.4)	27.3 (1.9)
% White	79.5 (16.6)	79.4 (9.7)
% Black	15 (19.9)	21.8 (19)
% Hispanic	7.8 (5.9)	9.6 (10.7)
% Single	41.2 (4.6)	40.1 (2.5)
% Married	43.6 (4.4)	43.3 (2.3)
% Separated	9.7 (1.2)	10.8 (1.2)
% With Zero kids	73.3 (2.6)	72.8 (1.7)
% With No Education	6.0 (0.9)	6.6 (0.8)
% With high school degree	29.9 (3.7)	31.4 (3.4)

Poverty rate	11.12 (2.78)	14.7 (3.2)
Unemployment rate	5.34 (2.0)	6.2 (2.3)
Officer per 100,000	394.9 (141.7)	394.0 (95.4)
Observations	364	350

Notes: Standard errors are shown in parentheses. Data were analyzed 2006 to 2019 for the TEDS-A dataset. The Medicaid Part D data were analyzed from 2013 to 2014. States with hydrocodone prescription rate below the median of 11.1 kg per 100,000 persons were classified as low HPR states while states with hydrocodone prescription rate above the median rate were classified as high HPR states.

Table 2.3 Effect of the Rescheduling of Hydrocodone Combination Products on Crime: Analysis 2006 – 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Violent	Property	Homicide	Rape	Robbery	Assault	Larceny	MV Theft	Burglary
Post * HPR	1.751**	2.01	0.03	0.1	0.5	1.10**	2.4	0.848	-1.2
	[0.3, 3.2]	[-5.7, 9.7]	[-0.0, 0.1]	[-0.1, 0.2]	[-0.2, 1.3]	[0.1, 2.1]	[-1.9, 6.7]	[-1.8, 3.5]	[-3.5, 1.1]
Implied Effects of the Rescheduling at Mean Pretreatment Hydrocodone Prescription Rate									
Post * HPR	23.9**	27.4	0.4	1.2	7.3	15.0**	32.3	11.6	-16.4
	(10.1)	(52.3)	(0.3)	(1.0)	(5.3)	(6.6)	(29.2)	(18.2)	(15.4)
State F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	714	714	714	561	714	714	714	714	714

Notes: Means and confidence intervals are reported. Standard errors, clustered at the states level. Data were analyzed from 2006 to 2019. The first row in each column reports the estimated coefficient of the rescheduling of hydrocodone combination products on the outcome variable. All estimates are weighted using the state's population.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Does Expanding Health Insurance Coverage Lead to an Increase in Substance Abuse Treatment Utilization?

3.1 Introduction

Despite the growing number of persons with substance use disorder (SUD), only a small proportion of these individuals seek and complete any SUD treatment. According to the National Survey on Drug Use and Health (NSDUH), in 2019, over 20.4 million people above the age of 12 suffered from alcohol use disorder, illicit drug use disorder, or both in the United States (U.S). Similarly, the percentage of adults with any mental health illness increased from 17.7% in 2018 to 20.6% in 2019. Yet, only 1.5% of these individuals with substance use disorder received treatment in 2019 (Substance Abuse and Mental Health Service Administration, 2020). In addition, another 30% of individuals with SUD receiving treatment leave the treatment facility against medical advice (Ti and Ti, 2015). One of the significant factors contributing to the low treatment rates for substance abuse is the lack of health insurance coverage. As a result, I investigate the impact of the Affordable Care Act's (ACA) Medicaid expansion on the access and the utilization of substance use disorder treatment in this chapter.

Several studies have shown that a history of substance use disorder and mental illness has an adverse impact on labor market outcomes, education, and health. Individuals with mental health disorders and substance use disorders earn significantly lower wages on average. Similarly, employees with SUD report more missed workdays than their counterparts. A descriptive study of the occupational impact of substance abuse at the workplace by Goplerud et al. (2017) maintains that an employee with substance abuse disorder increases a company's expenditure by up to $13,000 per year. SUD patients that fail to complete treatment are exposed to a greater level of in-hospital mortality (Choi, Kim, Qian, & Palepu, 2011). Substance abuse at the national level increases the U.S deficit by about $ 740 billion annually (National Institute on Drug Abuse, 2020). These findings suggest that, when left untreated, substance use disorder exerts severe health and economic burden on both the individual and society.

In most cases, substance use disorder can be effectively treated after a thorough evaluation and assessment of the patient. A majority of substance abuse patients require long-term care, counselling, medication, and behavioral therapy to be effectively treated. Patients can also receive treatment in many different settings, including long-term residential treatment, short-term residential treatment, outpatient treatment programs, individualized drug counselling, and group counselling. The current substance abuse treatment resources available in the U.S include (1) allowing people with drug abuse disorder to gradually withdraw from the use of illicit drugs through detoxification; (2) the treating of the psychological aspect of the disorder through drug-free programs; and (3) the provision of medication under the medication maintenance program.

Early intervention and treatment mitigate the risk of mild substance use condition into developing into a severe disorder. The immediate benefits of receiving treatment include an improvement in the individual's physical health and social well-being. SUD treatment also generates positive externalities. Using cost-benefit ratio analysis, Zarkin et al., (2005) estimate that every $1 expenditure on methadone treatment generates $37.72 in benefits over a lifetime. Likewise, workers with substance use disorder and receiving treatment save employers almost $2,607 per employee annually (National Safety Council, 2016). Using data from the Health Insurance Flexibility and Accountability (HIFA) waivers, one study finds that a 10% increase in substance abuse treatment rate reduces criminal justice expenditure by about $2.9 billion. (Wen, Hockenberry, & Cummings, 2014).

While substance abuse treatment could lead to positive outcomes, there are several reasons why people do not seek treatment or fail to complete treatment. A significant barrier to receiving treatment is the decline in substance use disorder screening demand. Moreover, over 30% of individuals with a substance use problem do not have health insurance or cannot afford the cost of treatment (Substance Abuse and Mental Health Services Administration, 2016). Hence, theoretically, increasing access to affordable health care could potentially increase admissions into substance abuse disorder treatment facilities by reducing out-of-pocket treatment expenses. Other determinants of the likelihood of seeking or completing treatment include physical distance to a treatment center, type of substance, employment status, age at initiation, and gender (Beardsley, Wish, Fitzelle, O'Grady, & Arria, 2003; Greenfield et al., 2007).

3.2 Literature Review

Following the implementation of the Affordable Care Act, individuals with substance use disorder have greater access to treatment through various programs and policy changes. The Medicaid expansion provides health insurance coverage to individuals with income below 138% of the federal poverty line. The ACA integrated and extended the provisions of the 2008 Mental Health Parity and Addiction Equity Act (MHPAEA). By classifying the screening and treatment of substance use disorder as essential insurance benefits, the ACA requires the screening and treatment of substance abuse to be included in all health plans. Furthermore, insurance companies can no longer deny insurance coverage to individuals with a history of drug abuse treatment because of pre-existing conditions through regulatory insurance reforms.

Using a quasi-experimental difference-in-differences design, one research finds that the Medicaid expansion under the ACA led to a 14 percentage points decrease in the number of uninsured persons with SUD in expansion states (Olfson, Wall, Barry, Mauro, & Mojtabai, 2018). Similarly, private health insurance coverage increases by about 5.4 percentage points (Saloner, Antwi, Maclean, & Cook, 2017). Wen et al. (2017) find an increase in buprenorphine utilization and Medicaid-assisted treatment for SUD after the Medicaid expansion. Meinhofer and Witman (2018), like the Maclean and Saloner (2017) study, use the Treatment Episode Data Set Admissions (TEDS-A) from 2007 to 2015 to evaluate the early effects of the Medicaid Expansion on opioid admissions to speciality treatment facilities. Meinhofer and Witman (2018) results show that Medicaid expansion led to an 18% increase in overall opioid admissions, which was mostly driven by rehabilitation and medication-assisted treatment admissions. Similarly, Maclean and Saloner (2019), using a difference-in-differences approach, find that Medicaid expansion increased aggregate admissions in expansion states by 7.8% and Medicaid-reimbursed prescriptions in outpatient settings increased by 43%.

This study makes one significant contribution to the literature on the impact of the ACA Medicaid expansion on substance use disorder treatment. I provide evidence of the ACA's effect on the utilization of drug abuse treatment and the treatment completion rates among substance use disorder patients. I use the Treatment Episodes Dataset (TEDS) to study the variations in treatment completion rates across states following the implementation of the enactment of the ACA.

I found that the ACA Medicaid expansion led to a 36 % decrease in the number of uninsured substance abuse patients and a 90% increase in Medicaid insurance coverage among the same group. Following the gains in insurance coverage among substance abuse patients, one would expect an increase in substance abuse treatment utilization. I measured substance abuse treatment utilization using the number of admissions per 100,000 non-elderly adults and treatment completion status. The results indicate that the ACA's Medicaid expansion had no statistically significant effect on substance abuse treatment admissions. Similarly, the policy had no statistically significant effect on the likelihood of dropping out of substance abuse treatment and the likelihood of substance use disorder patients being terminated by the treatment facility. However, there remains some evidence of a decrease in the number of SUD patients who complete their treatment following the implementation of the policy.

3.3 Data and Empirical Strategy

This empirical analysis attempts to estimate the causal effect of the ACA's Medicaid expansion on several outcomes: insurance coverage (i.e., Medicaid, private insurance, uninsured), source of payment for treatment (i.e., Self-pay, government assistance, insurance), and SUD treatment utilization (admissions and discharges) among substance use disorder patients.

The primary source of data for this study is the Treatment Episode Data Set (TEDS), which is collected by the Substance abuse and Mental Health Services Administration. The TEDS is a compilation of data of admissions and discharges from substance abuse treatment centers in the U.S. While the data does not include every admission into treatment facilities in the U.S, it captures a large percentage of admissions nationwide[13]. The data reported to TEDS is obtained from certified state substance abuse agencies that provide substance abuse treatment.

[13] According to SAMHSA, nearly 2 million individuals are admitted into 10,000 publicly and privately funded treatment programs each year.

Each record in the TEDS table represents admission into a treatment facility. The TEDS data contains demographic information, date of admission, substance use behavior, and primary substance use at the admission of substance abuse patients, number of previous admissions, length of stay, and reason for discharge for individuals who are 12 years old or older. Data from 2005 to 2018 TEDS-A and TEDS-D surveys were retrieved for this study.

I examined the Medicaid expansion's impact on insurance coverage among individuals seeking admission into a SUD program for my first analysis. While the Medicaid expansion led to an increase in eligibility, it may not necessarily translate into an increase in access and utilization due to several factors. Barriers to utilization of healthcare include work responsibilities, the patient's perception that they will receive improper treatment due to being enrolled in Medicaid, lack of available appointment times, and the fear that they might incur an additional cost for treatment.

Between 2005 and 2018, 22 U.S states did not report respondents' health insurance status to the TEDS. As a result, I confined the health insurance coverage analysis to 29 states and the District of Columbia. I refer to the states that report the health insurance status in this study as the health insurance sample. Using the insurance status data, I constructed four dependent variables: private insurance status, Medicaid insurance status, other insurance, and uninsured. The equation that estimates the model is specified as:

$$\textbf{Insurance Status}_{st} = \beta_0 + \beta_1\textbf{Medicaid}_{st} + \beta_2\textbf{X}_{st} + \delta_s + \gamma_t + \textbf{e}_{st} \qquad \textbf{(1)}$$

$\textbf{Insurance Status}_{st}$ is an indicator for Medicaid, private health insurance, and uninsured. $\textbf{Medicaid}_{st}$ is an indicator for whether or not a state has expanded its Medicaid in year t. $\textbf{X}_{st}$ is a set of economic and demographic control variables. $\boldsymbol{\delta}_s$ is the state fixed effect, and $\boldsymbol{\gamma}_t$ is the year fixed effect. $\textbf{e}_{st}$ is the error term.

In my second analysis, I examined the effect of the ACA's Medicaid expansion on substance use admissions and treatment completion rates. To measure admissions into SUD facilities, I followed Maclean and Saloner (2019) by constructing a variable that measures the number of individuals admitted into a treatment facility per 100,000 adults in a state-year. I collected annual population estimates from the U.S census bureau. The proportion of individuals between 18 to 64 years is derived using Current Population Survey(CPS) data downloaded from the Integrated Public Use Microdata Series (IPUMS).

I constructed additional outcome variables using the TEDS-D. They include an indicator for whether an individual completed a SUD treatment program, left treatment against professional advice, and treatment terminated by facility due to non-compliance. These variables were constructed from the TEDS-D survey question that asks "REASON FOR DISCHARGE" where the options include "TREATMENT COMPLETED", "LEFT AGAINST PROFESSIONAL ADVICE", "TERMINATED BY FACILITY", "TRANSFERRED TO ANOTHER FACILITY", "INCARCERATED", "DEATH" or "OTHER". I categorized individuals who completed treatment or got transferred to another facility as having completed treatment. These measures have not been used in previous studies, and so I break new ground in this area.

$$\mathbf{Y_{st} = \beta_0 + \beta_1 Medicaid_{st} + \beta_2 X_{st} + \delta_s + \gamma_t + e_{st}} \qquad \mathbf{(2)}$$

Equation (1) estimates the differences in health care coverage and substance abuse admission and treatment completion rates by exploiting the variation in the timing of the Medicaid expansion across states. The outcome variable, $\mathbf{Y_{st}}$ is equal to the count of persons admitted into a substance abuse treatment facility per 100,000 persons between the age of 18 and 64 years. It is also a binary measure of whether substance abuse treatment was completed (i.e, completed treatment, left against medical advice, terminated by treatment facility). $\mathbf{Medicaid_{st}}$ is an indicator for whether or not a state has expanded its Medicaid in year t. $\mathbf{X_{st}}$ is a set of economic and demographic control variables. $\boldsymbol{\delta_s}$ is the state fixed effect, and $\boldsymbol{\gamma_t}$ is the year fixed effect. $\mathbf{e_{st}}$ is the error term. Standard errors are clustered at the state level. I estimated the outcomes using the population of individuals between the ages of 18 and 64 as weights.

I included several control variables that are associated with substance use disorder treatment in the regression model. The state-level independent control variables can be classified into demographic or economic characteristics. I obtained data on age, sex, education, marital status, and poverty level from the Current Population Survey dataset. Lastly, I control for state-level unemployment data collected from the Bureau of Labor Statistics.

I obtained data on whether states implemented the Medicaid expansion from the Kaiser Family Foundation policy. In the majority of the states that adopted the Medicaid expansion, the policy became effective on January 1, 2014. A few states, including California, Connecticut, Minnesota, New Jersey, Washington, and the District of Columbia, expanded their Medicaid program before 2014. In contrast, Maine and Virginia implemented their Medicaid expansion in 2018. I assigned an expansion date to each state that adopted and implemented the policy. By 2018, a total of 34 states in the TEDS expanded their Medicaid program.

I performed an event study analysis to evaluate the assumption that differences in admission and treatment completion rates across states would have continued with the same trends in the absence of the Medicaid expansion. The event study model is stated as Equation (3).

$$\mathbf{Y_{st}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_j} \sum_{j=-m}^{q} \left(\text{Medicaid}_{\text{st(t=k+j)}}\right) + \boldsymbol{\beta_2} \boldsymbol{X_{st}} + \boldsymbol{\delta_s} + \gamma_t + \boldsymbol{\varepsilon_{st}} \qquad \mathbf{(3)}$$

In equation 3, I included m leads and q lags to control for the multiple treatment periods. The base year(i.e., j=0) is the year before a state expanded its Medicaid program. Assuming there are identical counterfactual trends in both treatment and control states, the β_j coefficient for all the leads should be statistically insignificant. Similarly, if the effect of the Medicaid expansion multiplies over time, the coefficients of β_j for j>0 will increase in j.

3.4 Results

In Table 3.1, I present the means and standard deviations for the outcome and control variables in expansion and non-expansion states using data from 2013 (i.e., the year before most states expanded their Medicaid program). I estimate a substance use disorder admission rate of 1041.9 per 100,000 elderly adults in expansion states and a rate of 852.6 per 100,000 elderly adults in non-expansion states in 2013. The data also shows that a higher proportion of SUD patients completed the SUD treatment in non-expansion states compared to expansion states. Similarly, while only 23.04 percent of patients dropped from the SUD treatment program in non-expansion states, the dropout rate for patients in expansion states was 25.05 percent.

I estimate that 55.4% of all substance abuse disorder patients in expansion states had no insurance, 12.6% had private insurance, 21.4% had Medicaid insurance, and 10.8% had other types of insurance. However, in non-expansion states, I estimate that 70% of substance disorder patients had no insurance, 7.1% had private insurance, 16.3% had Medicaid insurance, and 7.2% had other types of insurance coverage. The state characteristics are also nearly comparable across the groups. The non-expansion group had an average age of 40.18 years, while the expansion group had an average age of 40.57 years. Similarly, while 51.1% of the expansion group were female, 51.2% of the non-expansion group were female. On average, families in the expansion group earn $8,422.69 more than families in the non-expansion group. Lastly, the expansion group had a higher unemployment rate on average than the non-expansion group.

I continue with the discussion of the results by presenting the implied effect of the ACA Medicaid expansion on health insurance status. The analysis in Table 3.2 is restricted to states that provide data on the insurance status of the substance abuse disorder patient. Column (1) reports the effect of the ACA's Medicaid expansion on the uninsured. Column (2) reports the impact of the Medicaid expansion on Medicaid insurance coverage. Column (3) and Column (4) report the effect of the Medicaid expansion on private health insurance coverage and other types of insurance, respectively. I find that the ACA's Medicaid expansion is associated with a 20 percentage points decrease in the uninsured rate, which translates to a 36.36% decrease relative to the mean in the expansion group in 2013. The policy is also associated with a 19 percentage points increase in Medicaid insurance coverage which translates to a 90% increase in Medicaid insurance coverage relative to the mean in the expansion group in 2013. The Medicaid expansion had no statistically significant effect on private health insurance coverage and other types of insurance coverage among substance use disorder patients.

Table 3.3 reports the effect of the Medicaid expansions on SUD treatment admissions and treatment completion rates. I find that the Medicaid expansion had no statistically significant effect on the number of patients per 100,000 non-elderly adults admitted into a substance abuse treatment program. For substance abuse discharges, I find that the Medicaid expansion decreases the likelihood of completing substance use disorder treatment. The ACA's Medicaid expansion led to a 3.9 percentage points decrease in the likelihood of a patient completing a substance abuse treatment program. The policy is also associated with an increase in the likelihood of dropping out of substance abuse treatment and the likelihood of SUD patients being terminated by the treatment facility. However, these effects are not statistically distinguishable from zero.

Figure 3.1 Effect of the Medicaid expansion on Insurance Status

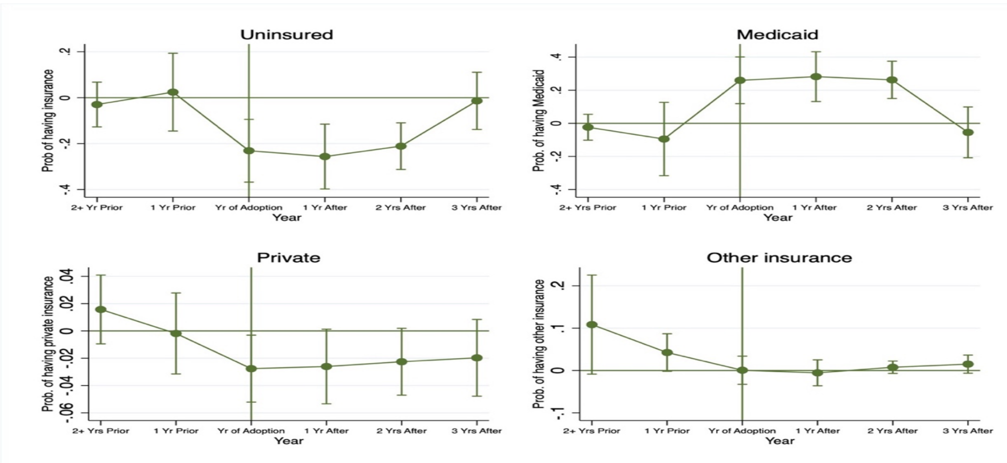
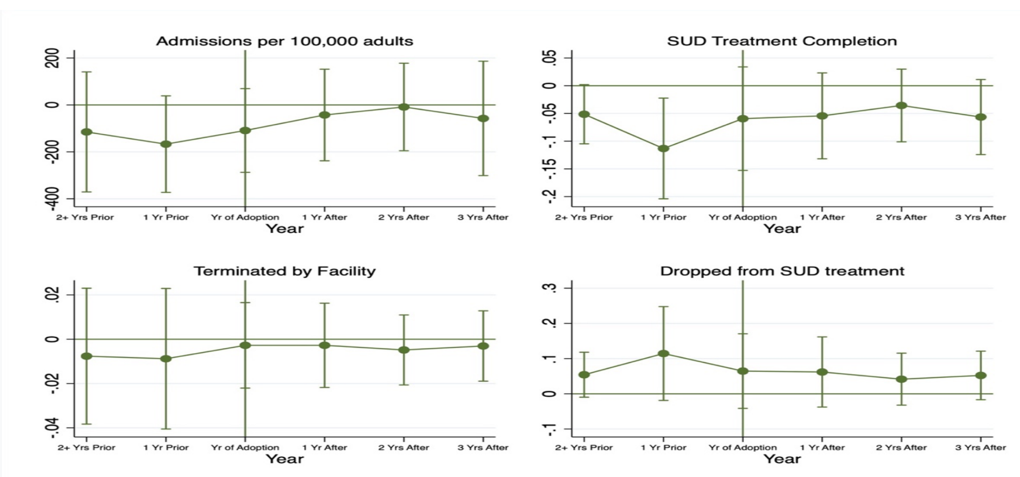


Figure 3.2 Effect of the Medicaid Expansion on Substance Abuse Treatment Utilization



As indicated in Figure 3.1, the event study model suggests that the ACA Medicaid expansion led to increases in the year-by-year likelihood of having Medicaid insurance among substance use disorder patients. The increase in Medicaid coverage began immediately after the adoption of the ACA's Medicaid. However, there was no statistically significant effect of the expansion on the probability of having Medicaid insurance coverage by year three. The likelihood of being uninsured began declining immediately after the implementation of the ACA Medicaid expansion. Similarly, with respect to private insurance coverage, I observe a decline in the probability of having private health insurance coverage over time, even among substance abuse patients. Figure 3.2 presents the event study results for substance abuse admissions and treatment status. I observe evidence of non-parallel trends in the pre-treatment period for admissions per 100,000 non-elderly adults and SUD treatment status. While I observe an upward trend in admissions into substance abuse treatment program following the expansion of Medicaid insurance coverage, the effect is statistically insignificant. I also find limited evidence of the impact of the ACA's Medicaid expansion on SUD treatment status.

3.5 Conclusion

In this chapter, I study the effect of the ACA's Medicaid expansion on health insurance coverage and healthcare utilization among substance abuse patients. Under the ACA's Medicaid expansion, individuals with income below 138% of the federal poverty line can obtain health insurance coverage through the Medicaid insurance program. Various studies have shown that individuals with substance abuse problems have lower income levels and are more likely to be unemployed. Hence, by providing affordable health insurance to these individuals, we could expect an increase in healthcare coverage and utilization among substance abuse patients. Consistent with other studies, evidence from this research shows that the ACA's Medicaid expansion led to a 90% increase in Medicaid insurance coverage among substance abuse patients. I also find that the Medicaid expansion is associated with a 36% decline in the number of uninsured persons with substance abuse disorder.

One major contribution of this study is that I provide evidence of the impact of the ACA's Medicaid expansion on treatment completion status and admissions into substance abuse treatment program. I find that the ACA's Medicaid expansion had no statistically significant effect on the number of persons admitted into substance abuse treatment programs. This implies that access to health insurance coverage alone may not impose a significant barrier to seeking substance abuse treatment. This study also shows that the ACA's Medicaid expansion had no statistically significant on the probability of dropping out of substance abuse treatment program and the probability of substance use disorder patients being terminated by the treatment facility. On the contrary, I find that the ACA's Medicaid expansion is associated with a decrease in the number of SUD patients who complete their treatment following the implementation of the policy.

Table 3.1 Summary Statistics

Substance use disorder Treatment Utilization		
	Expansion States	Non-Expansion States
Admissions per 100,000	1041.9 (654.8)	852.6 (646.7)
% Completed Treatment	55.7 (16.2)	58.95 (8.9)
% Dropped from Treatment	25.05 (15.6)	23.04 (8.9)
% Treatment terminated by facility	8.77 (5.5)	9.6 (7.5)
Insurance status		
Private insurance	0.126 (0.09)	0.071 (0.041)
Medicaid insurance	0.214 (0.197)	0.163 (0.131)
Other insurance	0.108 (0.101)	0.072 (0.06)

Uninsured	0.554 (0.210)	0.70 (0.170)

State characteristics		
Age	40.57	40.18
Female	0.511	0.512
Male	0.489	0.488
White	0.783	0.803
Black	0.083	0.117
Other races	0.134	0.129
Hispanic	0.093	0.077
Foreign born	0.092	0.069
Less High School	0.294	0.311
High School	0.305	0.31
Some College	0.184	0.19
College degree	0.133	0.122
Married	0.425	0.437
Divorced/Separate	0.16	0.163
Never married	0.416	0.399
Not metro	0.212	0.285
Disabled	.061	0.065
Family income	77,840.34	69,417.65
Unemployment rate	7.942	7.48
Poverty rate	14.268	15.293
Population	3411271.4	4171554.8
Observations	31	20

Notes: Standard errors are shown in parentheses. Data were analyzed from 2005 to 2018 from the TEDS dataset. Expansion states refer to states that expanded their Medicaid program under the ACA and non-Expansion states refer to states that did not expand their Medicaid program.

Table 3.2 Effect of ACA Medicaid Expansions on Insurance Status

	(1) Uninsured	(2) Medicaid	(3) Private Insurance	(4) Other Insurance
MedicaidExpansion$_{st}$	-0.2*** [-0.3, -0.1]	0.19*** [0.1, 0.3]	-0.01 [-0.03, 0.01]	0.021 [-0.01, 0.1]
Pre-treatment Mean	0.55	0.21	0.126	0.10

Implied Percentage change	36.4%	90.5%	7.7%	21%
State F.E	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes
Demographic and Economic Controls	Yes	Yes	Yes	Yes
Observations	255	255	255	255

Notes: Data were analyzed from 2005 to 2018. Insurance state sample includes the following states: AK, AL, AR, CO, DC, DE, HI, IA, IL, IN, KS, KY, MA, MD, ME, MO, MT, ND, NE, NH, NJ, NV, OR, PA, SC, SD, TN, TX, and UT. Standard errors are robust at the state level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.3 Effect of ACA Medicaid Expansions on Admissions and Treatment Completion Rates

	(1)	(2)	(3)	(4)
	Admissions Per 100,000	Completed Treatment	Dropped Treatment	Terminated by Facility
MedicaidExpansion$_{st}$	115.7 [-39.9, 271.4]	-0.039** [-0.08, -0.002]	0.015 [-0.01, 0.05]	0.005 [-0.01, 0.02]
Pre-treatment Mean	1041.9	0.56	0.25	0.08
Implied Percentage change	11%	7%	6%	6.25%
State F.E	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes
Demographic and Economic Controls	Yes	Yes	Yes	Yes
Observations	450	426	426	426

Notes: Data were analyzed from 2005 to 2018. The dataset for this sample includes all the 51 states. Standard errors are robust at the state level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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Vita

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