A Study of Addiction
The Opioid Epidemic: An Analysis at the State and County Level

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Abstract

Addictive diseases such as those stemming from the use of alcohol, cocaine and opioids lead to serious negative consequences at both the individual and societal level. Over the last two decades, there has been a significant increase in opioid prescriptions and addiction. The potential for addiction is related to factors that include genetics, prescriber behavior, user behavior and characteristics, in addition to environmental and systemic determinants. One measure of the seriousness of the opioid epidemic is the number of overdose deaths. In 2017, drug overdoses killed over seventy thousand Americans and overdose deaths are projected to increase in the future. Despite the risk of addiction and overdose, opioids are commonly prescribed to combat pain. This paper uses cross-sectional county and state level data to examine the socioeconomic, demographic, and community level factors that are important in explaining opioid overdose deaths in an econometrics model.

Theory

Because addiction is a chronic disease, it is related to theories in health economics. The most well-known theories that serve as a basis for the empirical work that follows are Grossman's (1972) model of the demand for health and Becker's and Murphy's (1988) model of rational addiction.

A. The Production of Health

Grossman (1972) developed a model to explain an individual's health. Grossman begins by assuming that people derive utility from health and a composite of all other goods. The utility function is:

$Ut = Ut\ (Ht, Gt)$

where Ht = the stock of Health and Gt = all other goods.

Health is modeled as a production process. The production function of health summarizes the relationship between health inputs such as medical care and lifestyle and health outcomes such as life expectancy. The model treats investment in one's stock of health as a form of investment in human capital.

B. Rational Addiction

Behavioral factors that involve addictions to goods such as cigarettes, alcohol, and illicit drugs are inputs in the production of health that have a negative impact on health status. However, if addictive goods change the utility function of individuals, preferences may not be time-consistent. Becker and Murphy (1988) develop a model in which individuals rationally choose to consume addictive goods. Their theory is based on the assumption that individuals incorporate all available information into their calculations of utility and that they are aware of the addictive properties that may change their future preferences. Therefore, preferences are time-consistent in their model. Current consumption increases the desire for future consumption, and, as tolerance increases, the need to consume additional quantities of the addictive good in order to achieve the same effect.

Becker et al (1991) extend Becker and Murphy's model by adding addictive capital stock to the utility function. In this model, consumption of the addictive good leads to addictive capital stock that reinforces the desire for consumption of the addictive good as it makes future consumption more pleasant.

State Level Analysis

The state-level empirical model uses state level panel data for the years 2014-2015 to examine factors related to opioid overdose deaths in the United States. Only the states that had values for all of the variables used in the empirical model were included in the analysis. The states include: Arizona, Arkansas, Colorado, Florida, Georgia, Hawaii, Iowa, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Nebraska, Nevada, New Jersey, New Mexico, New York, North Carolina, Oregon, Rhode Island, South Carolina, Texas, Vermont, Virginia, Washington, West Virginia, and Wisconsin. All of the data excluding the cannabis law data was obtained from the State Health Access Data Assistance Center (SHADAC). Data for cannabis laws was gathered from a historical timeline on ProCon.org. The initial specification of the empirical model is:

(S1) $Y = \beta 0 + \beta 1\ PSO + \beta 2\ PSH + \beta 3\ UR + \beta 4\ SUI + \beta 5\ PH + \beta 6\ ED + \beta 7\ BD + \beta 8\ Ci + \beta 9\ F + \beta 10\ T + \varepsilon$

where Y = the natural and semi-synthetic opioid overdose deaths excluding heroin per 100,000 persons.

An explanation of the variables and descriptive statistics is in Table 1.

Table 1

Label	Variable	Mean	Std. Dev.	Expected Sign
Y	Natural and semi-synthetic opioid overdose deaths excluding heroin per 100,000 persons	5.05	3.59	
PSO	Prescription sales of oxycodone per 100,000 persons	20.53	6.58	+
PSH	Prescription sales of hydrocodone per 100,000 persons	10.44	6.05	+
UR	Unemployment rate	0.06	0.01	Ambiguous
SUI	Firearm suicides per 100,00 persons	7.04	2.92	+
PH	Preventable hospitalizations per 100,000 persons	1360	283.19	+
ED	Rates of civilians who visited the emergency department during the past year	0.019	0.04	+
BD	Percent of adults binge drinking during the past 30 days	0.164	0.03	Ambiguous
C	Presences of legal medical or recreational cannabis legislation	0.57	0.5	-
F	State public health funding per person	40.5	39.09	Ambiguous
T	State cigarette excise tax rate	1.78	1.12	Ambiguous

Regression analysis was used to evaluate three model specifications of the model in Microsoft Excel and the results are shown in Table 2.

Table 2
State Level Results
Dependent Variable: Y

Independent Variables	Coefficients (P-values)		
	(S1)	(S2)	(S3)
PSO	0.2004*** (0.0084)	0.2052*** (0.0018)	0.2199*** (0.0010)
PSH	-0.0141 (0.8917)	—	—
UR	32.3403 (0.4437)	29.4469 (0.3953)	44.4092 (0.1964)
SUI	0.5341* (0.0794)	0.5028*** (0.0046)	0.2991** (0.0193)
PH	0.0034 (0.1644)	0.0031* (0.0901)	—
ED	19.6655* (0.0925)	20.2890* (0.0517)	29.2283*** (0.0020)
BD	8.8295 (0.6509)	8.1984 (0.6529)	-1.2274 (0.9448)
C	0.0025 (0.9982)	-0.0156 (0.9867)	-1.1506* (0.0926)
F	0.0410*** (0.0001)	0.0406*** (0.00001)	0.0379*** (0.00003)
T	0.0070 (0.9891)	—	—
Constant	-15.8263** (0.0247)	-15.3909** (0.0122)	-10.1782
Adjusted R^2	0.6506	0.6653	0.6514

***Significant at the 1% level
**Significant at the 5% level
*Significant at the 10% level

County Level Analysis

The county level empirical model uses county level cross-sectional data for the year 2017 to examine factors related to opioid overdose deaths in the United States. Observations from counties in Kentucky, Ohio, Pennsylvania, Virginia, and West Virginia are used in this analysis. All the data for the independent variables in the model was obtained from the County Health Rankings & Roadmaps database. Data for the dependent variable, opioid overdose deaths, was obtained from the CDC Wonder database. The initial specification of the model is:

(C1) $Y = \beta 0 + \beta 1\ FMD + \beta 2\ BD + \beta 3\ UR + \beta 4\ UR + \beta 5\ OPR + \beta 6\ CP + \beta 7\ HS + \beta 8\ PCP + \beta 9\ PUD + \beta 10\ PHS + \beta 11\ UI + \varepsilon$

where Y = the crude rate of accidental poisoning by and exposure to narcotics and psychodysleptics [hallucinogens].

An explanation of the variables and descriptive statistics is in Table 3.

Table 3

Label	Variable	Mean	Std. Dev.	Expected Sign
Y	Crude rate of accidental poisoning by and exposure to narcotics and psychodysleptics [hallucinogens]	24.484	15.672	
FMD	Percent of adults reporting frequent mental distress	11.537	1.361	+
BD	Percent of adults reporting excessive drinking	17.431	2.256	Ambiguous
UR	Unemployment Rate	5.014	0.951	Ambiguous
OPR	Opioid Prescribing Rate per 100 persons	63.791	16.692	+
CP	Percent of Children in Poverty	19.506	7.866	+
HS	High School Graduation Rate	84.475	8.292	-
PCP	Crude rate of primary care physicians	79.589	25.922	Ambiguous
PUD	Average number of reported physically unhealthy days per month	3.670	0.546	+
PHS	Preventable hospital stays; discharges for ambulatory care sensitive conditions/Medicare enrollees * 1,000	54.142	12.053	+
UI	Percent of adult population uninsured	10.197	2.227	Ambiguous

Regression analysis was used to evaluate three model specifications of the model in Microsoft Excel. The empirical results for all specifications are reported in Table 4.

Table 4
County Level Results
Dependent Variable: Y

Independent Variables	Coefficients (P-values)		
	(C1)	(C2)	(C3)
FMD	2.3615 (0.7989)	—	—
BD	2.3615 (0.6209)	-1.7659* (.0886)	-1.0264 (0.2680)
UR	-9.4963*** (0.0011)	-9.6217*** (0.0008)	-7.3811*** (0.0027)
OPR	0.1855 (0.1551)	0.1800 (0.1631)	0.2429* (0.0523)
CP	0.6733 (0.2735)	0.8263 (0.1189)	—
HS	0.1656 (0.4900)	0.1471 (0.5318)	-0.0300 (0.8857)
PCP	-0.0140 (0.8236)	-0.0134 (0.8297)	-0.0024 (0.9698)
PUD	7.5456 (0.5011)	12.0032 (0.5014)	17.9789*** (0.0017)
PHS	0.1063 (0.6478)	0.0852 (0.7074)	—
UI	-1.1012 (0.3710)	-1.3321 (0.2400)	-0.2866 (0.7562)
Constant	13.8110 (0.7989)	29.4623 (0.5014)	1.8438 (0.9628)
Adjusted R^2	0.4515	0.4586	0.4448

Conclusions

Empirical results at the state level show that there is a highly significant positive association between natural and semi-synthetic opioid overdose deaths and prescription sales of oxycodone, emergency department visits, and state funding (α= .01). Firearm suicide rates were also found to be significant and positively correlated with opioid overdose deaths (α= .05). These results imply the importance of prescriber behavior as well as the mental and physical health of the individual in explaining opioid overdose deaths. The presence of legal cannabis legislation has a slight significant negative association with opioid overdose deaths. These results suggest that cannabis and opioids may be substitutes, possibly because both drugs relieve pain.

Empirical results at the county level indicate that there is a strong significant positive association between opioid overdose deaths and average monthly physically unhealthy days (α= .01). Opioid prescription rates were also found to have a significant positive correlation with opioid overdose deaths (α= .05). These results imply that the physical health of the individual and prescriber behavior are important in explaining opioid overdose mortality. The results at the county level suggest a highly significant negative association between opioid overdose deaths and the unemployment rate (α= .01). This result differs from the insignificant positive association with unemployment found in the state level analysis. However, the empirical literature on the relationship of unemployment and opioid abuse is mixed and this is evident in this study. In both the state and county analysis, binge or excessive drinking is negatively correlated with opioid overdose deaths. Even though the relationship is insignificant, this may imply that alcohol and opioids may be weak substitutes.

While my empirical results were consistent with much of the previous literature, there are ways in which my study could be improved and expanded. As more data becomes available, incorporating additional variables, observations, and modeling techniques could improve the ability of the model to predict opioid overdose deaths. For example, I initially planned to examine the impact of state laws passed to limit prescription opioids (PDMPs) on opioid overdose mortality. Despite the potential opportunities for improvement and expansion, this study is important in developing an understanding of the factors impacting the opioid crisis on the state and county level. The results of this study are consistent with previous ones that find opioid prescribing rates to be a significant factor in determining opioid overdose deaths. Additionally, policies such as laws allowing legal cannabis legislation may also be helpful in reducing opioid overdose deaths.

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