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

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Abstract

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 for the gravity of the crisis is overdoses. In 2017, drug overdoses killed over seventy thousand Americans and overdose deaths are projected to increase in the future under current policies. Despite the risk of addiction and overdose, opioids are commonly prescribed to combat pain. This research uses mathematical modeling and cross-sectional time-series state level data to examine the socioeconomic, demographic, and community level factors that are important in explaining synthetic opioid overdose deaths.

Mathematical Models

Modelling was used to build a standard for comparison or reflect as a pattern or type. Mathematical models represent a process usually in the form of a set of equations that describing a number of variables (Drakes 2012). While there are several variations for the definition of math modelling, this paper will use the following: "A mathematical model" is … "a description of a system using mathematical concepts and language to facilitate proper explanation of a system or to study the effects of different components and to make predictions on patterns of behavior" (Abramowitz and Stegun, 1964).

Applied mathematical models relating to economics fall into the econometrics field. This paper models the synthetic opioid overdose death rates for states.

Theory

As addiction is a chronic disease, it is related to theories in health economics. The one of the most common theories of addiction and health relates is Grossman's (1972) model of the demand for health. Grossman's (1972) theoretical production function of health summarizes the relationship between health inputs and health outputs over a specified period of time. This model treats investment in health as a form of investment in human capital; health is a consumption and production. Health care is considered an input into the production of health stock which is the output. This model of health treats the demand for health as being conditional on both the cost of health capital and the rate of depreciation of health stock. Similar to other investments, health can require maintenance to remain in good standing. The inputs for Investment Model of Health can include health care, income, education, biology, environment, lifestyle, and chemical dependency. Thus, the Health Status function: HS = HS(Health care, Education, Biology, Environment, Lifestyle).

State Level Analysis

This paper uses 2014-2015 panel state level data to examine the impact of prescriber behavior, user behavior and characteristics, and environmental factors opioid overdose deaths in the United States. The majority of the data used in this paper was extracted from the Shadac's State Health Compare Web Tool. Data for prescription drug monitoring programs was extracted from Prescription Drug Monitoring Program Training and Technical Assistance Center (PDMP TTAC). Data for cannabis laws was gathered from a historical timeline on ProCon.org.

Initial Specification: (1)$Y = \beta_0 + \beta_1 PSO + \beta_2 PSH + \beta_3 UR + \beta_4 SUI + \beta_5 PH + \beta_6 ED + \beta_7 BD + \beta_8 Ci + \beta_9 F + \beta_{10} T + \beta_{11} MB + \beta_{12} P + \beta_{13} MH + \varepsilon$

Table 1 contains an explanation of the variables and descriptive statistics.

Table 1

Label	Variable	Mean	Std. Dev.	Expected Sign
Y	Synthetic opioid overdose deaths excluding heroin per 100,000 persons	3.402	3.326	
PSO	Prescription Sales of Oxycodone Per 100,000 Persons	21.157	6.354	+
PSH	Prescription Sales of Hydrocodone Per 100,000 Persons	10.645	6.225	Ambiguous
UR	Unemployment Rate	0.057	0.010	Ambiguous
SUI	Firearm suicides per 100,00 Persons	7.242	2.879	+
PH	Preventable Hospitalizations Per 100,000 Persons	1380.3	281.056	+
ED	Rates of civilians who visited the emergency department during the past year	0.191	0.034	+
BD	Percent of Adults Binge Drinking During the Past 30 Days	0.161	0.026	+
C	Presences of Legal Medical or Recreational Cannabis Legislation	0.577	0.499	-
F	State Public Health Funding Per Person	35.971	33.055	+
T	State Cigarette Excise Tax Rate	1.767	1.105	Ambiguous
MB	Percent who had trouble paying off medical Bills in the past year or were paying off medical Bills	0.286	0.059	Ambiguous
P	Percent of Adults with Fair or Poor Health Status	0.147	0.035	+
MH	Average Days During the Past Month When an Adult's Physical or Mental Health was Not Good	3.727	0.462	+

Regression analysis was used to evaluate the model specifications in Microsoft Excel. The empirical results are reported in Table 2. The F test I performed showed that the variables are jointly significant at α= 0.001. The first specification has one variable significant at α= .01 (ED), two variables significant at α= .05 (BD, P, and MH), and eight insignificant variables (PSO, UR, SUI, PH, C, F, T, and MB). All but one variable (SUI) had the excepted slope estimator.

I tested for superfluous variables by removing the variable in question from the regression specification and then comparing the resulting adjusted R^2 with original adjusted R^2 and changes in t stats and slope estimates. I then preformed formal an omitted variable test (OVT). Four variables (T, UR, C and PSO) were found to be superfluous and removed from the model. The adjusted R^2 increased from 0.5706 in equation (1) to 0.5862 in equation (2), which suggests better explanatory power. The second specification has two variables significant at α= .01 (ED and PSH), two variables significant at α= .05 (MB and P), two variables significant at α= .10 (BD and MH), and three insignificant variables (SUI, PH, and F). Multicollinearity occurs when two or more independent variables are significantly related. This makes it difficult to determine which variable is causing the observed effects. Generally, if there is multicollinearity, the variances will increase and t-scores will fall. If there is a small amount of multicollinearity, it may be better to leave the equation unchanged. I found that SUI and PSH as well as P and MH were fairly correlated by creating a correlation matrix (Table 3) of the independent variables. However, this only does not prove multicollinearity. Tests for multicollinearity revealed one variable (SUI, PH, and P) with VIF above 5, however, none of the variables' VIFs were above 5.5. The multicollinearity was thus deemed only a mild issue and the equation (2) remained unchanged.

Table 2

Dependent Variable: Y

Independent Variables	Coefficients (P-values)	
	(1)	(2)
PSO	-0.0087 (0.9202)	—
PSH	-0.1671 (0.2251)	-0.1950*** (0.0042)
UR	-44.1983 (0.3532)	—
SUI	-0.5282 (0.2213)	-0.3087 (0.2077)
PH	0.0013 (0.7096)	0.00217 (0.3764)
ED	42.8350*** (0.0081)	45.8896*** (0.0004)
BD	26.9372** (0.1881)	28.7322* (0.0979)
C_i	1.2255 (0.3552)	—
F	0.0017 (0.9113)	0.0023 (0.8636)
T	-0.6679 (0.3040)	—
MB	-16.1392 (0.1457)	-16.2282** (0.0372)
P	56.2161** (0.0355)	49.5557** (0.0258)
MH	2.4988** (0.0364)	1.9739* (0.0540)
Constant	-15.1486 (0.1046)	-18.1762*** (0.0042)
Adjusted R^2	0.5706	0.5862

***Significant at the 1% level

**Significant at the 5% level

*Significant at the 10% level

Table 3

Correlation Matrix

	PSH	SUI	PH	ED	BD	MB	P	MH	F
PSH	1								
SUI	0.64	1							
PH	0.34	-0.24	1						
ED	0.24	0.28	0.28	1					
BD	-0.40	-0.41	-0.33	-0.33	1				
MB	0.52	0.42	0.22	0.47	-0.17	1			
P	0.67	0.55	0.43	0.54	-0.62	0.59	1		
MH	0.59	0.39	0.36	0.40	-0.55	0.30	0.69	1	
F	-0.01	-0.08	0.21	0.33	-0.34	-0.02	0.43	0.33	1

Heteroscedasticity is when the variance of the error terms varies with the variables. If the variance of the error terms is not constant, it violates a classical assumption. The White test indicated that heteroscedasticity was not present in equation (2) at the 5% level. Serial correlation occurs when current observations are dependent on previous observations. This can cause problems when using time-series or panel data. Durbin-Watson test is a more reliable test for serial correlation than a "Runs" test. I ran a Durbin-Watson test and found that test for positive serial correlation is inclusive. Thus, equation (2) remained unchanged.

Conclusions

The final specification has two variables significant at α= .01 (ED and PSH), two variables significant at α= .05 (MB and P), two variables significant at α= .10 (BD and MH), and three insignificant variables (SUI, PH, and F). There is no evidence of serial correlation or heteroscedasticity. However, the model has some mild multicollinearity. This is likely due to the limit observations and omitted variable as the opioid epidemic is a complex going issue. As there were limited observations, the adjusted R2 of 0.5862 is decent in terms of explanatory power given the limited amount of data.

The final specification (2) is fairly consistent with theory. However, it does have some flaws. SUI has a negative slope estimate when theory implies it should have a positive slope estimate. However, this variable is not significant and the incorrect slope estimator may be caused by an omitted variable due to limited observations.

This model indicates that multidrug toxicity may play a significant role in synthetic opioid overdose deaths has both binge drinking was significant positive determinant. Prescription sales of hydrocodone may decrease synthetic opioid overdose deaths by increasing other drug overdoses such as semi-synthetic opioid overdose deaths. Poor health – mental and physical – also is a positive determinant for synthetic overdose deaths.

In conclusion, it is clear that government policies, prescriber behavior, and user characteristics are significant factors in the opioid epidemic. Despite the limitations of the data, it is fairly clear that the type of drug overdose death is affected by accessible drugs and synthetic opioid overdose deaths are largely influenced by the physical and mental health of individuals. This suggests that part of the solution to the opioid epidemic needs to considered the mental well-being of individuals.

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