Relationship Between Opioid Prescriptions and Opioid Overdoses: Insight from California Counties

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1 Introduction

In a 1980 letter on the risk of opioid addiction, Drs. Hershel Jick and Jane Porter claimed that opioids have a low chance of causing addiction when prescribed for chronic pain. This letter was noted by many physicians and medical providers and played a role in fueling a rapid increase in opioid prescriptions (Leung et al., 2017). The Centers for Disease Control (2011) used data from 1999 to 2008 to analyze the rates of fatal opioid analgesic overdoses, and found that prescriptions of opioids were positively related to opioid overdose rates. The focus of this research will be between the relationship of opioid prescriptions and opioid overdose deaths. More specifically, I am asking whether prescriptions are a main driver of the opioid epidemic —are prescriptions tied to the drastic increase in opioid related deaths? Due to such a substantial increase in opioid overdoses, this phenomenon, which started in the late 1990's and has continued to present day, has been deemed an epidemic and can formally be defined as the rapid increase in the use of prescription and non-prescription opioids (opioid analgesics).

To contribute to the current literature, data from 58 of the California counties from 2008 to 2014 will be used to examine whether opioid prescriptions are still driving the opioid epidemic. Panel data regressions will be used to evaluate this relationship, and the econometric model will be introduced in a later section of this paper.

2 Review of the Literature

Opioid analgesics are in high demand, as they are an effective means to control moderate to severe chronic pain, while also improving the overall quality of life of the patient (Chou et al., 2009). Patient demand for opioids has grown, but not just for prescription use; it was found that in 2016 a total of about 11.8 million US residents 12 years and older misused opioids (NSDUH, 2016). The majority of those opioids misused were among white residents, and higher among men than women (NSDUH 2016). In addition, it is worth

noting the lack of patient knowledge concerning opioids and their addictive properties as a big factor in the opioid epidemic. Conrardy et al. (2016) found, in the setting of an emergency department, that some patients did not know opioids were addictive, while others underestimated their own risk of addiction. In contrast, some patients feared the risk of addiction, which resulted in inadequate pain management.

To understand the fundamental difficulty of the opioid epidemic and to really pinpoint the consumption behavior of the individual, the economic model of rational addiction can be used as a lens. Consumption of an addictive good, in this case opioids, increases an individuals desire to have more of that good. Assuming consumers are rational, they will maximize their utility by consuming even more of the addictive good. This economic definition of addiction reveals how opioid addicts are to be viewed as rational consumers, rather than irrational agents attempting to harm themselves. Additionally, increased exposure to the good causes consumption to grow even more (Stigler and Becker, 1977). Becker and Murphy (1988) made further advances to the model by introducing the role of prices, showing that an increase in past consumption is positively correlated with an increase in current consumption.

Due to this increased consumption from addiction, individuals seek opioids for consumption in many ways, which results in a behavior called "doctor shopping". "Doctor shopping" or "physician shopping" is when a patient or drug abuser visits multiple prescribers to obtain prescriptions for personal use or sale (Lineberry and Bostwick, 2004). Cepeda et al. (2012) claims that in order to evaluate the shopping behavior within an empirical model, while distinguishing opioids from other prescriptions, one should include the number of pharmacies. This allows the data to capture the overlap of prescriptions from different providers, which are then filled at multiple pharmacies. In essence, this approach captures the shopping behavior. The Prescription Drug Monitoring Program (PDMP) attempts to capture this behavior by asking physicians to report individual's prescriptions; which medications, how much, and when it was filled or prescribed. In theory, this would prevent another physician from prescribing more opioids to the same individual, thus eliminating doctor shopping. Unfortunately, many states do not require medical professionals to report.

The prominence of doctor shopping reveals that the principal source of opioids for consumers appears to be prescription from physicians. But according to Cicero et al. (2011), 66.6% of opioid-dependent participants in their study revealed obtaining opioids from dealers and 54.6% obtained their opioids from sharing with family and friends. Interestingly, 13.8% of respondents received their opioids through doctor shopping, while a small 12.5% received theirs from a single physician. The remaining 11.1% was attributed to theft. It is evident that opioid-dependent consumers use drug diversion, the practice of obtaining leftover doses from a friend or family members' prescription, as a means to obtain prescription opioids. They found that the use of drug dealers was more likely among younger, white, opioid-dependent consumers (Cicero et al. 2011).

No matter the source of obtaining opioids, physicians play a huge role in the supply of prescriptions opioids, regardless of where consumers eventually obtain them. Thus, understanding the physician's role as a supplier is essential. Horseburgh (2010) says that opioids are an effective and useful means of fighting chronic pain and are used as a "front-line treatment technology" for physicians to treat their patients. The big push for

prescribing opioids came from chronic pain being under-treated, which was a result of very few doctors specializing in chronic pain treatment (Libby 2006). Despite this shortage in pain doctors, the behavior of physicians and their prescribing patterns comes from a concept called "peer effects" (Nair 2010). Peer effects are when a consumer has a strong influence over another consumer, including their attitude and behavior. Nair (2010) explains that between physicians, there is an "opinion leader" whom other physicians are reliant upon for information to reduce uncertainty. Chen et al. (2016) notes that opioid prescribing patterns are concentrated within the pain specialists, as well as physical medicine and rehabilitation physicians. However, they found that total prescriptions, by volume, are predominantly general practitioners.

One difficulty in appropriately prescribing opioids is the problem with an information lag regarding safety for each patient and propensity for addiction. Physicians prescribe opioids to patients that come to them in pain, and it can be very difficult to determine an individual at risk for addiction. Zedler et al (2014) identified the different factors attributed to patients at risk for opioid toxicity. "Predictors of serious opioid toxicity included ages 55-64 years and 65 and above, non-Hispanic white race, never married, widowed, and those receiving care in the western region of the United States" (Zedler et al 2104). In addition, they also found that patients who were hospitalized for one or more days were almost three times as likely to experience opioid toxicity in comparison to those not hospitalized.

Interestingly, prescribing patterns are superior among younger physicians. But it is suggested that the time at which the medical degree was obtained is a better predictor for prescribing patterns; the more recent the degree was awarded, the more appropriate prescribing patterns were (Becker et al. 1972). Not surprisingly, additional formal training was also positively correlated with "prescribing appropriateness" (Becker et al 1972). On the other hand Becker at al. (1972) concluded that physicians who supported learning from "detail-men," learning by trial and error, and wanted to de-emphasize generics, were physicians classified as less appropriate prescribers.

Another physician behavior to consider in the realm of opioid use pertains to supplier-induced demand (SID). First introduced by Newhouse (1970), the fundamental concept of SID is the relationship between physician density and physician fees. If the stock of physicians increases, then medical service prices rise. Pauly et al. (1980) calls this the "perverse" relationship that requires explanation. In short, it is believed that prices may rise because the market for physician services is assumed to be monopolistic, thus allowing physicians to raise prices due to consumer ignorance concerning price and information about the product. It was found that, in the short run, physicians would maximize their profits creating a demand inducement behavior and rising fees (Newhouse 1970). In his research, Fuchs (1978) found there to be a positive correlation between physician fees and physicians per capita. Bradford and Martin (1995) take the model further by emphasizing market competition in their empirical model. They argue that in a monopolistic market, physicians would have no need or incentive to induce demand. But in a more competitive market, they would have more to gain by inducing demand due to the price setting ability that comes with a monopolistic market. A physician can choose prices subject to the level of demand, while in a competitive market they have less flexibility to do so. As a result, demand inducement may become more appealing to physicians as

increasing patient use of their medical services would increase their short-run profits.

Another important participant in the market for opioids is the pharmaceutical industry. Pharmaceutical firms also play a key role in this relationship with physicians. Lexchin (1989) states that pharmaceutical firms, through "detailing" activities, are influencing physician prescription behavior. Detailing includes contacting the physician and provide them with "details" —approved scientific information, adverse events, benefits, and side effects. Ziegler 1995 says "detailing" is used as a primary source of information for physicians about the newest drugs and existing ones, too. In this way, pharmaceutical companies use detailing as a means of increasing the physician's use of the pharmaceutical company's products. This strategy of detailing may include targeting the "opinion leaders" of physicians, and by doing so, create a multiplier effect (Nair 2010). Opinion leaders are physicians who are more educated and have more experience within a certain area like pain management, for example. They have influence over other physicians and are a source of information for them. The multiplying effect comes into play when the pharmaceutical companies induce physicians to prescribe more, this targeting of "opinion leaders" results in other physicians following suit. As a result, the opinion leaders pass on the information obtained from pharmaceutical companies to other physicians.

In addition to physicians and pharmaceutical firms, insurance companies play an important role in the supply of opioids, both by granting access to opioids and by prohibiting them. Insurance companies can dictate which drugs they will cover and which drugs they will not, which is why the insurer's behavior is also important to understand. For example, United Healthcare chose not to cover a less addictive drug because there was a cheaper alternative (Ornstein, 2017). Buprenorphine is an opioid analgesic that is less addictive than an alternative like morphine, but is also used to treat opioid addiction (Johnson et al., 2000). However, morphine is far cheaper than Buprenorphine, so insurance companies can choose not to cover the more expensive drug (Ornstein, 2017). Coulson (1995) found that, on an aggregate level, an increase in health insurance increases the utilization of drugs. However, on an individual level, insurers may have preferences over the cheaper alternative. Not surprisingly, some private insurers wish to maximize shareholder value. One way to do this is to control costs through the use of less expensive and presumed equally effective inputs. This conflict of incentives can lead to unintended consequences. In most cases, insurance companies label drugs as preferred and non-preferred. If a physician wants to prescribe a non-preferred drug, they have to obtain pre-authorization from the insurance company (Dillender, 2016). Seabury et al. (2014) examined the monetary and social costs of formulary restrictions for patients with schizophrenia and bipolar disorder. Seabury et al. (2014) found "patients with schizophrenia subject to formulary restrictions were more likely to be hospitalized, had 23% higher inpatient costs, and 16% higher total costs." Thus, restricting physicians' choices over the appropriate prescription can have adverse effects on the overall cost to insurers, patients, and to patient health.

3 Data

All data used comes from three sources: California Department of Public Health (CDPH), California Office of Statewide Health Planning and Development, and California Department of Justice. This data is for 58 of the California counties from the years 2008 to 2014. The dependent variable is opioid overdose deaths (*OD*), which is measured as a count of acute poisoning deaths involving opioids such as prescription opioid pain relievers, heroin, and opium. The independent variable of interest is opioid prescriptions written (*Rx*), which is measured as a count of opioid prescriptions filled at a pharmacy. The hypothesis is that the more opioids prescribed, the greater chance of opioid overdose due to the increased supply of the addictive good. Another independent variable is a count of emergency department visits (*ED*) caused by non-fatal acute poisonings due to the effect of all opioids. Similarly, the independent variable *Hosp* is a count of hospitalizations caused by non-fatal acute poisoning due to the effects of opioids. The remaining explanatory variables are also measured per county from the years 2008 to 2014: number of physicians (*Phys*), population (*Pop*), unemployment (*Unem*), which was included due to the time dimension intersecting with the recession, the percent uninsured (*Unins*), and finally, median household income (*Inc*). Included in the regression is a generated variable, which measures the number of physicians per 1,000 residents (*physpop*).

Summary statistics of the aforementioned variables can be found in Table 1 stating the number of observations, mean, standard deviation, minimum, and maximum.

Variables		Mean	Standard Deviation	Minimum	Maximum
OD	**overall**	**33.58673**	**57.43621**	**0**	**292**
	between		57.29371	.4285714	257.4286
	within		8.168306	-26.69898	68.15816
Rx	**overall**	**395793.7**	**641774.9**	**5409**	**4497379**
	between		643762.8	6134.857	4120699
	within		61676.71	-177175.9	772474.1
ED	**overall**	**66.16837**	**95.67548**	**0**	**690**
	between		95.24742	.2857143	557.8571
	within		14.86407	-21.68878	198.3112
Hosp	**overall**	**77.53061**	**117.6668**	**0**	**748**
	between		117.8559	0	702.4286
	within		12.98534	-.8979592	156.9592
physpop	**overall**	**20.74547**	**12.39242**	**3.190584**	**74.64512**
	between		12.44588	3.737507	71.87332
	within		1.024206	15.38847	24.76901
Unins	**overall**	**17.93597**	**3.818572**	**8.4**	**26.1**
	between		3.233814	11.41429	23.57143
	within		2.069883	11.59311	21.0074
Inc	**overall**	**34550.36**	**6825.464**	**22841**	**59896**
	between		6708.487	23592.29	53402.43
	within		1507.9	29319.94	41306.94
Unem	**overall**	**.1133816**	**.0392545**	**.0426**	**.2886**
	between		.0337602	.0614714	.2628286
	within		.0204609	.0653245	.1486388

Table 1: Descriptive Statistics

The maximum values for *OD*, *Rx*, *ED*, and *Hosp* all occur in the Los Angeles County. It is important to note this observation and emphasizes the use of the control variable *Physpop*, which controls for both population and the number of physicians simultaneously. However, the highest number of physicians per 1,000 residents is in San Francisco which reports higher than average overdose deaths, emergency department visits, and hospital admissions, but far less than average prescriptions filled. Interestingly, the average amount of prescriptions across California from 2008 to 2014 is highest among women, yet we see higher overdose deaths of men across the US. However, it was found that women are more sensitive to pain (Riley et al., 1998) and more likely to have chronic pain (Gerdle et al., 2008), which could explain the higher prescription rates among women in California.

Both the average unemployment rate and uninsured rate are inflated because of the global financial crisis in 2008, the year this dataset starts. It is important to note this

catastrophic event and include control variables for it because it had life altering, adverse effects on people. We know that jobs were lost and many things can happen as a result, whether that be loss of insurance or as extreme as drug addiction as a coping mechanism. Including variables such as the unemployment rate and uninsured rate can control for effects due to this global catastrophe.

Further, Table 2 shows the correlations between the variables in Table 1.

Variables	*OD*	*Rx*	*ED*	*Hosp*	*physpop*	*Unins*	*Inc*	*Unem*
OD	1.0000							
Rx	0.8650	1.0000						
ED	0.9052	0.9697	1.0000					
Hosp	0.9008	0.9804	0.9725	1.0000				
physpop	0.2868	0.2420	0.3114	0.2770	1.0000			
Unins	0.0860	0.1030	0.0788	0.0832	-0.4640	1.0000		
Inc	0.0866	0.0834	0.0960	0.0861	0.7040	-0.7745	1.0000	
Unem	-0.2103	-0.1756	-0.1897	-0.1903	-0.5790	0.5270	-0.6485	1.0000

Table 2: Correlations

Table 2 suggests that there is multicollinearity found between some independent variables. Since *Rx*, *ED*, and *Hosp* are all multicollinear, they will be used in separate models along with control variables in order to separate their effects. Additionally, *Unins*, *Inc*, and *Unem* are all highly collinear, thus we can examine how much their variance is inflated by this collinearity using variance inflation factors (VIF).

4 Panel Data Advantages

This study uses panel data regression to analyze the relationship between opioid prescriptions and opioid overdose deaths. This approach has many distinct, important advantages. Due to panel data having both cross-sectional and time-series dimensions, it includes more degrees of freedom and more sample variability than cross-sectional data or time-series, which leads to improved efficiency of econometric estimates (Hsiao1985). This is a key feature for this paper because it follows the 58 California counties across 7 years. If this were to be analyzed through cross-sectional analysis, there would be fewer degrees of freedom and thus less efficient estimates. Importantly, panel data has a greater ability to capture the complex behavior of humans (Hsiao 1985). Ben-Porath (1973) discusses the differences in the ability of cross-sectional and panel data to capture the behavior of women and their participation in the work force. In short, cross-sectional analysis was not a perfect predictor of a woman's future work status due to the lack of a time-dimension. Panel data adds this time dimension, thus allowing a woman's current work status to be a predictor of future work status. This paper examines the human behavior of addiction, in which a time-dimension is necessary to properly capture the behavior an opioid addict might have.

Additionally, panel data has the ability to control for omitted variable bias - when the effect of a certain variable in a model is correlated with the independent variables included in the model. Controlling for effects of unobserved variables may be made possible through panel data's natural ability to contain a time-series dimension, in addition to the individual observation (cross-sectional). Lastly, it is worth noting that panel data can effectively uncover dynamic relationships. Just like in time-series regressions, lags can have an important effect on the dependent variable because last year's consumption can impact todays consumption. In time-series estimations, lags can be highly collinear. Panel data's observations of "inter-individual differences," can reduce this collinearity (Hsiao 1985, Pakes and Griliches 1984). This is essential for this study of addiction, due to the economic definition of addiction that past consumption increases current consumption (Becker and Murphy 1988). These advantages give greater insight into panel data's popular use for policy analysis; following the same group over time can give great insight into the effects a policy (or need for one) has on that group.

5 Fixed-Effects Negative Binomial Econometric Model

Due to the dependent variable being a a count, it appears to take on a Poisson distribution, which would call for a Poisson regression model (Atkins and Gallop, 2007). Poisson regressions share many similarities with Ordinary Least Squared (OLS) regression, but the dependent variable has a Poisson distribution (Atkins and Gallop, 2007). It is important to note a few critical components of the Poisson regression method. As mentioned before, the dependent variable must be measured as non-negative integers. Second, the shape of the distribution is strongly controlled by the mean; when the mean is close to zero, the distribution is strongly, positively skewed (Atkins and Gallop, 2007). Importantly, it is critical to know that a Poisson distribution assumes the conditional mean and conditional variance are equal, which in many cases is not a property real data has. When the conditional variance exceeds the conditional mean, it is called over-dispersion, in which case a Poisson regression is not appropriate. Since this data shows over-dispersion, we can turn to the negative binomial regression model, which has an over-dispersion parameter to handle the excess conditional variance.

The use of panel data necessitates a Hausman test to differentiate between a random effects model and fixed effects model. The fixed effects model is represented by b and B denotes the random effects model. The Hausman test will evaluate whether the difference in coefficients b and B is systematic or not. Another way to interpret this is to consider the correlation between explanatory variables and the unobserved effects. If there appears to be no correlation, then we do not reject the null hypothesis and conclude that random effects are efficient. If there is, in fact, correlation between the regressors and the unobserved effects, then we reject the null hypothesis and conclude that random effects is inconsistent and use fixed effects.

To determine whether to use random effects or fixed effects, we use the Hausman test.

	(*b*) Fixed	(*B*) Random	$(b-B)$ Difference	$\sqrt{V_b - V_B}$ S.D.
Rx	-4.82e-08	-7.02e-08	2.21e-08	6.80e-08
Hosp	.0009545	.0017375	-.000783	.0002868
ED	.0010646	.0012567	-.000192	.0002605
Unins	-.0190257	-.0091692	-.0098565	
Inc	-.0000323	-.0000243	-7.98e-06	6.20e-06
Physpop	-.0346745	-.0041277	-.0305468	.0042793

Table 3: Hausman Test

When interpreting the Hausman test results, we let b mean consistent estimators under the null hypothesis and the alternate hypothesis, and we let B mean inconsistent under the alternate hypothesis. The null hypothesis states that the difference in coefficients is not systematic.

$$\begin{aligned} \chi^2(5) &= (b-B)'[(V_b - V_B)^{-1}(b-B) \\ &= 34.95 \\ p-value &< 0.0000 \end{aligned} \tag{1}$$

With a p-value of 0.0000, the Hausman test suggests that we reject the null hypothesis and conclude that random effects estimators are inconsistent. Thus, we conclude that the difference in coefficients is systematic and that there is a correlation between the explanatory variables and the unobserved effects, so we choose fixed effects. A fixed effects model exploits the variation within the model to identify potentially causal relationships; it fixes for the effects across the counties that cannot be directly observed.

The Fixed-Effects Negative Binomial econometric model used to examine the relationship between opioid prescriptions and opioid overdoses is:

$$\mu_{it} = e^{\ln(t_{it}) + \beta_{it} X_{it}} + \eta_i + \varepsilon_{it} \tag{2}$$

where X_{it} is a vector of covariates and β_{it} is the coefficient for each independent variable. η_i is the fixed-effects parameter and ε_{it} is the error term. μ_{it} is the mean incident rate and t_{it} represents the exposure for a particular observation. Thus, we can see the dependent variable is defined as:

$$Y_{it} = \frac{\mu_{it}}{t_{it}} \tag{3}$$

I expect the coefficient on *Rx* to be positive because the more prescriptions written, the more opioids there are supplied and consumed, given the assumption that the individual consumes all opioids that are prescribed. Thus, as past consumption increase,

present consumpstion is increased, leading to potentially fatal overdose. Additionally, I expect both *ED* and *Hosp* to be positive due to how the variable is measured. Since these are admissions due to acute opioid poisonings, these variables are expected to follow the perpetual downward spiral as presented in the Theory of Rational addiction, where consumption continues once consumption begins. We also don't expect one emergency department visit or hospital admission to solve the problem of addiction. *Physpop* is expected to be positive due to the increase of "suppliers" in the market. As physicians per 1,000 residents increases in a county, the amount of prescriptions supplied in that county are expected to increase. *Unem* is expected to have a negative coefficient due the fact that an increase in unemployment could lead to a loss in insurance, which theoretically cuts off access to prescription opioids, decreasing the chances of being addicted. This is also why *Unins* is expected to have a negative coefficient. *Inc* can be expected to have a negative coefficient. The assumption is that the lower the income you have, the worse off your health status is (Pritchett and Summers1996), which can also be viewed as the higher your income, the higher the opportunity cost is for a decrease in health status.

6 Results

With negative binomial regressions, the coefficients on the independent variables cannot be interpreted directly. We have to note the relationship and definition of our dependent variable as well as how that corresponds with the vector of independent variables. We can see that our coefficients are to the power of e and that our dependent variable is a ratio between the mean incident rate and the exposure term. Thus, we can use the incident rate ratio to evaluate the effect of the covariates on the independent variable. Essentially, we are calculating the percent change in the dependent variable as the independent variable changes. The calculation can be seen here:

$$IRR_{it} = e^{\beta_{it}} \tag{4}$$

Results are presented in tables 4 and 5 below. Coefficients are presented as the incident rate ratio as defined above and standard errors are given in parentheses. Included in the tables are the log likelihood functions and the Chi^2 p-values, which shows the explanatory power of the independent variable(s). First in table 4, we examine three models with the dependent variable regressed on only one independent variable. In model 1, we regressed overdose deaths on the number of prescriptions. In model 2, we regressed overdose deaths on emergency department visits due to acute opioid poisonings, and model 3 we regressed overdose deaths on hospital admissions due to acute opioid poisonings.

Model	1	2	3
Independent Variables			
Rx	1.025**		
	(.0096)		
ED		1.016**	
		(.0052)	
Hosp			1.016**
			(.0056)
constant	20.55***	21.03***	19.64***
	(4.184)	(4.283)	(4.066)
Number of Observations	392	392	392
Number of Groups	56	56	56
Degrees of Freedom	2	2	2
Log-Lokelihood	-940.278	-939.451	-939.603
Chi^2 p-value	.0087	.0023	.0045

*Significant at 90%
**Significant at 95%
***Significant at 99%

Table 4: Results

In model 1, we can see that on average, over time, all else constant, an increase in 100,000 prescriptions yields a 2.5% increase in opioid overdose deaths and is statistically significant at the 5% significance level. From model 2, we can see that an increase in 10 emergency department visits due to acute opioid poisonings yields a 1.6% increase in opioid overdose deaths on average, over time, holding all else constant and is significant at the 5% significance level. Lastly, model 3 shows that on average, over time, all else constant an increase in 10 hospital admissions due to acute opioid poisonings increases opioid overdose deaths by 1.6% and is significant at the 5% significance level.

What else can I comment on?

In the next three models, we add all of the control variables and examine the signs and significance of our variables.

Model	4	5	6
Independent Variables			
Rx	1.022**		
	(.0100)		
ED		1.015***	
		(.0055)	
Hosp			1.014**
			(.0059)
Physpop	0.969***	.967***	.969***
	(.0113)	(.0117)	(.0114)
Unins	0.978**	.982*	.979**
	(.0084)	(.0098)	(.0084)
Inc	0.999**	.999**	.999**
	(.0000)	(.0000)	(.0000)
Unem	.681	.575	.542
	(.7881)	(.6680)	(.6390)
constant	386.68***	391.03***	359.46***
	(296.166)	(301.797)	(275.027)
Number of Observations	392	392	392
Number of Groups	56	56	56
Degrees of Freedom	6	6	6
Log-Lokelihood	-928.680	-927.933	-928.234
Chi^2 p-value	.0000	.0000	.0000

*Significant at 90%
**Significant at 95%
***Significant at 99%

Table 5: Results

From model 4, we can see that an increase in 100,000 prescriptions yields a 2.2% increase in opioid overdose deaths on average, over time, holding all else constant and is significant at the 5% significance level. For our control variables, we can see that the IRR is less than 1, whch means their effect on the dependent variable is negative. For example, in model 4, an increase in 1 physician per 1,000 residents yields a decrease in 3.3% overdose deaths, on average, over time, and all else held constant and is statistically significant at the 1% significance level. We can see that *Unins*, *Inc*, and *Unem* have negative effects as well. *Unem* is statistically insignificant in all models, but is jointly significant with all other variables in the model.

In model 5 we see that on average, over time, and all else constant an increase in 10 emergency department visits due to acute opioid poisonings yields a 1.5% increase in opioid overdose deaths and is statistically significant at the 1% significance level. As with model 4, all the control variables are negative and have similar negative effects on the dependent variable.

Lastly, model 6 shows that on average, over time, all else constant an increase in 10 hospital admissions due to acute opioid poisonings increases opioid overdose deaths by 1.4% and is significant at the 5% significance level.

However, from table 2 we noted that some of the variables appeared to be highly collinear, which is concerning in terms of our models being effected by multicollinearity. In order to examine whether these variables and their collinearity are significantly impacting our models, we can examine their variances to see how inflated they are. In table 6 below, the variance inflation factor (VIF) as well as the tolerance are given for each variable within each model. There are a couple different standards and rules by which researchers follow. Most researchers use the rule of 4 and 10, meaning that a VIF exceeding 4 is a clear sign of multicollinearity causing issues and others use 10 as their threshold (O'Brien 2007). Naturally, a higher tolerance (with 1 being the highest) is a good sign that multicollinearity is less of a concern since it is the reciprocal of VIF.

Independent Variables	VIF	Tolerance
Model 3		
Rx	1.16	0.86
Physpop	2.25	0.44
Unins	2.77	0.36
Unem	1.87	0.53
Inc	**4.29**	0.23
Model 4		
ED	1.21	0.83
Physpop	2.37	0.42
Unins	2.73	0.37
Unem	1.86	0.54
Inc	**4.28**	0.23
Model 5		
Hosp	1.18	0.85
Physpop	2.31	0.43
Unins	2.73	0.37
Unem	1.87	0.53
Inc	**4.28**	0.23

Table 6: VIF

We can see that, according to some econometricians and statisticians, *Inc* could be a concern for causing problems within our models. Although there is an argument to keep

Inc in the model by using the rule of 10, we can also examine these models without *Inc* to avoid issues that arise with multicollinearity and to see if our results significantly change.

In Table 7 results are presented with without *Inc*.

Model	7	8	9
Independent Variables			
Rx	1.025**		
	(.0102)		
ED		1.015***	
		(.0057)	
Hosp			1.016***
			(.0059)
Physpop	0.958***	.956***	.958***
	(.0106)	(.0108)	(.0105)
Unins	0.982*	.986	.977*
	(.0084)	(.0098)	(.0092)
Unem	2.97	2.57	2.28
	(2.8600)	(2.4943)	(2.2620)
constant	101.613***	101.350***	96.104***
	(48.585)	(49.918)	(45.603)
Number of Observations	392	392	392
Number of Groups	56	56	56
Degrees of Freedom	5	5	5
Log-Lokelihood	-931.251	-930.593	-930.723
Chi^2 p-value	.0000	.0000	.0000

*Significant at 90%
**Significant at 95%
***Significant at 99%

Table 7: Results

Independent Variables	VIF	Tolerance
Model 7		
Rx	1.16	0.86
Physpop	1.69	0.59
Unins	1.56	0.63
Unem	1.76	0.57
Model 8		
ED	1.21	0.83
Physpop	1.76	0.57
Unins	1.59	0.62
Unem	1.75	0.57
Model 9		
Hosp	1.18	0.85
Physpop	1.72	0.58
Unins	1.59	0.63
Unem	1.76	0.57

Table 8: VIF

Introduce Information Criterion

$$AIC = -2\ln(likelihood) + 2k \tag{5}$$

$$BIC = -2\ln(likelihood) + \ln(N)k \tag{6}$$

where k is the number of parameters estimated and N is the number of observations

Model	4	5	6
Information Criterion			
AIC	1869.362	1867.866	1868.468
BIC	1893.189	1891.694	1892.296
Model	7	8	9
Information Criterion			
AIC	1872.503	1871.185	1871.445
BIC	1892.360	1891.041	1891.302

Table 9: Information Criterion

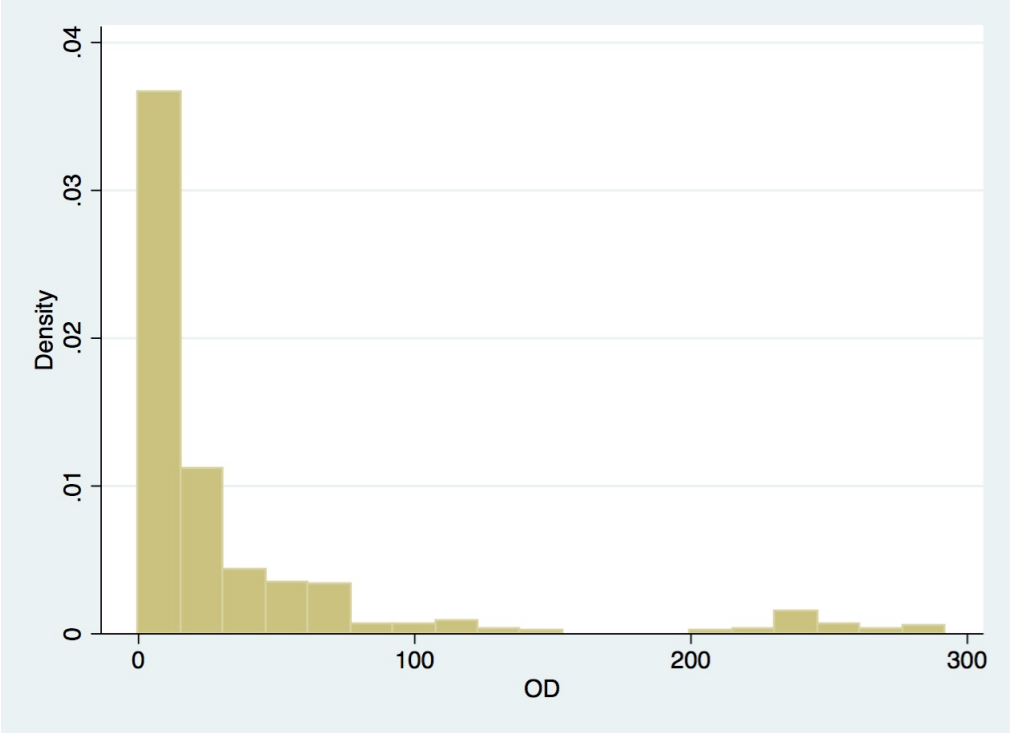

Figure 1: *OD* Histogram