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Cross Sectional Analysis of the Demand for Prescription Pain Killers

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Abstract

This paper is a cross-sectional analysis of the demand for prescription painkillers. Demand was broken down into illegal adult use of painkillers, illegal adolescent use, and legal prescriptions per capita for each state. Data for 2012 were taken from the National Survey on Drug Use and Health (NSDUH) and the National Prescription Audit as well as from other sources such as the Census Bureau. Prescription drug monitoring programs were found to decrease illegal use, while medical marijuana laws and poverty rates increased legal use and use among teens. Both white population and number of officers decreased illegal use among adults, but increased legal demand. Regions with more very religious people saw increased legal demand, while regions with higher education rates saw decreased demand. Single mothers reduced illegal use among teens. Future studies should look at demand over a longer period of time and try to find measures of illegal use with more variation.

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In the 2013 National Drug Threat Assessment Summary, the DEA listed controlled prescription drugs as the fastest growing drug abuse threat in the United States. The most widely abused category of prescription drugs is prescription painkillers, which account for 73 percent of the nonmedical users of prescription drugs (DEA, 2013). The CDC has declared prescription drug abuse as an epidemic (ONDCP). Emergency room visits resulting from prescription drug misuse or abuse increased 114 percent from 2004 to 2011 (DHHS, 2013). The cost for the medical treatment resulting from prescription drug abuse has been estimated at over $72 billion per year (DHHS, 2013). The most startling consequence of this epidemic has been the number of overdoses. According to the NIH, more people die each year from prescription opioid (painkiller) abuse than all other drugs combined.

When taken improperly, these medications can have effects similar to heroin. Many users end up turning to heroin, because it is cheaper and easier to obtain. Recent studies have found that among young intravenous heroin users, almost half began by abusing prescription drugs (NIDA, 2014). This should be especially concerning considering that prescription drugs are second only to marijuana as the most commonly abused drugs among young people (ONDCP). The rise in intravenous heroin and prescription drug abuse also raises the risk of HIV among users through the sharing of needles (NIDA, 2014).

What's fueling this epidemic of abuse? Part of the problem is that there has been a dramatic rise in prescriptions issued. The number of prescriptions issued increased by 400 percent from 1999 to 2010 (CDC, 2015). Some of these prescriptions are coming from facilities known as "pill mills." These are clinics that sell a large amount of medication without giving comprehensive exams, usually on a cash-only basis (DHHS, 2013). Another popular source of prescription opioids for addicts is emergency rooms. Thirteen percent of those receiving treatment report that they received their painkillers from emergency rooms. Addicts choose emergency rooms because it is harder for doctors to get a complete history on patients, which makes it harder for them to identify those with addictions (DHHS, 2013). Of course, these drugs are also available through dealers and over the internet, but only 5 percent of those abusing painkillers get them from these sources (ONDCP). The biggest source of prescription drugs is actually friends and relatives. Seventy percent of people who abuse prescription drugs reported getting them from friends and relatives (ONDCP).

This paper will use cross-sectional analysis to determine what is driving this demand for prescription drugs, both legally and illegally obtained. A special focus will be placed on the role of prescription drug monitoring programs and medical marijuana laws, which are discussed in more detail below. Since the literature on this topic is very sparse, this paper will instead try to draw from the general literature on drug abuse. The sparse literature also lends itself to a more experimental approach to modeling, as one will see in the model section.

1.1 Prescription Drug Monitoring Programs (PDMPs)

In order to combat this growing threat, states have begun setting up programs to collect, monitor, and analyze data on the distribution of prescription drugs. There are currently 49 states with active PDMPs and the District of Colombia has recently passed legislation to set up their own. The only state without a PDMP is Missouri (Brandeis, 2012). The first state to set up a prescription drug monitoring program was New York in 1918 (Brandeis, 2012). While there were more states that started up programs going back to the 1930s, about 70 percent of PDMPs were established between 2000 and 2010 (Brandeis, 2012).

These programs have been very successful in reducing the misuse of prescription drugs. Florida, home to 90 of the top 100 oxycodone purchasers, enacted legislation in 2010 and in 2012 saw a 50 percent decrease in oxycodone overdose deaths (DHHS, 2013; CDC, 2015). One year after modifying their programs to require physicians to check state databases before handing out prescriptions, both New York and Tennessee saw drops in the number of patients seeing multiple doctors by 75 percent and 36 percent respectively (CDC, 2015). Oregon was able to decrease the amount of poisoning deaths due to opioid abuse by 38 percent between 2006 and 2013 thanks to their program (CDC, 2015),

While almost all states have PDMPs, they vary in how they collect data, who can access the data, and how the data is used. This paper will focus on states with mandatory PDMP laws to see how effective they are versus non-mandatory laws. This is similar to how Pacula (2013) broke down medical marijuana laws into states with registries and dispensaries in her study.

1.2 Medical Marijuana Laws (MMLs)

Today, 23 states and the District of Colombia have medical marijuana laws (NCSL, 2015). These laws vary in the conditions that can be treated with marijuana and the amount an individual is allowed to possess (HOPES, 2012). Some states, such as New Mexico, only allow medical marijuana to be used for certain conditions such as HIV/AIDS, cancer, and glaucoma (HOPES, 2012). Other states, like California, allow medical marijuana use for a long list of conditions including migraines and chronic pain (HOPES, 2012). The ability for patients to take marijuana for pain relief (in both sets of states) should have some impact on the amount of legal opioid prescriptions. This lowered demand for legal prescriptions should result in a reduced supply of illegal opioids, which would increase the price and lower the illegal demand for prescription opioids.

Another effect of medical marijuana laws is a decrease in the price of marijuana, especially higher grade strains (Anderson, 2013). This decreased price should tell us about the relationship between marijuana and prescription drug abuse. If the two are true substitutes, then prescription drug abuse should go down in states that pass medical marijuana laws. If they are complements, then one would expect to see higher prescription drug use in states with medical marijuana laws. Due to data limitations, this paper will not be able to determine which, if either, of these relationships these two drugs have. It is still important to note that one of these effects may be taking place.

2. Literature Review

Previous literature on the economics of drug use is quite diverse. On the subject of drug addictions, there have been a variety of factors considered by different authors. In his rational addiction model, Becker focused heavily on how the past consumption of addictive goods influenced their current consumption (Stigler and Becker, 1977; Becker and Murphy, 1988). When thought of as inputs to produce certain effects (such as euphoria), the present use of drugs increases the cost of producing the same effects in the future (Stigler and Becker, 1977). This is a demonstration of tolerance, when addicts must use more of the same drug to get the desired effect (Becker and Murphy, 1988). The model explains that those with higher discount rates will be more prone to addiction, which is why some drug users do not become addicts (they have lower discount rates) (Becker and Murphy, 1988). Becker's model also helps to explain that stressful events can trigger addiction because they lower an individual's utility while raising the marginal utility of addictive goods (like drugs) (Becker and Murphy, 1988). Bachman et al. (1998) looked at whether lifestyle factors or societal factors were more important in teen marijuana use over the past several decades. They found that lifestyle factors play a major role in an individual's decision. But when it came to usage rates among groups, the more important factors were perceived risk and societal acceptance. While Bachman et al. focused only on young people, it will be important to consider both of these sets of factors when studying the general population. In a 2007 study on criminal penalties and marijuana use, Pacula et al. found that lower criminal penalties and medical marijuana laws raised prices. This increase in price was concluded to be from a large increase in demand, due to both lower risk and more social acceptance of the drug, and little change in supply because of the low risk premium. Of course, there are differences between the markets for prescription painkillers and marijuana, but these studies are still important in determining what types of factors may play a role in demand.

Another strand of literature concerns the relationship between two different drugs. One of the earliest researchers to address this topic was Denice Kandel (1976). Kandel found that drug use comes in stages. Most adolescents start with alcohol or tobacco, then begin using marijuana, and finally moving to harder drugs. This would eventually become known as the gateway effect. There are some who question whether or not there actually is a "gateway effect." Morral et al. have suggested that marijuana may not cause the use of harder drugs, but rather those who use marijuana are already more likely to use hard drugs and are just exposed to marijuana first. After surveying the literature, Hall and Lynskey (2005) found that while common factor models like the one posited by Morral et al. explain some of the correlation between marijuana use and hard drug use among youth, a gateway effect is still present. Specifically, they find that early use of marijuana and higher frequency of use lead to a higher probability of hard drug use.

While the gateway drug use debate is an important part of the literature, one will notice that it focuses only on youth. This is an important point because there is evidence that marijuana affects the brain of an adolescent differently than it does that of an adult. Medical researchers have found that adolescent rats injected with THC exhibited changes in the brain that made them more susceptible to opiate addictions (Ellgren et al., 2006). In their analysis on the impact of medical marijuana laws on marijuana use, drinking and hard drug use, Wen and colleagues broke the sample down into two different age groups. Their first age group was those who were between 12 and 20, and the second was those 21 years old and over (Wen et al., 2014). They found that marijuana use rose for those over 21, but not for the first age group. They also found that binge drinking increased for those over 21, but medical marijuana laws had no effect on underage drinking. Neither group experienced a change in hard drug use. The final result of their study somewhat conflicts the results of Chu (2013), who found that proportion of adults (18+) seeking treatment for heroin addiction actually fell in medical marijuana states. However, this conflict could be due to the fact that Chu uses the proportion of heroin treatments versus total treatments; therefore it is possible that some of this decline is caused by an increase in treatments for other drugs. This paper will also divide up the age groups, but in a different fashion than in Wen et al. (2014). A relationship between medical marijuana laws and prescription drug use is still hypothesized despite Wen et al.'s findings that marijuana did not affect the use of harder drugs because of the different nature of prescription drugs.

3. Model

In order to get a fuller picture, this paper will examine three different types of demand for prescription drugs. The first type of demand will be for illegal prescription drugs among those 18 years of age and older, which will be estimated using the following model:

$$\text{ILPDUA}_s = \beta_0 + \beta_1\,\text{ManPDMP}_s + \beta_2\,\text{MML}_s + \beta_3\,\text{Prescripts}_s + \beta_4\,\text{White}_s + \beta_5\,\text{Old}_s + \beta_6\,\text{College}_s + \beta_7\,\text{Poverty}_s + \beta_8\text{Officers}_s + \beta_9\,\text{VeryReligious}_s + \varepsilon_s.$$

The dependent variable $ILPDUA_s$ is the estimated percentage of the adult (18+) population in each state that misused prescriptions drugs in 2012. Using estimates as a dependent variable does pose some problems, but there are limited sources of data for illegal prescription drug use. Therefore this paper will continue to use these estimates provided by the National Survey of Drug Use and Health. The first independent variable, $ManPDMP_s$, is a dummy variable that indicates the presence of a prescription drug monitoring program with mandatory enrollment. MML_s is a dummy variable that indicates the presence of a medical marijuana law. $Prescripts_s$ measures the number of prescriptions for painkillers issued per 100 people for each state. $White_s$ is the percentage of population in each state that is white. Having this variable helps to control for differences in use related to culture or access. Old_s is the percentage of the population over 65 years of age in each state. This variable is meant to capture a possible supply factor, since a vast majority of prescriptions for painkillers are issued for individuals in that age group. $College_s$ is the percentage of population in a state with at least a bachelor's degree. $Poverty_s$ is the percentage of the state's population living under the poverty line. Both of these variables represent a potential opportunity cost of using illegal drugs, with those receiving bachelor's degrees having a higher cost and those under the poverty having a lower cost due to potential total lost income[1]. Those under the poverty line might also gain greater utility from using these drugs because of a need to have an escape from their current circumstances. $Officers_s$ is the number of police officers employed in a state as a percentage of the population. The purpose of this variable is to capture the legal risk for drug abusers. $VeryReligious_s$ is the percentage of people in each state that identify themselves as such. This variable is to test if states with more religious populations are less likely to have problems with prescription painkiller abuse than less religious states. With most drugs this variable would be assumed to be negative, but since

[1] It should be noted that the value of a lost dollar of income is greater for the poorer person.

prescription drugs come from doctors there is a possibility that their use is more acceptable in these communities and thus will face less competition from other drugs. In this case, a positive relationship is plausible.

Next, this paper will examine the illegal prescription painkiller demand for adolescents, those from ages 12 to 17. In order to estimate this demand the following model will be used:

$$ILPDUY_s = \beta_0 + \beta_1\ ManPDMP_s + \beta_2\ MML_s + \beta_3\ Prescripts_s + \beta_4\ White_s + \beta_5\ Old_s + \beta_6\ College_s + \beta_7\ Poverty_s + \beta_8 Officers_s + \beta_9\ VeryReligious_s + \beta_{10}\ SMom_s + \varepsilon_s.$$

As one can see, the model is almost identical to the model for illegal prescription opioid abuse among adults. The biggest difference is the last variable, *$SMom_S$*, which represents the percentage of households headed by a single mother in each state. The hypothesis is that adolescents living with single mothers will have higher rates of opioid use due to less supervision. A more subtle difference is the estimated effect of the bachelor's degree variable. Instead of representing an opportunity cost of using illegal prescription painkillers, it is now hypothesized to have an impact on the environment of the youth. If the teen is growing up in a state with higher rates of education, the perceived risk of illegal drug use may be higher than in other states.

The third and final type of demand that will be studied is the demand for legal prescription painkillers. As mentioned in the introduction, there has been a dramatic rise in the amount of legal prescriptions over the past several years. While these are legally obtained, at least a portion of these drugs will likely be misused. The model for the demand for legal prescriptions will be the following:

$$Prescripts_s = \beta_0 + \beta_1\ ManPDMP_s + \beta_2\ MML_s + \beta_3\ White_s + \beta_4\ Old_s + \beta_5\ College_s + \beta_6\ Poverty_s + \beta_7 Officers_s + \beta_8\ VeryReligious_s + \varepsilon_s.$$

The dependent variable in this model is the same independent variable measuring number of prescription painkillers issued per 100 people used in the previous models. All of the variables are expected to have the same effect on legal prescription drug demand that they have on illegal prescription demand.

Other variables that were tested in these models, but rejected include state unemployment rates, insurance rates, single father households, and dummy variables for region of the country. These variables were rejected because they were insignificant. Results for models with these variables and more explanation for why they were rejected are included in Appendix A.

4. Data

Summary statistics for the variables included in the models and their data sources can be seen below in Table 1.

Table 1. Summary Statistics and Data Sources[a]

Variable Name	Variable	Mean	Standard Deviation	Minimum	Maximum
ILPDUA	Illegal Prescription Drug Abuse for Adults	4.337761	0.6218594	3.401962	5.595697
ILPDUY	Illegal Prescription Drug Abuse for Adolescents	5.087339	0.8630669	3.525025	7.151932
Prescripts	Prescriptions for Painkillers per 100 people	87.39216	22.43308	52	143
MML	Dummy for presence of medical marijuana law	0.3921569	.4930895	0	1
ManPDMP	Dummy for presence of mandatory	0.3137255	0.4686233	0	1

	pdmp				
White	% population white	70.0833	16.12817	22.84817	94.14479
Old	% population over 65 years old	13.97704	1.708854	8.544273	18.16851
College	Proportion of state with at least a Bachelor's degree	26.50953	5.634821	17.31328	48.41218
Poverty	% of population living under poverty line	15.21569	3.273309	10	24.2
Officers	Number of officers per 100 people	0.2163405	0.0798358	0.1206395	0.6824044
VeryReligious	% of state population that identify as very religious	39.76471	9.036788	23	59
SMom	Proportion of households headed by single mothers	12.40109	2.283076	8.064782	19.22118

a. ILPDUA and ILPDUY taken from 2012 *National Survey on Drug Use and Health (NSDUH)*. Prescripts comes from IMS National Prescription Audit via a CDC *Vital Signs* report. MML data comes from the National Conference of State Legislators (NCSL). ManPDMP comes from Brandeis University's Training and Technical Assistance Center (TTAC). White, Old, College, Poverty, and SMom come from the Census Bureau. Officers was taken from the FBI's Police Employee Data. Very Religious comes from a 2011 Gallup Poll.

In this model, Medical Marijuana Laws are present in 20 states and mandatory PDMPs are present in 16 states. Southern states are generally the most religious states and also have some of the highest prescription rates for prescription pain killers, although not all of the states with high prescription rates are very religious. Both *ILPDUA* and *ILPDUY* have low standard deviations meaning that our results from these models will be limited because we are measuring small differences between states. Both of these models will be kept in the paper for general interest and to learn what variables may be important if better data becomes available in the future.

5. Results

Table 2 displays the results of each of the models and their significance. An additional table is available in Appendix C that shows the economic significance of the variables for the *Prescripts* model. Surprisingly, *MML* was not very economically significant even though it was statistically significant. *Officers* was more significant, but *Old* was almost as economically significant even though it was not statistically significant.

Table 2. Final Results

Variables	ILPDUA	ILPDUY	Prescripts (robust se)
ManPDMP	-0.3597441**	-0.46673*	0.973143
MML	0.3033757	0.761195**	13.08175**
Prescripts	0.0172406**	0.0142172*	N/A
White	-0.0138188**	-0.0183286	0.637359**
Old	-0.0722657	-0.0097175	0.9416391
College	0.0161832	0.0196863	-1.081213*
Poverty	0.0545355	0.1467168 **	2.558175**
Officers	-2.836871**	-0.6177977	81.06522**
VeryReligious	-0.0161768	0.0174525	1.297201**
SMom	N/A	-0.1664375**	N/A
Constant	4.801676**	3.862535*	-55.25522
Adjusted R^2	0.4623	0.3914	0. 6822 (non-adjusted)

a. * denotes significant at 0.1 level. ** denotes significant at 0.05 level.

As one can see mandatory prescription drug monitoring programs and number of legal prescriptions both appear to affect illegal drug use for both adolescents and adults. States with PDMPs have lower misuse rates of 0.36 percentage points for adults and 0.46 percentage points for teens. Legal prescription drugs raise the rates of misuse by 0.017 percentage points among the adult population and 0.014 percentage points among youth. States with more predominately white populations have lower rates of drug abuse for adults. A one percentage point increase in the white population decreases illegal drug use for adults by 0.014 percentage points.

There are some variables that affect one population, but do not affect the other. Medical marijuana laws raise youth abuse by 0.76 percentage points, but do not affect adult use. The youth population is also affected by poverty rates and the proportion of households headed by single mothers. Higher poverty rates increase prescription drug abuse, while a greater proportion of single mothers decrease use. A 1 percentage point increase in poverty rates increases abuse by 0.146 percentage points and a 1 percentage point increase in rates of single mothers decreases abuse by 0.166 percentage points. The ratio of police to civilians has an effect on the adult population, but not on the youth population. A 1 percentage point increase in the officer population leads to a 2.84 percentage point decrease in prescription drug abuse among adults.

Legal drug prescriptions are influenced by medical marijuana laws, poverty rates, education, race, religion, and the ratio of police to civilians. States with medical marijuana laws had 13.08 more prescriptions per 100 people. Poverty increased legal prescription use, with a 1 percentage point increase in the poverty rate leading to an increase in legal drug prescriptions by 2.56 prescriptions. States with higher education rates saw the amount of legal prescriptions drop by 1.08 prescriptions per 100 people. While having a more predominantly white population led to lower illegal painkiller use among adults, it also led to higher legal prescription drug use with a 1 percentage point increase leading to an increase of 0.64 prescriptions. More religious states also saw higher legal prescription drug use with a 1 percentage point increase in the proportion of population that identifies as very religious leading to an increase of 1.30 prescriptions. The number of police officers had a very strong positive relationship with the number of legal prescriptions issued in the state. A 1 percentage point increase in the proportion of police officers to the general public increased the number of prescriptions by 81.07 prescriptions.

6. Robustness

All three models were tested for heteroscedasticity using the Breusch-Pagan/Cook-Weisberg test. The test showed that heteroscedasticity was present for the model for legal demand (*Prescripts*), but not for the other two models. In order to correct for the heteroscedasticity, robust standard errors were used. The positive test for legal demand can be seen below in Figure 1. Multicollinearity was also tested using correlation matrices and the variance inflation factor (vif). The vif was below 5 for every variable and none of the correlation matrices had a value over 0.7, so multicollinearity was determined not to be a problem.

An alternate model using a dummy variable for states in the southern region of the country (as defined by the Census Bureau) was also performed. The results can been seen in Appendix B. This model had minimal effects on *ILPDUA* and *ILPDUY* models, but prescription drugs issued had a marked increase in explanatory power as well as some changes in the significance of other variables. While it is clear from the data that the region with the most prescription drugs is the south, what is not clear is why. Nothing about its geographic location would seem to have an effect, so there is something else that must be driving the higher demand. Since a causal relationship cannot be established between the south and prescription drug demand, it was decided that this model would not be used.

Figure 1: Heteroskedasticity Test for *Prescripts* model

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     3.46
         Prob > chi2  =   0.0631
```

7. Discussion

From the results above (in Table 2), one can see that PDMPs seem to be serving their intended purpose. Illegal use of prescription drugs is lower in states with PDMPs, but the legal demand is unaffected. It is somewhat surprising that legal demand did not go down since these laws are aimed at pill mills and other legal sources of painkillers for addicts. This might be due to the timing of the passage of these laws. If they were passed around 2012, their effects may not be felt yet.

States with legalized medical marijuana saw higher illegal use of prescription painkillers among teens and higher legal demand for painkillers. The higher demand by teens may be due to a lower risk perception because it is now classified as something that can be medicinal. Adults are more likely to have already formed an opinion on the risk that marijuana poses, which may explain why medical marijuana laws do not have the same effect on that population. The higher legal demand is unexpected. It is likely that the restrictions on medical marijuana in many of these states prevents a substitution effect, but the positive effect is difficult to explain. There could be a higher acceptance of drug use in these states and those who abuse painkillers are known to get them from legal sources.

This also explains why the variable for legal prescriptions led to more illegal use of prescription drugs. Even if these legal prescriptions do not go directly to abusers, there is still a higher supply of drugs in these states. It was predicted that the variable for the percentage of population over age 65 would have a similar effect since they are the biggest legal users of prescription drugs, but there was no effect from the older population.

The proportion of population that are white had different effects on legal and illegal prescription drug demand. Legal prescriptions were higher in states with more white populations. This could be due to differences in the access to prescription drugs or healthcare in general. A report by the Department of Health and Human Services found that minorities are subject to poorer healthcare in several areas in the United States (AHRQ, 2012). The lower illegal demand among adults is more difficult to explain, but may be linked to the quality of care mentioned above. Higher quality of care may mean that doctors are better equipped to identify those who may have developed a dependency on these drugs. Other possible explanations are that there are unidentified economic differences, or it may just be cultural differences.

Neither education nor poverty rates have an effect on the illegal demand of prescription drugs among adults, but they do affect legal demand. An increase in the percentage of the population with a bachelor's lowers the legal demand while an increase in the poverty rate raises it. This could be due to the opportunity cost that was discussed earlier. It could also have to do with the information available to those with a higher education about the risk of these drugs, and a lack of information for those under the poverty line. Quality of healthcare is a third possibility, as those who are in poverty are likely to receive lower quality care (AHRQ, 2012), which may lead to more prescriptions being handed out without alternatives being considered. A final possibility is that, due to the nature of their likely occupations, those who are below the poverty line may have more need for pain medications because of accidents or greater stress being put on their bodies.

Poverty rates and the proportion of single mother households also had an effect on illegal drug use among teens. Poverty was positively related to illegal teen use, which is most likely attributable to a lower opportunity cost. The percentage of single mother households had a negative effect on teen prescription drug use. Since poverty is already controlled for, it is likely that these are working mothers. These working mothers may not have time to go to obtain or use prescription painkillers, meaning their children have less access to these drugs.

The number of officers in each state had different effects for legal and illegal demand. Illegal demand for prescription painkillers among adults is negatively affected by the number of officers. This is most likely due to the fact that the legal risk is higher when there are more police and the supply of these drugs is more likely to be disrupted. The demand among youths, however, is unaffected by the number of police. This may be due to a lower perceived risk among youths or the belief that taking these drugs is not illegal since they have been prescribed by a doctor. Interestingly, legal demand was positively related to the number of officers. There is anecdotal evidence that illegal prescription drug use is linked to higher crime (Goodnough, 2010; Becker, 2011; Sanburn, 2015). It is likely that the states with higher legal demand also have higher illegal demand and have had this higher demand previous to 2012; therefore it may have been necessary for these states to hire more law enforcement. However, this connection would be better studied in another paper due to the potential endogeneity.

8. Conclusion

The demand for prescription drugs has been growing at an alarming rate and more work needs to be done to understand this demand. This paper has examined some interesting relationships between prescription drug abuse and different factors including medical marijuana laws, prescription drug monitoring programs, legal prescriptions, and poverty rates. However, these relationships require further evaluations because of the low standard deviations of the dependent variables.

Legal prescription painkiller demand was also examined in this paper and it did not suffer from low variability. The demand for legal prescriptions does offer some insight into illegal demand, because many drug abusers obtain their drugs from legal sources. The legal demand was not affected by prescription drug monitoring programs, but was affected by medical marijuana laws. Demand was also affected by race, poverty, education, religion, and the amount of law enforcement.

To get an even better understanding of what affects prescription drug abuse, future studies should examine the demand over time. Unfortunately, the data on the number of legal prescription painkillers per state is only available for 2012. Not having this data also hurts the ability to model illegal use of prescriptions over time. Different measures for illegal use may also prove useful. Other variables may also become more useful over time, such as the legalization of recreational marijuana.

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Appendix A: Rejected Variables

Table 3: Results with *Unemployment* included

Variables	ILPDUA	P-value	ILPDUY	P-value	Prescripts	P-value
ManPDMP	-0. 3607777**	0.028	-0.4781753 **	0.050	0. 8425853	0.859
MML	0. 2969129	0.195	0. 7974287**	0.023	12.00157*	0.070
Prescripts	0. 0168254 **	0.003	0. 0144051*	0.087	N/A	
White	-0. 0130916*	0.054	-0. 0177678	0.158	0. 6793656 **	0.000
Old	-0. 0701304	0.139	-0. 0166896	0.809	1.100042	0.427
College	0. 0156426	0.465	0. 01936	0.544	-1.089534*	0.080
Poverty	0. 0496189	0.170	0. 1574605 **	0.005	2.015234 *	0.053
Officers	-2.810459 **	0.034	-0. 6703927	0.723	80.40697**	0.031
VeryReligious	-0. 0146351	0.347	0. 0130252	0.568	1.38829 **	0.001
SMom	N/A		-0. 1389537	0.119	N/A	
Unemployment	0.0195533	0.686	-0.0599101	0.442	1.775659	0.212
Constant	4.638357 **	0.002	4.025933 *	0.075	-68.00287*	0.097
Adjusted R^2	0.4623	0.4511	0.3853		0.6270	

Unemployment (taken from Bureau of Labor and Statistics) was tested with the theory that those without jobs have more time to use drugs and less disincentive to use them because they do not have to worry about job loss. As one can see from the above table, *unemployment* was not significant. This does make sense even though one may be unemployed, they are still seeking work and failing a drug test would be a significant hurdle in getting a job. (In this case, the *Prescripts* model was found not to be heteroskedastic, as shown by the figure below).

Figure 2: Heteroskedasticity test for *Prescripts* model with *Unemployment* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     2.08
         Prob > chi2  =   0.1488
```

Table 4: Results with *Uninsured* included

Variables	ILPDUA	P-value	ILPDUY	P-value	Prescripts (robust se)	P-value
ManPDMP	-0.3588687**	0.029	-0.4668821*	0.056	0. 9026982	0.854
MML	0.3054206	0.183	0.7718847**	0.027	12.82426**	0.034
Prescripts	0.0173619**	0.002	0.0144013*	0.088	N/A	
White	-0.0135022**	0.043	-0.0166203	0.198	0.6094301**	0.000
Old	-0.0678675	0.177	0.0054606	0.941	0. 6216404	0.622
College	0.0185894	0.429	0.0276085	0.428	-1.242558 *	0.066
Poverty	0.0506958	0.176	0.1324405**	0.024	2.808475**	0.001
Officers	-2.791444**	0.037	-0.4538755	0.813	77.14681**	0.021
VeryReligious	-0.0157429	0.301	0.0190239	0.395	1.255278**	0.008
SMom	N/A		-0.1604344*	0.053	N/A	
Uninsured	0.0047047	0.802	0.016336	0.558	-0.3336338	0.469
Constant	4.585219**	0.006	3.037325	0.250	-39.43005	0.411
Adjusted R2	0.4497		0.3814		0.6849 (non-adjusted)	

The rates of uninsured people in each state (obtained through the Census Bureau) was tested to see if the lower prices of prescription drugs and doctors' visits that come with insurance increased usage or not. It was found to not have an effect. This could be because of the higher insurance rates after the Affordable Care Act. The effect of this law on prescription drug usage could be a very good topic for a future paper, but since this variable is insignificant it will be left out of this paper. Below in Figure 3, one can see the positive test for heteroscedasticity for this model.

Figure 3: Heteroskedasticity test for *Prescripts* model with *Uninsured* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     2.84
         Prob > chi2  =   0.0921
```

Table 5: Results (for *ILPDUY*) with *SDad* included

Variables	ILPDUY	P-value
ManPDMP	-0. 5139595 **	0.041
MML	0. 8922962 **	0.013
Prescripts	0. 0071663	0.366
White	-0. 0098539	0.431
Old	-0. 035234	0.633
College	-0. 013851	0.716
Poverty	0. 1211335 **	0.022
Officers	-0. 8691623	0.663
VeryReligious	0. 0116326	0.626
SDad	-0.3587824	0.287
Constant	5.371138	0.172
Adjusted R^2	0.3433	

SDad was tested with the same theory of *SMom*, that children from single parent homes have less supervision and are more likely to use drugs. *SDad* and *SMom* are strongly correlated, so only one of these variables could be used in the model. As one can see *SDad* was not significant, so *SMom* was used instead.

Table 6: Results with *North*, *West*, and *Central* included

Variables	ILPDUA	ILPDUY	Prescripts (robust se)
ManPDMP	-0. 3453801*	-0. 5160549*	-4.345907
MML	0. 1715878	0. 6029428*	15.59375 **
Prescripts	0. 0200084**	0. 0104378	N/A
White	-0. 0165777**	-0. 0034482	0. 8523499**
Old	-0. 0481967	0. 0534455	-0. 3913381
College	0. 020719	0. 031312	-0.768733
Poverty	0. 0338861	0. 1011762	3.067884**
Officers	-2.663993 **	-0. 4487119	43.52883
VeryReligious	-0. 0169574	0. 0121773	1.037677**
SMom	N/A	-0. 0418402	N/A
North	-0.0202129	-0.6683271	-12.10605**
West	0.2922601	0. 2863919	-20.27261**
Central	0. 006553	-0. 3390909	-18.27354
Constant	4.590491**	1.493396	-48.73748
Adjusted R2	0.4497	0.4080	0.7783 (non-adjusted)

Dummy variables for different regions of the country were also tested. Above is the model that tested *North*, *West*, and *Central* in relation to the *South*. The test produces some results for the *Prescripts* model, but these variables are left out due to a lack of economic theory. More regional results can be seen in the next appendix. The positive test for heteroscedasticity can be seen in the figure below.

Figure 4: Heteroskedasticity test with *North*, *West*, and *Central* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     5.06
         Prob > chi2  =   0.0245
```

Appendix B: Alternate Model with South Variable

Different combinations of regional dummy variables were added to the three original models because of the observation that most of the states with the highest rates of legal prescriptions were in the south. The *South* variable was consistently significant in the *Prescripts* model, but because there was no economic theory to explain why, none of these regional variables were included. The results for these alternative models can be seen below. The heteroscedasticity tests for the *Prescripts* models is also included (none of the other tests ever had a positive result).

Table 7: Results with *South* included

Variables	**ILPDUA**	**ILPDUY**	**Prescripts (robust se)**
ManPDMP	-0.3570404**	-0.5008216 **	-2.646314
MML	0.299564	0.8100008 **	14.50314**
Prescripts	0.0174449 **	0.0116384	N/A
White	-0.0140342 *	-0.0159024	0. 7436254**
Old	-0.0720262	-0.0128918	0. 4031175
College	0.0163115	0.0182986	-0. 9657992*
Poverty	0.054219	0.1517821**	2.301233**
Officers	-2.823442 **	-0.8051157	43.67148
VeryReligious	-0.0160751	0.01602	. 8400425**
SMom	N/A	-0.1713371 **	N/A
South	-0.0154482	.2096734	19.26433**
Constant	4.795837 **	4.00186 *	-33.90059
Adjusted R^2	0.46165	0.3820	0.7631 (non-adjusted)

Figure 5: Heteroskedasticity test for *Prescripts* model with *South* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
        Ho: Constant variance
        Variables: fitted values of prescriptionsper100people

        chi2(1)      =     3.24
        Prob > chi2  =   0.0717
```

Table 8: Results with *North*, *West*, and *South* included

Variables	**ILPDUA**	**ILPDUY**	**Prescripts (robust se)**
ManPDMP	-0. 361778 **	-0. 4699904 *	-3.462777
MML	0. 1821372	0. 6030981	16.67339 **
Prescripts	0. 0192594 **	0. 0122614	N/A
White	-0. 015821**	-0. 007982	0. 7425648 **
Old	-0. 0482411	0. 0407067	-0. 216779
College	0. 0199383	0. 0269658	-1.102196 **
Poverty	0. 0342127	0. 0945936	2.595198**
Officers	-2.702581**	-0. 476467	39.66824
VeryReligious	-0. 0169318	0. 0095347	0. 8870978 **
SMom	N/A	-0. 0534048	N/A
North	-0.0034613	-0.3820208	4.262954
West	0.3070262	0.5101605	-5.552083
South	0.0614397	0.2082239	17.79226**
Constant	4.602519**	2.037204	-26.6831
Adjusted R2	0.4506	0.3990	0.7752 (non-adjusted)

Figure 6: Heteroskedasticity test for Prescripts model with *North*, *West*, and *South* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     4.31
         Prob > chi2  =   0.0379
```

Table 9: Results with *North*, *Central*, and *South* included

Variables	**ILPDUA**	**ILPDUY**	**Prescripts (robust se)**
ManPDMP	-0. 3629687*	-0.520799 **	-3.836716
MML	0. 2122771	0. 5657897	15.93024**
Prescripts	0. 0183469 **	0. 0104059	N/A
White	-0. 0133993*	0. 0003865	0. 7188042**
Old	-0. 048086	0. 0704414	-0. 0712077
College	0. 0238124	0. 0387641	-1.165238 **
Poverty	0. 0482356	0. 1048218*	2.350822 **
Officers	-2.713705**	-0. 2820168	41.66161
VeryReligious	-0. 0155068	0. 0149259	0. 9027998**
SMom	N/A	-0. 0184699	N/A
North	-0. 2580257	-1.070223*	8.034006
Central	-0. 2322728	-0.7137509*	2.358119
South	-0. 1835557	0. 4294051	21.50416**
Constant	4.376063 **	0.6817264	-25.965
Adjusted R2	0.4367	0.4133	0. 7708 (non-adjusted)

Figure 7: Heteroskedasticity test for *Prescripts* model with *North*, *Central*, and *South* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     3.77
         Prob > chi2  =   0.0522
```

Table 10: Results with *West*, *Central*, and *South* included

Variables	ILPDUA	ILPDUY	Prescripts (robust se)
ManPDMP	-0. 3424142*	-0.5160315*	-4.30806
MML	0. 1809221	0. 6337203*	16.29506**
Prescripts	0. 0195157**	0. 0126732	N/A
White	-0. 016297**	-0. 0124215	0. 7803311 **
Old	-0. 0496895	0. 0273371	-0. 0162032
College	0. 0202097	0. 019921	-1.01563 **
Poverty	0. 0328182	0. 1004658	2.727536 **
Officers	-2.728475**	-0. 5167082	40.6747
VeryReligious	-0. 0185014	0. 013152	0. 9602353 **
SMom	N/A	-0. 0935403	N/A
West	0. 3427405	-0.6116386	-10.20687**
Central	0. 0696306	0. 1056438	-6.746073
South	0. 1050674	0. 3835207	12.1354 **
Constant	4.670923**	2.78905	-33.92507
Adjusted R2	0.4517	0. 3881	0.7787 (non-adjusted)

Figure 8: Heteroskedasticity test for *Prescripts* model with *West*, *Central*, and *South* included

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of prescriptionsper100people

         chi2(1)      =     5.08
         Prob > chi2  =   0.0242
```

Appendix C: Economic Significance of *Prescripts*

Table 11: Economics Significance Calculation of *Prescripts* Model

variable name	coeff.	mean	coeff*mean	% of total accounted for
ManPDMP	0.973143	0.313726	0.3053	0.00152671
MML	13.08175	0.392157	5.130099	0.025654045
White	0.637359	70.0833	44.66822	0.223372041
Old	0.941639	13.97704	13.16133	0.06581575
College	1.081213	26.50953	28.66245	0.14333209
Poverty	2.558175	15.21569	38.9244	0.194648942
Officers	81.06522	0.216341	17.53769	0.087700595
Very Religious	1.297201	39.76471	51.58282	0.257949827
Total			199.9723	1

As one can see, the most economically significant variable in this model is *VeryReligious*. While it is a little surprising that it accounts for this much change in the model, it does make sense when one looks at the data and sees that many of the most religious states are in the south. This is also the region where one sees some of the highest rates of legal prescription pain killer demand. The next three most economically significant variables are *White*, *Poverty*, and *College*. All of these variables are almost twice as significant as the next most significant variable, *Officers*. The high significance of these variables does make sense when one considers the theory behind them. The opportunity costs for those with college degrees and above the poverty line does seem to be a strong factor. The quality in healthcare, which is reflected in all three variables could also be playing a major role.