# Breaking Bad: Are Meth Labs Justified in Dry Counties?

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**Abstract**

This paper examines the influence of alcohol prohibition in terms of wet/moist/dry county status on the number of methamphetamine lab seizures in Kentucky. We apply five different estimation methods to three different data sources of meth manufacturing while controlling for county status using religious affiliation at time of vote as an instrumental variable. We find dry counties have two additional meth lab seizures per 100,000 population than in wet and moist counties. Alcohol prohibition status is influenced by the percentage of the population that is Baptist, consistent with the bootleggers and Baptists model. The state could reduce the number of meth lab seizures by 17 to 30 percent per year if all counties were wet.

**Breaking Bad: Are Meth Labs Justified in Dry Counties?**

Chief Mullen: "Someone in Harlan is going into the meth business in a big way."
Arlo: "Or the folks in Harlan are really, really congested" from *Justified*

This paper examines the influence of alcohol prohibition on the number of methamphetamine labs. The 21st amendment repealed the federal ban on alcohol sales/production, but still allowed states to impose local bans of alcohol. Local option ordinances allow municipalities or counties to choose their wet/dry status. Most previous studies have considered the effects of these bans on alcohol related events.[1]

This paper extends the literature by studying the influence of local alcohol laws on the prevalence of methamphetamine (herein meth) labs in wet and dry counties within Kentucky. We apply four different methods to estimate the relationship between alcohol restrictions and meth lab seizures. We find that, relative to wet counties, dry counties have roughly two additional meth lab seizures annually per 100,000 population.

I. Background

The federal prohibition of alcohol sales and production was repealed in 1933 ending a 14 year ban. After repeal, some states permitted localities to adopt local option ordinances, and 12 states still contain jurisdictions where the sale of alcohol is prohibited. Four types of alcohol local option ordinances exist: (1) "Wet" status allows the sale of alcohol; (2) "Dry" status bans the sale of alcohol in all forms; (3) "Moist" status is where a wet municipality exists within the

[1] **Campbell, Carla Alexia; Robert A Hahn; Randy Elder; Robert Brewer; Sajal Chattopadhyay; Jonathan Fielding; Timothy S Naimi; Traci Toomey; Briana Lawrence and Jennifer Cook Middleton.** 2009. "The Effectiveness of Limiting Alcohol Outlet Density as a Means of Reducing Excessive Alcohol Consumption and Alcohol-Related Harms." *American journal of preventive medicine*, 37(6), 556-69, **Conlin, M.; S. Dickert-Conlin and J. Pepper.** 2005. "The Effect of Alcohol Prohibition on Illicit-Drug-Related Crimes*." *Journal of Law and Economics*, 48(1), 215-34..

borders of an otherwise dry county; and (4) “Limited” allows the sale of alcohol only in restaurants where some percentage of total receipts are from food expenditures.

Toma (1988) argues that local options are endogenous and give voters an opportunity to affect the price of alcohol through the way that it is obtained. A ban increases the costs of obtaining alcohol; thereby discouraging alcohol consumption. As Yandle (1983) argues, bootleggers and Baptists have both historically supported such bans: Baptists for religious/moral reasons and bootleggers for economic reasons. In either case, local alcohol laws would be affected by the religious, cultural and economic characteristics of the area. Furthermore, local restrictions may be enacted to decrease the incidence of alcohol related events such as DUI. Campbell et al. (2009) survey the literature and find that alcohol bans are most effective when the dry county does not border a wet county.

Access to alcohol can also have indirect effects on property crime, public nuisance crime, and drug use. (Carpenter, 2005) finds that zero tolerance policies against drunken driving have been found to reduce property crime among 18-21 year old males by 3.4 percent and reduce the incidence of nuisance crimes, but have no effect on violent crime. Substantial evidence exists that higher alcohol excise taxes reduce alcohol consumption as well as certain types of property and violent crime (see Carpenter and Dobkin, 2008 for a full survey).

Importantly for this study, alcohol bans flatten the punishment gradient for alcohol drinkers to engage in other illicit activities (Miron and Zwiebel, 1995), thus encouraging illicit drug use by raising the relative price of a substitute. Conlin et al. (2005) find a change in the status of Texas counties from “dry” to “wet” lowers drug-related mortality by approximately 14 percent. DiNardo and Lemieux (2001) use state variation in minimum drinking age laws to find that higher minimum drinking ages reduce alcohol consumption by high school seniors, but increase marijuana consumption. However, Pacula (1998) finds that increases in the beer tax reduce both drinking and marijuana use among young adults, suggesting the two goods are complements.

We contribute to this literature by considering the effects of alcohol restrictions on meth laboratory seizures in Kentucky. Gonzales et al. (2010) report that meth use has increased threefold between 1997-2007. In an effort to limit the supply of meth, several states and the federal government passed laws between 1995-2006 restricting access to over-the-counter pseudoephedrine (e.g., Sudafed), a key input in the production of meth. Early attempts to disrupt the supply of meth in the 1990's resulted in a temporary decrease in meth production, but had no influence on property or violent crimes (Cunningham and Liu, 2003, 2005, Dobkin and Nicosia, 2009). However, reforms in 2005-2006 restricting pseudoephedrine had a significant influence on meth production reducing the number of DEA recorded meth lab seizures nationally by nearly 300 which remained three years after the law passed (Weisheit and Wells, 2010).

The Drug Enforcement Administration (DEA) reports the number of meth lab seizures per 100,000 residents is highest in the Midwestern United States at 9.12 (Weisheit and Wells, 2010). In Kentucky, the meth lab seizure rate is 15.24 per 100,000 residents.[2] Kentucky contains 120 counties with large variation in wet and dry status across counties, making it an ideal area to study the effects of alcohol restrictions on meth use and production.

## II. Data and Model

The data are a panel of meth lab seizures and local option ordinances for Kentucky counties from 2004 to 2010. The lab seizure counts are from the DEA's National Clandestine

[2] Between 2004 – 2008 the ten states with the highest meth lab seizure rates (from highest to lowest) are Missouri, Arkansas, Iowa, Tennessee, Indiana, Kentucky, Alabama, Oklahoma, Kansas, and Mississippi

Laboratory Register.[3] The DEA provides the physical street addresses for all meth lab seizures as a public service due to the potential public health risk from chemical contamination.

Similar to national trends, meth lab seizures in Kentucky initially fell by 50 percent in between 2004 to 2007, but have increased more than three-fold by 2010. Our data indicate that the number of meth lab seizures per capita is higher in dry counties than in wet counties. Further, the level of alcohol restrictions is associated with the number of meth lab seizures in descending order: dry > moist > wet. As seen in Figure 1, the highest rates of meth lab seizures occur in the southern counties bordering Tennessee and in the center of the state.

As an additional robustness check, we collect meth associated crime data from the FBI Uniform Crime Reports (UCR) and the Kentucky State Police. The UCR data contain arrest counts by county per year for synthetic drug sales and manufacturing arrest. These data capture a broader group of illicit drugs that can be manufactured in any climate and can serve as a substitute to the plant based illicit drugs. Examples of synthetic drugs in addition to meth are demerol, methadone, Percocet, and crunch, which is a combination of Xanax and cough syrup. The Kentucky State Police data contain data on different meth associated crimes. These activities include meth manufacturing, sales, possessions, dump sites, and unlawful possession of meth precursors. At this time, we use the sum of these offenses as our variable of interest.

Comparing Figure 1 with Figure 2, which shows wet/dry status, the relationship between dry status and higher meth lab seizures appears to hold. The mean meth lab seizure rate is 2.10 in wet, 2.07 in moist, 3.35 in limited, and 4.2 in dry counties (see Table 1). The means are consistent with Campbell et al. (2009) who find that alcohol bans are less effective when the county is not sufficiently geographically isolated. Moist counties are arguably less geographically isolated with respect to alcohol bans than dry counties.

[3] These data do not include independent seizures conduct by the Kentucky State Police.

County local option ordinance data are from the Kentucky Department of Alcoholic Beverage Control.[4] We group the ordinances into three major groups: wet; dry; and moist as described above. In 2013, Kentucky had 33 wet counties, 38 dry counties, 35 moist counties, and 15 counties (excluded from our analysis) with limited alcohol restrictions.

Next, we collect county-level demographic variables from the U.S. Census and American Community Survey. As suggested by Yandle (1983), the demographic composition of voters influences local option ordinances. Counties are more likely to adopt restrictive alcohol policies as population, income, percent black, and percent college educated decrease; or as poverty and unemployment increase. In addition, we collect data on religious membership from 1936 to capture religious attitudes at the time of wet/dry status votes.[5] The effect of religion depends on the mixture of religious types. As the percentage of Baptist congregations increases relative to other religious groups the likelihood of alcohol restrictive policies increases. Table 1 shows the means of several key variables and how they vary by county status each of which is statistically different at the 1% between wet and dry.

These observational differences between wet and dry counties suggest the adoption of local option ordinances should not be treated as exogenous. Votes for local option ordinances experienced great activity immediately after the repeal of prohibition from 1933 – 1936. Since then some counties have had votes to repeal dry county status. Since vote totals are not available for all counties we use the percentage of the population in each county belonging to churches of various denominations including Methodist, Baptist, Other Protestant; and percentage of the population belonging to any religious organization in 1936 as an instrument.

[4] http://www.abc.ky.gov/

[5] The historic religious data are obtained from Michael Haines, "Historical, Demographic, Economic, and Social Data: The United States, 1790-2002 (ICPSR 2896)"

To determine the robustness of our results we apply three different models. First, we consider a standard least squares model with year fixed effects and county level demographics to estimate the treatment effect.

$$Meth\ Crime\ rate_{it} = \alpha_t + \gamma_1 dry_{it} + X_{it}\beta + e_{it}$$

We cannot consider county fixed effects because the wet/dry status was determined before our sample time period. The matrix X is a rich set of demographic controls including median household income; county population and population density; county location (latitude and longitude); female labor force participation; and the percentage of the population who are married, male, black, living in poverty, receiving public assistance, under age 21 and over 65. Additionally, we include border dummy variables for surrounding states and if the dry county borders a wet or moist county.

The variable of interest in the regression is the county status variable, *dry*. We use two measures for this variable. The first is a standard dummy variable taking the value of unity when the county is dry and zero otherwise. The second definition takes more seriously the presences of moist counties by reporting the percent of the county that is dry. We calculate the percentage by subtracting the county population that lives in a wet municipality from the county population and dividing by the county population. In the case of wet counties, this variable holds the value of zero and in dry counties it is equal to one.

Second, we utilize the ability of religion following Prohibition to influence a county's status. We use the religious membership by denomination data from 1936 as a proxy for votes. We find strong evidence that as past religious membership increases, particularly among some protestant groups (e.g. Baptists) the likelihood of current dry county status increases. A likelihood ratio test of all the religious parameters equaling zero is rejected at the 1 percent level.

We use three methods to control for endogeneity. The first is a standard two-stage least squares approach where the first stage is a linear probability model of the likelihood a county is dry. The second approach is a two-step maximum likelihood approach where the first stage is a probit model of the probability a county is dry, then the second stage uses the predicted probability in the meth crime regression. The third method is a first stage tobit model when the treatment variable is percent dry. After estimating the first stage, we used the predicted treatment variable in the second stage and obtain bootstrapped standard errors using county specific clusters.

Finally, we use the county demographic variables and religion instruments to perform propensity score matching. Again, we only consider the case of dry versus non-dry counties. The advantage of the propensity score matching is the removal of observations that are very observationally different than other counties in the sample. Counties that are not found on the common support tend to be either large metropolitan areas or dry counties that are geographically isolated (i.e. they do not border a moist or wet county).

## III. Results

The results for our primary dataset on Meth Lab Seizures are found in Table 2. Results are consistent across all models showing that dry counties have more Meth Lab seizures per capita than non-dry counties. The point estimates of the treatment effect range from 1.7 to 4.99 more meth labs for the discrete treatment effect and 0.71 to 4.04 more meth labs when using percent dry as the treatment variable. All the treatment effect estimates are found to be statistically significant at the 10 percent level.

The IV and LIML specifications produce larger point estimates than the OLS case, except when using a first stage Tobit for the dry treatment variable. The instrumental variables in the IV specifications yield large first stage Cragg-Donald F-statistics greater than 28. Both specification fail to reject the Hansen J overidentification test, where null hypothesis is that the equation is overidentified, at the 10 percent level. The wide range in the point estimates of the treatment effect are caused in part by the linear probability assumption. When we bound the predicted treatment indicator to be bounded between zero and one, as in the LIML and IV/Tobit specifications, we produce treatment effect estimates that are slightly larger than the OLS estimates.

If we take these estimates at face value, then removing all forms of alcohol prohibition would decrease the total number of meth lab seizures in the state of Kentucky by 30 to 43 labs or an equivalent decrease of 17.8 to 26 in meth lab within 2010.

We repeat these models for Synthetic Drug Arrest in Tables 3 – 5 and Total Meth incidences in Table 6. In Table 3, we provide the estimates for Total Synthetic Drug Arrests. Qualitatively, dry counties are again found to have more arrest associated with synthetic drugs than non-dry counties. The LIML and IV/Tobit models suggest 4.2 to 5.7 more arrest in dry counties per capita. The IV models estimate a treatment effect of 20 to 27 more arrest in dry counties and these estimates are significant at the 5 percent level.

If we consider only drug arrest due to possession, then the relationship becomes weaker. The OLS estimates do not find a statistically significant relationship between county status and possession arrest. The IV/Tobit model finds an increase of only 1.92 arrest per capita and is significant at the 10 percent level. In the IV models, the estimated treatment effect is 10 to 12 additional arrest in dry counties and is significant at the 10 percent.

The relationship between county status and drug arrest due to manufacturing/sale is similar. All the point estimates find a positive relationship between alcohol prohibition and synthetic drug production. The IV models find estimates of 10 to 15 additional arrest in dry versus non-dry counties per capita. These estimates are significant at the 10 percent level for the dry indicator and 5 percent level for the percent dry variable. The LIML and IV/Tobit estimates are smaller in magnitude with 2 additional arrest per capita, but only the IV/Tobit estimate is significant at the 10 percent level.

We find a stronger relationship for meth related crime as reported in Table 6. If we concentrate on the results using the dry indicator variable only, then there is a strong association with alcohol prohibition and meth related crimes. All the point estimates are positive and statistically significant at the 5 percent level. Meth related crime increases by 35 to 77 arrest in dry counties versus non-dry counties per capita. The point estimates remain positive when we consider percent dry, but are found with less precision.

Finally, we run least squares on property and violent crime as a falsification test. If our results are driven by unobservable differences in enforcement or overall criminal activity, we should see differences in other crimes by county status. When we test for the joint significance of the status indicators we cannot reject the null hypothesis of no effect for on any property or violent crime rate.[6] We report these estimates in Table 7.

Additionally, we replicate the analysis using a poisson assumption of the dependent variable instead of crime rates. The results remain qualitatively the same. We also consider enforcement by including the property crime rate as a regressor and do not find qualitative difference in the point estimate, but there is some loss of precision. The estimates for meth lab seizures and total meth related crimes remain robust to the inclusion of the property crime rate. These additional results are not reported.

## IV. Conclusion

[6] We also try sub-categories of violent and property crime: rape, robbery, burglary, sex offenses, and assault. We do not find a significant relationship with these crimes. These data are extracted from the FBI Uniform Crime Reports by county by year.

Local option ordinances have led to a variety of alcohol sales restrictions. Local alcohol bans increase the costs of obtaining alcohol, which reduces the relative price of illicit drugs. Additionally, these restrictions flatten the punishment gradient encouraging individuals who are willing to obtain alcohol illegally to also obtain illicit drugs. The results of this research are consistent with the unintended consequences of local alcohol bans predicted by economic theory. We exploit variation in religious membership following the repeal of Prohibition to identify the effect of alcohol restrictions on the prevalence of known meth labs. We find legal access to alcohol reduces per capita meth lab seizures by about 17.5%.

Figure 1: Meth Lab Seizures per county (darker green higher values)

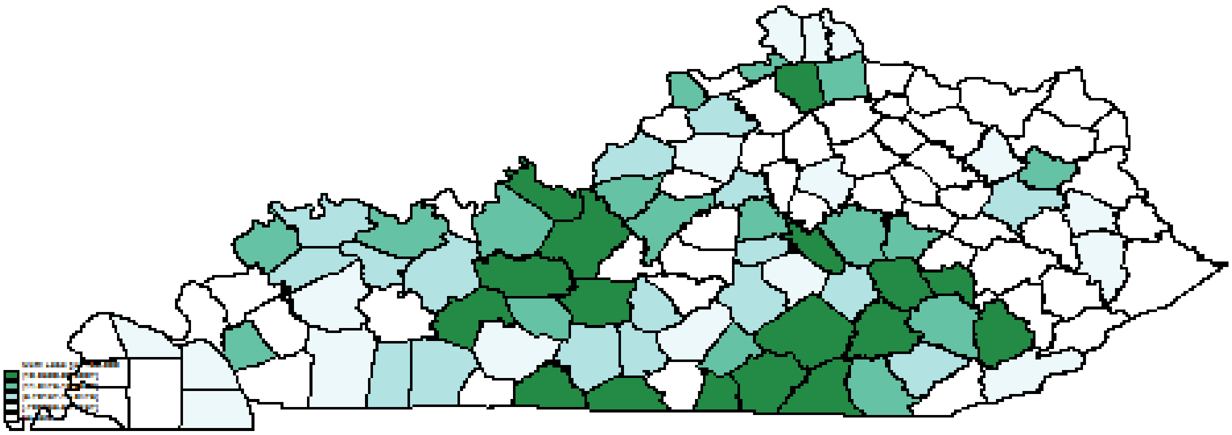

Figure 2: Wet (darkest, red), Moist, and Dry (lightest, yellow) County Status

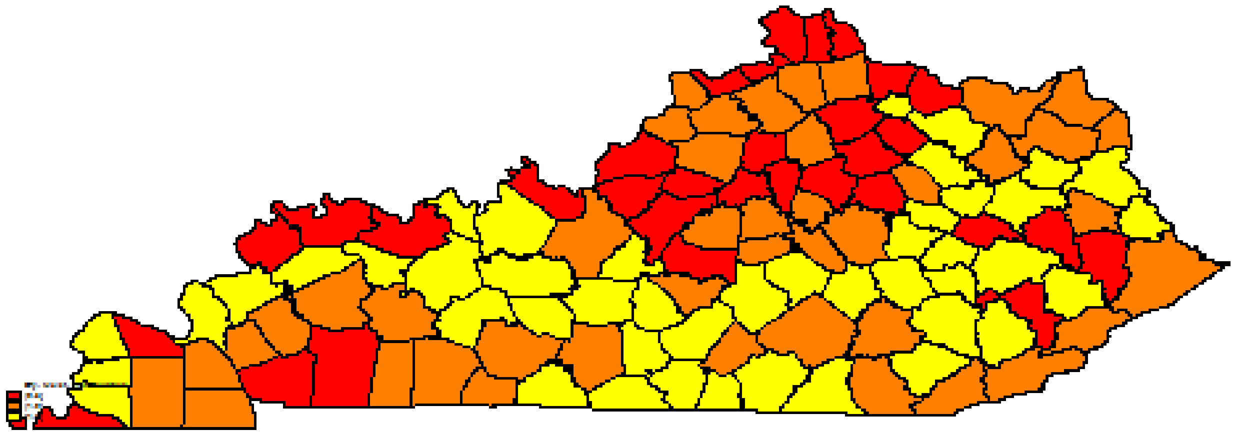

**Table 1: Means of control variables**

| County Demographic Variables | Wet | Moist | Dry |
|---|---|---|---|
| **Meth lab seizures rate (DEA)** | 2.10 | 2.07 | 3.70 |
| **Synthetic Drug Arrest rate (KSP)** | 51.69 | 34.48 | 71.65 |
| **Synthetic Drug Possession rate (UCR)** | 32.34 | 35.22 | 22.57 |
| **Synthetic Drug Sale/Manufacture rate (UCR)** | 17.41 | 25.13 | 20.50 |
| **All Meth Related Incidences (KSP) rate** | 58.48 | 68.33 | 117.7 |
| **Population (1000's)** | 68.19 | 36.95 | 21.32 |
| **Population Density** | 258.3 | 111.4 | 60.90 |
| **Median Household Income ($1000)** | 40.75 | 37.14 | 32.49 |
| **Pct. Black** | 5.64 | 4.03 | 3.16 |
| **Pct. College** | 16.18 | 14.90 | 11.75 |
| **Pct. Female Labor Force Participation** | 33.06 | 31.00 | 28.80 |
| **Pct. Male** | 49.20 | 49.00 | 50.18 |
| **Pct. Married** | 54.40 | 56.26 | 56.05 |
| **Pct. Widowed** | 6.89 | 7.53 | 8.12 |
| **Pct. Poverty** | 17.19 | 19.14 | 20.93 |
| **Pct. Poverty under 18 years old** | 23.81 | 25.26 | 27.78 |
| **Pct. Public Assistance** | 2.48 | 2.67 | 2.66 |
| **Pct. Under 21 years old** | 28.60 | 28.02 | 26.6 |
| **Pct. Over 65 years old** | 12.54 | 13.33 | 14.59 |
| **Pct. Baptist in 1936** | 13.24 | 11.92 | 13.38 |
| **Pct. Black Baptist in 1936** | 3.10 | 2.61 | 1.63 |
| **Pct. Protestant Mainline in 1936** | 28.05 | 27.84 | 26.27 |
| **Pct. Other Protestant in 1936** | 6.22 | 5.99 | 3.73 |
| **Pct. Any Religion** | 52.20 | 52.74 | 51.62 |
| **Pct. Any Religion in 1936** | 37.73 | 30.97 | 27.54 |
| **Pct. Baptist of All Religion in 1936** | 37.96 | 37.54 | 48.01 |
| **Population in 1936 (1000's)** | 36.22 | 28.62 | 16.39 |

Note: DEA = Drug Enforcement Agency, KSP = Kentucky State Police, and UCR = FBI Uniform Crime Report. County level demographics are collected from the American Community Survey. Religion characteristics in 1936 are collected from Hayes (2010) and contemporary religion data are collected from the Association of Statisticians of American Religious Bodies. All rates are calculate per 100,000 people in the county population.

**Table 2: DEA Meth Lab Seizures per 100,000**

| | Dry | | | | Pct. Dry | | |
|---|---|---|---|---|---|---|---|
| **VARIABLES** | OLS | IV | LIML | PS | OLS | IV | IV/Tobit |
| **Treatment Effect** | 2.01*** | 4.99** | 3.48*** | 1.70* | 2.26*** | 4.04** | 0.71** |
| | (0.60) | (1.69) | (0.94) | (1.01) | (0.74) | (1.69) | (0.32) |
| **R-squared** | 0.17 | 0.14 | | | 0.17 | 0.16 | 0.17 |
| **First Stage F - test** | | 28.4 | | | | 39.9 | |
| **Hansen J test** | | 0.398 | | | | 0.138 | |
| **Observations** | 889 | 889 | 889 | 863 | 889 | 889 | 889 |

Robust standard errors clustered by county in parentheses, except for propensity score which uses Abadie–Imbens robust standard errors. *** p<0.01, ** p<0.05, * p<0.1
All specifications use current county demographic information, current religious organization membership, county latitude and longitude, year fixed effects, as well as state border and non-dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments.

**Table 3: Synthetic Drug Arrest per 100,000 (UCR)**

| | Dry | | | | Pct. Dry | | |
|---|---|---|---|---|---|---|---|
| **VARIABLES** | OLS | IV | LIML | PS | OLS | IV | IV/Tobit |
| **Treatment Effect** | -1.24 | 20.78** | 5.71 | 2.55 | 3.74 | 27.0** | 4.19** |
| | (4.55) | (9.99) | (6.66) | (9.20) | (4.84) | (11.7) | (2.13) |
| **R-squared** | | 0.29 | | | 0.31 | 0.29 | 0.32 |
| **First Stage F - test** | | 28.4 | | | | 39.9 | |
| **Hansen J test** | | 0.105 | | | | 0.199 | |
| **Observations** | 889 | 889 | 889 | 863 | 889 | 889 | 889 |

Robust standard errors clustered by county in parentheses, except for propensity score which uses Abadie–Imbens robust standard errors. *** p<0.01, ** p<0.05, * p<0.1
All specifications use current county demographic information, current religious organization membership, county latitude and longitude, year fixed effects, as well as state border and non-dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments.

**Table 4: Synthetic Drug Possession per 100,000 (UCR)**

| | Dry | | | | Pct. Dry | | |
|---|---|---|---|---|---|---|---|
| **VARIABLES** | OLS | IV | LIML | PS | OLS | IV | IV/Tobit |
| **Treatment Effect** | -3.26 | 10.13* | 3.37 | 34.17*** | 0.98 | 11.77** | 1.92* |
| | (2.78) | (5.64) | (3.54) | (6.24) | (2.97) | (5.99) | (1.07) |
| **R-squared** | 0.36 | 0.33 | | | 0.36 | 0.34 | 0.37 |
| **First Stage F - test** | | 28.43 | | | | 39.91 | |
| **Hansen J test** | | 0.245 | | | | 0.238 | |
| **Observations** | 889 | 889 | 889 | | 889 | 889 | 889 |

Robust standard errors clustered by county in parentheses, except for propensity score which uses Abadie–Imbens robust standard errors. *** p<0.01, ** p<0.05, * p<0.1
All specifications use current county demographic information, current religious organization membership, county latitude and longitude, year fixed effects, as well as state border and non-dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments.

**Table 5: Synthetic Drug Sale/Manufacture per 100,000 (UCR)**

| | Dry | | | | Pct. Dry | | |
|---|---|---|---|---|---|---|---|
| **VARIABLES** | OLS | IV | LIML | PS | OLS | IV | IV/Tobit |
| **Treatment Effect** | 2.02 | 10.65* | 2.22 | 10.25*** | 4.72* | 15.25** | 2.27* |
| | (2.63) | (5.89) | (4.09) | (3.50) | (2.66) | (7.20) | (1.29) |
| **R-squared** | 0.36 | 0.35 | | | 0.36 | 0.35 | |
| **First Stage F - test** | | 28.44 | | | | 39.91 | |
| **Hansen J p-value** | | 0.107 | | | | 0.283 | |
| **Observations** | 889 | 889 | 889 | 863 | 889 | 889 | 889 |

Robust standard errors clustered by county in parentheses, except for propensity score which uses Abadie–Imbens robust standard errors. *** p<0.01, ** p<0.05, * p<0.1
All specifications use current county demographic information, current religious organization membership, county latitude and longitude, year fixed effects, as well as state border and non-dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments.

**Table 6: All Meth Related Incidences per 100,000 (KSP)**

| | Dry | | | | Pct. Dry | | |
|---|---|---|---|---|---|---|---|
| **VARIABLES** | OLS | IV | LIML | PS | OLS | IV | IV/Tobit |
| **Treatment Effect** | 35.1** | 77.0** | 54.0*** | 38.1*** | 27.0 | 75.4* | 14.4 |
| | (14.9) | (37.5) | (19.0) | (8.30) | (16.6) | (46.2) | (9.92) |
| **R-squared** | 0.30 | 0.29 | | | 0.30 | 0.28 | 0.30 |
| **First Stage F - test** | | 15.47 | | | | 22.2 | |
| **Hansen J test** | | 0.268 | | | | 0.201 | |
| **Observations** | 669 | 669 | 669 | 642 | 669 | 669 | 669 |

Robust standard errors clustered by county in parentheses, except for propensity score which uses Abadie–Imbens robust standard errors. *** p<0.01, ** p<0.05, * p<0.1
All specifications use current county demographic information, current religious organization membership, county latitude and longitude, year fixed effects, as well as state border and non-dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments.

**Table 7: Falsification Test - Property and Violent Crime Rates**

| | **Property Crime** | | **Violent Crime** | |
|---|---|---|---|---|
| **VARIABLES** | Dry | Pct. Dry | Dry | Pct. Dry |
| **Treatment Effect** | 5.56 | 7.15 | 1.27 | 0.49 |
| | (17.8) | (19.6) | (4.31) | (4.57) |
| **R-squared** | 0.61 | 0.61 | 0.61 | 0.61 |
| **Observations** | 889 | 889 | 889 | 889 |

Robust standard errors clustered by county in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All specifications use current county demographic information, current religious organization membership, county latitude and longitude, year fixed effects, as well as state border and non-dry county border dummies.

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