Breaking Bad: Are Meth Labs Justified in Dry Counties?

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Abstract

This paper examines the influence of local alcohol prohibition on the prevalence of methamphetamine labs. Using multiple sources of data for counties in Kentucky, we compare various measures of meth manufacturing in wet, moist, and dry counties. Our preferred estimates address the endogeneity of local alcohol policies by using as instrumental variables data on religious affiliations in the 1930s, when most local-option votes took place. Alcohol prohibition status is influenced by the percentage of the population that is Baptist, consistent with the "bootleggers and Baptists" model. Our results suggest that the number of meth lab seizures in Kentucky would decrease by 24.4 percent if all counties became wet.

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> Chief Deputy Art Mullen: "Someone in Harlan is going into the meth business in a big way."
> Raylin Givens: "Or the folks in Harlan are really, really congested"
> - *Justified*, Season 1, Episode 13, 2010

This paper examines the influence of alcohol prohibition on the number of methamphetamine (meth) labs in Kentucky. We begin by controlling for observable heterogeneity between counties using OLS and propensity score matching. We then address the remaining endogeneity of local alcohol laws by exploiting variation in religious affiliations in the 1930s, when most local-option votes took place. We find that, relative to wet counties, dry counties have roughly two additional meth lab seizures annually per 100,000 population. This suggests that, if all counties were to become wet, the total number of meth lab seizures in Kentucky would decline by about 25 percent.

The federal prohibition of alcohol sales and production was repealed by the 21st Amendment to the U.S. Constitution in 1933, ending a 14-year ban and giving states control over the sale of alcoholic beverages. Some states permitted localities to adopt local-option ordinances, and 12 states still contain jurisdictions where the sale of alcohol is prohibited. Four basic categories of county alcohol ordinances exist in Kentucky: (1) "Wet" allows the sale of alcohol; (2) "Dry" bans the sale of alcohol in all forms; (3) "Moist" allows wet jurisdictions to exist within an otherwise dry county; and (4) "Limited" only allows the sale of alcohol by the drink in certain types of restaurants based on the number of seats or share of sales from food.

More than a fourth of the 120 counties in the Commonwealth of Kentucky are dry. Although we do not have data on the intensity of enforcement, the Commonwealth's alcohol control laws describe potentially severe penalties for violations of local alcohol prohibition.[1] The first criminal offense is a class B misdemeanor, but the third offense is a felony that could result in a fine of up to $10,000 and as many as 10 years in jail.[2] Furthermore, the expected cost of civil asset forfeiture may be quite high, even for first-time offenders. The law requires that any premises or vehicle involved in "unlawfully selling, transporting or possessing alcoholic beverages in dry territory" be seized by law enforcement and forfeited to the state, regardless of whether anyone is convicted of a criminal offense.[3]

Alcohol bans flatten the punishment gradient for alcohol drinkers to engage in other illicit activities, encouraging illicit drug use by raising the relative price of a substitute (Miron and Zwiebel 1995). Also, information on the availability of illicit drugs may be greater when making alcohol transactions with illegal dealers than with legal liquor stores. Conlin, Dickert-Conlin, and Pepper (2005) find that a change in the status of Texas counties from dry to wet lowers drug-related mortality by approximately 14 percent. DiNardo and Lemieux (2001) find that higher minimum drinking ages reduce alcohol consumption by high school seniors, but increase marijuana consumption. On the other hand, Pacula (1998) finds that increases in the beer tax reduce both drinking and marijuana use among young adults, suggesting the two goods are complements.

Access to alcohol can also have indirect effects on property crime, public nuisance crime, and drug use. Carpenter (2005) finds that zero-tolerance drunk driving policies reduce property crime among 18-21 year old males by 3.4 percent and reduce the incidence of nuisance crimes.

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[1] Our source for this discussion is "A Review of the Commonwealth of Kentucky Alcohol Control Laws, 2007".

[2] The second offense is a Class A misdemeanor with a maximum fine of $500 and up to a year of jail time. The Class B misdemeanor associated with a first offense carries a maximum fine of $250 and up to 90 days in jail.

[3] In civil asset forfeiture cases, the burden of proof is shifted to the owner of the seized property, which increases the probability that someone (guilty or not) is punished for a crime.

Other studies find that higher alcohol excise taxes reduce alcohol consumption as well as certain types of property and violent crime (See Carpenter and Dobkin forthcoming, for a full survey).

Toma (1988) argues that local-options are endogenous and give voters an opportunity to increase the price of alcohol by increasing the cost of obtaining it. Yandle (1983) points out that both bootleggers and Baptists have historically supported alcohol 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. Restrictions could also be enacted in response to local problems related to alcohol such as the incidence of drunk driving. Furthermore, 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.

We contribute to this literature by considering the effects of alcohol restrictions on meth lab seizures in Kentucky. Gonzales, Mooney, and Rawson (2010) report that meth use in the United States increased threefold between 1997 and 2007. Weisheit and Wells (2010) find that Kentucky has one of the highest rates of meth lab seizures in the country, with 15.24 labs seized per 100,000 residents between 2004 and 2008.[4] Furthermore, they suggest that meth labs may be as prevalent as they are in Midwestern and Southeastern states because distance from the Mexican border raises the costs of imported meth relative to locally produced products.[5] Cunningham et al. (2010) support this conclusion, reporting that methamphetamine purity falls with distance from the borders with Mexico and Canada, which is consistent with local demand being met by production in small local labs. Kentucky's location, therefore, suggests that its 120

[4] 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.

[5] Weisheit and Wells (2010) point out that methamphetamine *use* appears to be higher in Western states than the Midwest or Southeast, but labs are relatively rare in Western states.

counties are an excellent setting to study the effects of alcohol restrictions on meth use and production.

I. Data

Our primary 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 Laboratory Register.[6] The DEA provides the physical street addresses for all meth labs seized as a public service due to the public health risk from chemical contamination. An advantage of these data is that they do not depend solely on arrests or other law enforcement interventions. The DEA also lists labs that are accidentally discovered following a fire or explosion.

County-level local-option ordinance data are provided by the Kentucky Department of Alcoholic Beverage Control.[7] In 2010, Kentucky had 32 wet counties, 39 dry counties, 20 moist counties and 29 counties with limited alcohol access. For the sake of simplicity, we treat counties with limited alcohol access as dry counties in our analysis.[8] Such a grouping should work against any findings supporting alcohol bans affect meth arrests.

As a robustness check, we also 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 sales and manufacturing of non-narcotic drugs, which includes meth as a subcategory.[9] The Kentucky State Police data contain data on different meth-related crimes. These activities include meth manufacturing, sales, possessions, dump sites, and unlawful

[6] These data do not include independent seizures conduct by the Kentucky State Police.
[7] http://www.abc.ky.gov/
[8] A few counties allow alcohol sales on vineyards, golf courses, or in two qualified historic Shaker districts; but are otherwise dry. We treat these counties as dry.
[9] The UCR also includes arrests for synthetic drug sales/manufacturing and possession. We provide estimates using these data in the appendix. We find similar results using these data.

possession of meth precursors. We use the sum of these offenses as a dependent variable in our robustness checks.

Similar to national trends, meth lab seizures in Kentucky initially fell by 50 percent between 2004 to 2007, but increased more than three-fold by 2010. 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. Comparing Figure 1 with Figure 2, which shows wet/dry status, there appears to be a relationship between dry status and meth lab seizures. The mean meth lab seizure rate is 2.17 in wet, 2.26 in moist, and 3.92 in dry counties per 100,000 residents (see Table 1). The means are also consistent with Campbell et al. (2009) who find that alcohol bans are less effective when a county is not sufficiently geographically isolated. Wet jurisdictions in moist counties likely reduce the geographic isolation of the rest of the county relative to counties that are entirely dry.

We use 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.

Furthermore, we use data from Haines (2004) on religious membership in 1936 to capture religious attitudes at the time of the initial wet/dry votes following the end of Federal Prohibition. We control for current religious attitudes using data from the Association of Religion Data Archives (1990).

Table 1 shows the means of several key variables and how they vary by local-option status. Wet counties are more densely populated on average than dry counties. Wet counties also have higher average levels of education, higher household income, and more minorities. Given the large observable differences between wet and dry counties, many of which are statisticaly significant at a 5 percent level, the adoption of local-option ordinances should not be treated as exogenous. Note also that religious participation and the share of Baptists, both of which are associated with restrictive alcohol policies, have increased across all county types since 1936.

II. Estimation

To determine the robustness of our results we apply three different estimation methods. First, we consider an ordinary least squares model with year fixed effects and county-level demographics to estimate the treatment effect:

$$Meth\ Crime\ rate_{it} = \alpha_t + \gamma WetStatus_{it} + X_{it}\beta + e_{it}$$

We cannot include county fixed effects because the wet/moist/dry status does not vary during our sample period.

The matrix X consists of a rich set of demographic controls including median household income; county population and population density; county location (latitude and longitude); female labor force participation; access to interstate highways; and the percentages of the county population who are married, male, black, living in poverty, receiving public assistance, under age 21 and over 65. We also include controls for current religious composition of the county. We use data from the American Community Survey on commuting patterns to construct the ratio of residents who work in the county to the total employment in the county. This variable serves as another proxy for geographic isolation, with higher values suggesting more isolation. Additionally, we include dummy variables for counties on the border of surrounding states, as well as whether the dry county borders a wet or moist county.

The variables of interest in the regression are the county alcohol *status* variables. We use three sets of measures for local-option status. The first set are dummy variables taking the value of one if the county is wet (or moist) and zero otherwise. The second measure exploits the variance between moist counties by measuring the percent of the county that is wet. We calculate this percent by dividing the population that lives in a wet municipality by the total county population. This variable equals one in wet counties and zero in dry counties. Lastly, we use the number of liquor stores per 100,000 residents, which provides an alternative measure of wetness that is not based on the state local-option data.[10]

After OLS, we estimate treatment effects using propensity score matching. In addition to more flexibly controlling for observable differences than OLS, estimating propensity scores allows us to identify and exclude observations that are not comparable to any observation from another treatment group. For example, the counties that contain Louisville and Lexington are both wet, more densely populated and otherwise different from any dry county in Kentucky. Also a few dry counties are so geographically isolated and sparsely populated that it is not possible to compare them to any wet county.

The propensity score matching estimates only evaluate binary treatment variables. We perform our analysis for two groupings: wet vs dry and moist vs dry. We also consider inverse propensity score weights, which do allow for multinomial treatment variables, and report these results in the appendix. The estimates based on inverse probability weighting are similar to those produced by the simpler matching estimates presented in the text.

Our third estimation procedure addresses endogeneity due to unobservable differences between counties. We exploit the influence of religious affilitiation following Prohibition on a

[10] Our counts of liquors stores in each county come from the Quarterly Census of Employment and Wages, which is collected by the Bureau of Labor Statistics with the cooperation of state agencies (U.S. Department of Labor, various years).

county's current wet/dry status. A flurry of local-option votes occurred shortly after the repeal of Prohibition in 1933. Since 1940, only a few counties have had votes to repeal dry status. We do not know the vote totals for all of the historical ballot initiatives; but we do have data on religious membership, including denomination, from 1936. We find strong evidence that religious membership and the percent Baptist in 1936 predicts current dry county status, even after controling for current religious affiliation. All of our regressions include current measures of the religion variables to ensure that the instruments are not proxies for present day beliefs, which would compromise the credibility of our exclusion restrictions.

For the main instrumental variables results, we only consider wet versus dry, and classify moist counties into the dry county group. Our instruments are strong when we only consider "wet" as the treatment variable, but they are not strong enough to identify wet and moist as separate treatments.[11] Further, this grouping should work against our finding an effect of alcohol bans as some counties in the dry group will have alcohol sales.

Additionally, we continue to restrict the sample for our instrumental variables estimates to those counties with propensity score values on the common support. We think that any attempt to identify exogenous variation is more plausible if it doesn't require us to compare Louisville and the Cinncinnati suburbs to isolated, sparsely populated counties with a predicted $P(\text{dry})$ above 0.999. For the sake of comparison, we also present a second set of OLS results for the restricted sample.

[11] The instrumental variables have a similar effect on the moist probability as the wet probability, but with less precision.

III. Results

As described above, we examine the number of meth lab siezures per population using three different measures of county wet/dry status and three different estimation techniques. The three wet/dry measures are 1) dummy variables for wet and moist counties with dry counties as the comparison group; 2) A measure of the percent of the population wet which allows moist counties to vary between zero and one; 3) the number of liquor stores per capita. The three estimation techniques are ordinary least squares, propensity score matching and instrumental variables.

Table 2 presents the results for our primary outcome variable, DEA Meth Lab Seizures. In column 1, we show the OLS results using the observations from all counties, columns 2 through 4 show results for counties on the common support. Column 2 shows the propensity score results, column 3 shows OLS results for the restricted sample and column 4 presents the instrumental variable results.

All models suggest that dry counties have more Meth Lab Seizures per capita than other counties. Considering first the OLS estimates using the full sample, wet counties have 1.43 (0.61) fewer meth labs and moist counties have 1.23 (0.53) fewer meth labs than dry counties. Both treatment effect estimates are statistically significant at the 5 percent level. In the middle panel, the coefficient estimate for the percent wet treatment variable is slightly smaller in magnitude, suggesting that an entirely wet county has 1.1 (0.59) fewer meth lab seizures than a completely dry county. In the bottom panel, the point estimate for liquor stores per capita is also negative, but is not statistically significant.

Next, we use propensity score matching to estimate the treatment effects. As indicated by the descriptive statistics in Table 1, wet and dry counties are observably different from one another. To ensure that we are comparing similar counties to each other, we restrict the sample to the common support of the estimated propensity score. This restriction removes observations from four large urban (or suburban) wet counties that have a lower predicted probability of being dry than any dry or moist county, as well as four dry counties that have exceptionally high predicted probabilities of being dry.[12] This restriction reduces the sample size from 840 to 770 observations. As mentioned above, we estimate treatment effects for wet vs dry and moist vs dry separately, using samples of 655 and 445 observations.

The propensity score matching results in the second column of Table 2 again suggest that allowing alcohol sales in a county reduces the prevalence of meth labs. Wet counties have 2.62 (0.35) fewer labs and moist counties have 2.30 (0.45) fewer labs relative to dry counties. Both point estimates are statistically significant at the 1 percent level. As seen in Appendix table 7, these results are not sensitive to estimating separate binomial treatments. If anything, estimating multinomial treatments using inverse propensity score reweighting results in larger estimated treatment effects.

For the sake of comparison, the third column in Table 2 presents OLS results using the restricted sample. The estimates again compare "apple to apples" by excluding counties that are off the common support. This results in larger coefficient estimates compared to OLS using the full sample. We now find a reduction in the meth lab rate of 1.75 (0.64) labs for wet counties and 1.37 (0.53) labs for moist counties. The percent wet treatment variable suggests a reduction of 1.47 (0.62) labs when comparing completely wet and completely dry counties.

Finally, the fourth column of Table 2 presents our instrumental variable estimates. As noted above, we group moist and dry counties together in the first panel because the instruments

[12] Each of the five excluded wet counties (Boone, Fayette, Fulton, Jefferson, Kenton) has an estimated $P(\text{Dry})$ below 0.003. Each of the four excluded dry counties (Butler, Carlistle, Green, Lyon, Marshall has an estimated $P(\text{Dry})$ above 0.999.

cannot separately identify the wet and moist treatment effects.[13] The first stage Cragg-Donald F-statistics are statistically significant and well over the rule-of-thumb $F > 10$ suggested by Staiger and Stock (1997) for all of the models. Additionally, none of the tests of overidentifying restrictions cast doubt on the validity of our instruments, with p values in each case above 0.2.[14]

The IV results are consistent with the findings of the OLS and propensity score estimates. Wet counties are estimated to have 2.07 (1.11) fewer meth labs per 100,000 than moist and dry counties. The estimated effect of the percent wet treatment variable is -2.32 (1.25), which is larger in magnitude but less precisely estimated than the OLS estimate. Finally, the IV estimates suggest that liquor stores have a statistically significant, negative effect on the number of meth lab seizures, with a coefficient of -0.13 (0.06).

Taken at face value, these estimates suggest that repealing all alcohol prohibition in Kentucky would decrease the total number of meth lab seizures in the Commonwealth by 41. This translates to a 24.4 percent decrease in the prevalence of meth labs statewide, and a 37.3 percent decrease in moist and dry counties.

Alternative Measures

As a robustness check, we repeat our preferred estimates using the Uniform Crime Reporting (UCR) data files from the FBI, as well as arrest reports from the Kentucky State Police (KSP). The UCR data do not have a separate variable for methamphetamine. Instead, meth is categorized within a larger group labelled "Other Non-Narcotic Drugs." We report estimates for Non-Narcotic Drug sales/manufacturing in Table 3, and possession in Table 4.

[13] We find similar results when grouping wet and moist counties together.

[14] When we reestimate the IV results using the full sample (not shown), we find larger treatment effects than we do with the preferred sample; however, the p values for the Hansen J tests are much smaller. This is consistent with our intuition that any identification strategy is more credible when we aren't comparing the wealthiest urban counties to the poorest rural counties.

The OLS estimates are not statistically significant for sales and manufacturing arrests in Table 3, but the propensity score and IV estimates are. The propensity score matching estimates find a reduction of 43.42 (12.17) arrests for wet counties and 35.79 (10.92) arrests for moist counties per 100,000 residents. The IV estimates are similar, with a coefficient on the wet treatment in the first panel of -35.64 (20.75). In the second and third panels, the percent wet treatment variable has a coefficient of -39.55 (22.86), and liquor stores per capita has a coefficient of -1.78 (0.78). Given these values, removal of the local ordinance in dry counties would result in a 38 – 47 percent reduction in the non-narcotic sales/manufacturing arrest rate.

Although the propensity score estimates are similar, the IV results using possession arrests (Table 4) are weaker than the results for sales and manufacturing. The coefficient estimates are not only smaller for the IV results in Table 4 than in Table 3, but the Hansen *J* tests in Table 4 reject overidentification. This suggests that we are less able to identify causal effects for possession than we are for the supply side of the market.

We find a stronger relationship using KSP data for meth-related arrests, as reported in Table 5. The meth-related crimes include dumpsites, possession, sales, paraphanellia, and meth labs. Least squares estimates using both the full and restricted samples find 18 to 19 fewer meth-related arrests per 100,000 residents in wet counties and 15 to 17 fewer meth-related arrests in moist counties relative to dry counties. The wet county indicator is statistically significant at the 5 percent level, but the moist county indicator is only significant at the 10 percent level. The propensity score estimates find larger reductions, with wet counties having 27.57 (9.68) fewer meth-related arrests and moist counties having 18.05 (10.69) fewer meth-related arrests per 100,000 residents.

The largest treatment effect estimates with the KSP data are found using the IV approach. The IV estimates find a reduction of 31.85 (18.94) meth-related arrests per 100,000. The IV estimates for the percent wet and the liquor store treatment variables also find statistically significant reductions in meth-related arrests when alcohol sales are allowed. Unfortunately, the Hansen *J* tests again reject overidentification in these models.

The rejection of overidentifying restrictions in Tables 4 and 5 may reflect a well-known drawback of using arrest records.[15] Namely, the arrest rate is subject to both the crime rate and the enforcement rate. Our ability to identify causal effects for the supply-side of the illegal drug market (Tables 2 and 3) but not for drug possession could be explained by arrests for possession being more sensitive to the enforcement efforts of law enforcement.[16]

We now consider an alternative measure of meth lab production that does not depend on arrest data. The production process used to create meth requires corrosive chemicals and a heating element. Manufacturers of meth are prone to experience chemical and other burns. We obtained data on emergency room visits for burns from chemicals or hot substances from the Kentucky Injury Prevention and Research Center.[17] As indicated by the estimates in Table 6, there is a consistent pattern of fewer burns per 100,000 residents in wet counties. The least squares estimates in both samples indicate 20 fewer ER burn visits, which is similar to the propensity score estimate of 19 (9.54) fewer visits. The percent wet treatment variables estimates suggest a reduction of 15 to 16 ER burn vists.

[15] See Tabarrok, Heaton, and Helland (2010) for a discussion of the shortcomings of arrest data.

[16] Recall that our preferred outcome measure, the DEA lab seizure count, is not entirely dependent on arrests. Due to the environmental hazards posed by meth labs, a lab is reported regardless of whether it was seized through an arrest or discovered through some other means.

[17] These data refer to emergency room visits listed under ICD-9 code E924, which are accidental burns caused by hot substance or object, caustic or corrosive material, and steam. These data are provided by Svetla Slavova at the Kentucky Injury Prevention and Research Center.

The magnitude of the reduction in ER visits for burns increases dramatically when we use the IV estimates, pointing to a reduction of 58.86 (22.66) ER burn visits. The IV estimates find the number of liquor stores per capita reduce ER burn visits by 3.17 (1.18). Note also that the tests of overidentifying restrictions are once again well above any conventional threshold for rejection.

An important highlight of these results is that local prohibition appears to have a stronger effect on sale and manufacturing of methanphenatime, but a weaker effect on possession. The geographic position of Kentucky far from the country's borders and its sparse population may play a role in the type of illicit drugs used. Weisheit and Wells (2010) suggest that the prevalence of meth labs may be influenced by distance from the Mexican border, and Cunningham et al. (2010) find that methamphetamine purity falls with distance from the borders with Mexico and Canada. According to the DEA, methamphetamine and marijuana are the only illegal drugs that are easily produced by the users: "A cocaine or heroin addict cannot make his own cocaine or heroin, but a methamphetamine addict only has to turn on his computer to find a recipe identifying the chemicals and process required for production of the drug." (Keafe 2001).

Falsification and Robustness Tests

It is possible that our results are driven by unobserved health trends that are associated with both the demand for illicit drugs and the adoption of alcohol policy. If poor population health is a motivation for local prohibition, then we should observe "effects" on other health measures. In Table 7, we report the effects of local-option alcohol sales on childhood obesity as a falsification test. All of the estimates are close to zero in magnitude, they vary in sign and only one is statistically significant.[18] Given the number of estimates we present in Table 7, one statistically significant coefficient is not surprising.

Additionally, we replicate our analysis using two alternative specifications. First, we use a Poisson assumption for the dependent variables instead of linear crime rates. Second, as mentioned above, we use the inverse propensity score weighting instead of the matching. These results are presented in appendix tables 6 and 7. In each case, the results are qualitatively similar to those discussed in the text.

Finally, we consider potential bias due to enforcement efforts by adding the rate of property crime arrests as a regressor. We find no qualitative difference in the point estimates, but there is some loss of precision. These results are available upon request.

IV. Conclusion

We find strong evidence that local alcohol prohibition in Kentucky increases the prevalence of methamphetamine labs in dry jurisdictions. Our results suggest that, if all counties in Kentucky became wet, the number of meth labs in dry and moist counties would be reduced by 37 percent, and the number statewide would fall by nearly 25 percent. Although we consider data on arrests to be less reliable than the DEA's lab seizure data, our results based on arrest data are consistent with the results based on data from the Clandestine Laboratory Registry. Furthermore, we find that local alcohol prohibition increases the incidence of ER visits for burns, which is consistent with local labs being run by poorly trained amateur "cooks."

[18] We find similar results when using infant mortality as the dependent variable, despite the potential effects of alcohol consumption on fetal health.

We address the likely endogeneity of local-option status using a novel set of instrumental variables. While others have been able to address unobserved heterogeneity by exploiting changes in policy, none of the counties in our sample changed status during our sample period. Instead, we exploit the fact that there was a spate of votes following the end of national Prohibition with relatively few votes since the 1940s, and the outcome of those votes was strongly influenced by religious membership in the county at the time. Our instrumental variables based on religious composition of the counties in 1936 strongly predict current wet/dry status, even though we control for counties' current religious composition.

Our work adds to the literature documenting the unintended consequences of restricting access to alcohol. Our results are consistent with the previous empirical work of Conlin et al. (2005) and Dinardo and Lemieux (2001), both of which found evidence of substitution between alcohol and other drugs. Our results add support to the idea that prohibiting the sale of alcohol flattens the punishment gradient, lowering the relative cost of participating in the market for illegal drugs.

Finally, our work has implications for policy aimed at reducing the harm caused by the use and production of methamphetamines. The most notable policies intended to reduce the supply of meth have been restrictions on precursors beginning in the 1990s. Even though studies of the earlier interventions (Cunningham and Liu 2003, 2005; Dobkin and Nicosia 2009) found that these policies had only temporary effects on the supply of meth, most states and the Federal government had placed restrictions on the purchase of pseudoephedrine (a common cold medicine) by 2006. The most careful study we have seen of the effects of these precursor restrictions, Dobkin et al (2014), estimates that these restrictions reduced the number of meth labs in a state by around 36 percent, which is comparable to our estimate of the effect of ending local alcohol prohibition. Although it's not clear how well our results would generalize to other states or to substances other than alcohol, our study provides an example in which liberalizing the treatment of one substance can be an effective policy tool for another substance.

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

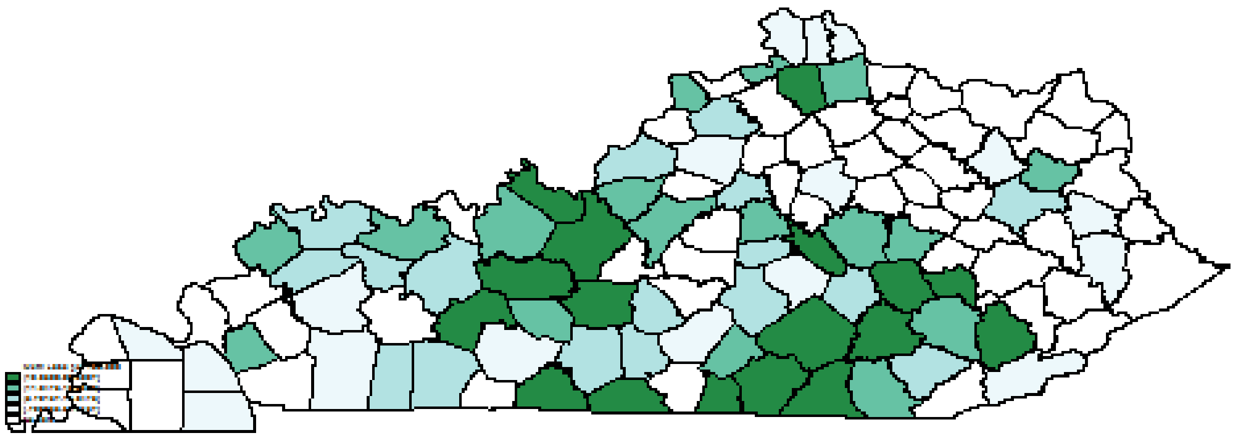

Figure 2: Wet (darkest, red), Moist, and Dry (lightest, yellow) County Status

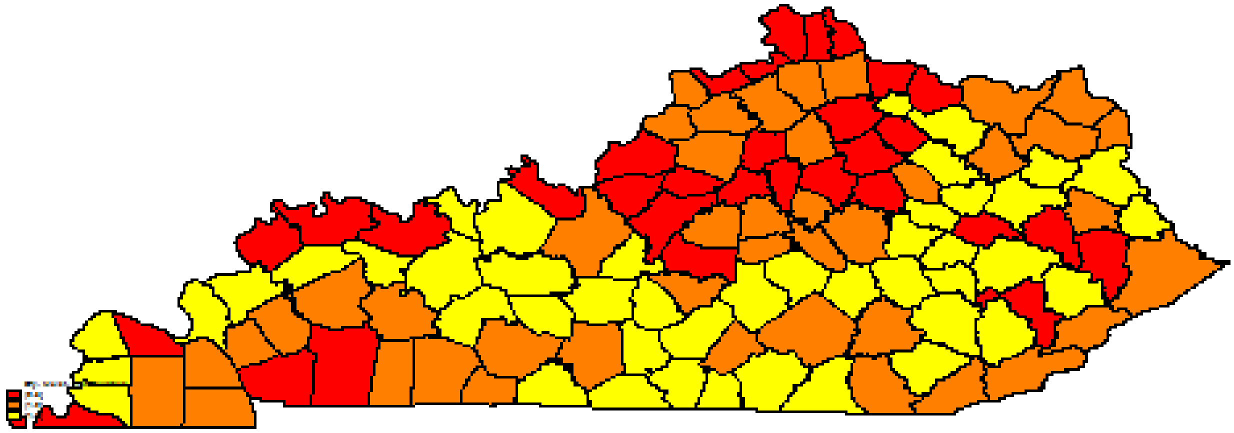

Table 1: Means of outcome and control variables

County Demographic Variables	Wet	Moist	Dry
Meth lab seizures rate (DEA)[a,b]	2.17	2.26	3.92
Non-narcotic Drug Possession rate (UCR)	98.8	95.9	90.8
Non-narcotic Drug Sale/Manufacture rate (UCR)	76.8	89.0	91.9
All Meth Related Incidences (KSP) rate [a,b]	42.2	55.5	81.2
Property Crime Rate [a,b,c]	451	358	267
Violent Crime Rate [a,b,c]	101	79.9	60.8
ER Burns rate[a]	132	137	149
Population (1000's) [a,b,c]	70.1	38.4	20.2
Population Density [a,b,c]	245	111	60.7
Median Household Income ($1000) [a,b,c]	40.4	37.2	32.5
Pct. Access to Interstate Highway [a,b]	40.1	43.0	21.6
Pct. Resident Workers/ Total Employment [a,b,c]	48.7	56.1	53.1
Pct. Black [a,b,c]	6.38	3.79	2.57
Pct. Children Obese	17.2	17.4	17.2
Pct. College [a,b]	16.3	15.6	11.5
Pct. Female Labor Force Participation [a,b]	34.1	32.4	30.0
Pct. Male [a,b]	49.0	49.0	49.6
Pct. Married [a,b,c]	54.0	55.5	56.5
Pct. Widowed [a,b]	7.13	7.28	8.16
Pct. Poverty [a,b,c]	17.7	19.3	21.4
Pct. Poverty under 18 years old [a,b]	24.3	25.2	27.9
Pct. Public Assistance[a]	2.64	2.72	2.93
Pct. Under 21 years old [a,b]	28.8	28.4	27.4
Pct. Over 65 years old [a,b]	12.6	12.9	14.4
Pct. Any Religion	53.1	50.8	50.5
Pct. Baptist[a,c]	30.0	32.8	35.2
Pct. Baptist of All Religion[a,c]	56.6	65.7	67.4
Pct. Any Religion in 1936 [a,b,c]	38.2	30.6	26.9
Pct. Baptist in 1936	12.8	12.0	13.5
Pct. Black Baptist in 1936 [a,b,c]	3.30	2.61	1.56
Pct. Baptist of All Religion in 1936 [a,b,c]	34.8	38.5	49.3
Population in 1936 (1000's)	37.1	27.7	15.9

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 calculated per 100,000 people in the county population. Equal means t-test at α=.05 are conducted for each pair of groups. Significant outcomes are indicated: a = wet vs dry, b = moist vs dry, c = wet vs dry.

Table 2: DEA Meth Lab Seizures per 100,000

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-1.43**	-2.62***	-1.75***	-2.07*[††]
	(0.61)	(0.35)	(0.64)	(1.11)
Moist	-1.23**	-2.304***	-1.37***	
	(0.53)	(0.450)	(0.53)	
R-squared	0.19		0.20	0.19
First Stage F - test				51.2
Hansen J (p-value)				0.22
Pct. Pop. Wet	-1.10*		-1.47**	-2.32*
	(0.59)		(0.62)	(1.25)
R-squared	0.18		0.19	0.19
First Stage F – test				49.23
Hansen J test				0.24
Liquor Stores per cap	-0.02		-0.05	-0.13**
	(0.02)		(0.03)	(.06)
R-squared	0.18		0.19	0.19
First Stage F - test				71.24
Hansen J test				0.25
Observations	840	655/445[†]	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).

[†] Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.

[††] Moist counties are included with dry counties in this estimation

Table 3: Other Non-Narcotic Drug Sale/Manuf. Arrest per 100,000 UCR

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-11.42	-43.42***	-11.67	-35.64*††
	(9.51)	(12.17)	(9.395)	(20.75)
Moist	-0.77	-35.79***	-5.093	
	(10.41)	(10.93)	(10.16)	
R-squared	0.69		0.69	0.69
First Stage F - test				51.20
Hansen J (p-value)				0.40
Pct. Pop. Wet	-9.97		-10.02	-39.55*
	(9.32)		(9.33)	(22.86)
R-squared	0.69		0.69	0.69
First Stage F – test				49.23
Hansen J test				0.41
Liquor Stores per cap	0.29		-0.24	-1.78**
	(0.43)		(0.45)	(0.78)
R-squared	0.69		0.69	0.69
First Stage F - test				71.24
Hansen J test				0.49
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).

† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.

†† Moist counties are included with dry counties in this estimation

Table 4: Other Non-Narcotic Drug Possession Arrest per 100,000 UCR

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-0.16	-34.32***	-1.47	-7.68††
	(10.81)	(9.46)	(11.13)	(24.41)
Moist	-6.14	-45.47*	-9.57	
	(7.69)	(25.74)	(8.17)	
R-squared	0.55		0.553	0.55
First Stage F - test				51.20
Hansen J (p-value)				0.05
Pct. Pop. Wet	2.66		1.03	-10.70
	(10.66)		(10.93)	(26.74)
R-squared	0.55		0.55	0.55
First Stage F – test				49.23
Hansen J test				0.05
Liquor Stores per cap	0.29		-0.018	-1.16
	(0.31)		(0.49)	(0.83)
R-squared	0.55		0.55	0.55
First Stage F - test				71.24
Hansen J test				0.11
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).

† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.

†† Moist counties are included with dry counties in this estimation

Table 5: All Meth-Related Arrests per 100,000 (KSP)

	Full sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-18.09**	-27.57***	-19.13**	-31.85*††
	(9.07)	(9.68)	(8.08)	(18.94)
Moist	-17.11*	-18.05*	-15.09*	
	(8.82)	(10.69)	(9.00)	
R-squared	0.33		0.330	0.33
First Stage F - test				51.20
Hansen J test				<0.001
Pct. Pop. Wet	-11.69		-14.10*	-41.78**
	(9.10)		(7.89)	(21.07)
R-squared	0.34		0.33	0.322
First Stage F – test				49.23
Hansen J test				<0.001
Liquor Stores per cap	0.101		-0.614	-2.268***
	(0.35)		(0.45)	(0.76)
R-squared	0.33		0.33	0.32
First Stage F - test				71.24
Hansen J test				<0.001
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).
† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.
†† Moist counties are included with dry counties in this estimation

Table 6: ER visits for Burns per 100,000

	Full sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-20.73**	-19.00**	-20.72**	-58.86***††
	(9.34)	(9.54)	(9.86)	(22.66)
Moist	-13.80	-59.83	-14.78	
	(9.83)	(44.35)	(9.888)	
R-squared	0.32		0.31	0.25
First Stage F - test				31.97
Hansen J test				0.56
Pct. Pop. Wet	-15.58*		-15.93	-67.12***
	(9.17)		(9.75)	(25.55)
R-squared	0.31		0.30	0.24
First Stage F – test				28.50
Hansen J test				0.52
Liquor Stores per cap	-0.45		-0.85*	-3.17***
	(0.35)		(0.49)	(1.18)
R-squared	0.31		0.30	0.25
First Stage F - test				35.71
Hansen J test				0.73
Observations	345		317	317

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).
† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.
†† Moist counties are included with dry counties in this estimation

Table 7: Pct. Children Obese

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	0.004	-0.004	0.004	-0.009††
	(0.005)	(0.005)	(0.005)	(0.009)
Moist	-0.002	-0.007**	-0.004	
	(0.004)	(0.003)	(0.004)	
R-squared	0.23		0.24	0.22
First Stage F - test				94.67
Hansen J test				0.0026
Pct. Pop. Wet	0.005		0.006	-0.01
	(0.005)		(0.005)	(0.01)
R-squared	0.23		0.24	0.22
First Stage F – test				87.52
Hansen J test				0.0024
Liquor Stores per cap	-4.09e-05		-0.0003	-0.0004
	(0.0002)		(0.0002)	(0.0004)
R-squared	0.22		0.21	0.23
First Stage F - test				35.71
Hansen J test				0.73
Observations	811	275/153	747	747

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).
† Propensity score estimates are constructed by comparing wet vs dry (n=275) and moist vs dry (n=153) separately.
†† Moist counties are included with dry counties in this estimation

Appendix 1: Means of outcome and control variables for Counties on the Common Support

County Demographic Variables	Wet	Moist	Dry
Meth lab seizures rate (DEA) [a,b]	2.34	2.26	3.79
Synthetic Drug Arrest rate (KSP)	42.2	42.7	53.7
Synthetic Drug Possession rate (UCR)[a,b]	29.9	36.5	23.4
Synthetic Drug Sale/Manufacture rate (UCR)	18.5	25.2	21.1
Non-narcotic Drug Possession rate (UCR)	98.0	95.9	90.8
Non-narcotic Drug Sale/Manufacture rate (UCR)	77.2	89.0	91.3
All Meth Related Incidences (KSP) rate[a]	44.9	55.5	76.3
Property Crime Arrest Rate [a,b]	390.1	385.3	272.0
Violent Crime Arrest Rate [a,b]	86.4	79.9	61.9
ER Burns rate[a]	134.6	138.6	149.3
Population (1000's) [a,b]	34.1	38.6	21.6
Population Density [a,b]	122.3	109.7	61.0
Median Household Income ($1000) [a,b, c]	37.9	35.9	30.9
Pct. Access to Interstate Highway [a,b]	32.2	43.0	20.2
Pct. Resident Workers/ Total Employment [a,b, c]	49.4	56.1	53.4
Pct. Black [a,b, c]	5.10	3.84	2.57
Pct. College [a,b]	14.1	15.3	11.2
Pct. Children Obese	16.9	17.2	17.3
Pct. Female Labor Force Participation [a,b]	37.6	36.1	34.1
Pct. Male [a,b]	49.1	49.0	49.4
Pct. Married[a]	55.5	56.1	57.3
Pct. Widowed [a,b]	7.29	7.31	8.06
Pct. Poverty [a,b]	17.7	19.0	21.7
Pct. Poverty under 18 years old [a,b]	23.7	24.2	28.0
Pct. Public Assistance[a]	3.02	3.04	3.59
Pct. Under 21 years old[a,b]	29.1	28.6	27.9
Pct. Over 65 years old[a,b]	12.6	12.8	14.0
Pct. Any Religion	51.9	50.8	49.3
Pct. Baptist[a,c]	30.3	34.6	34.7
Pct. Baptist of All Religion[a]	58.9	65.7	66.7
Pct. Baptist in 1936	13.2	12.0	13.2
Pct. Black Baptist in 1936[a,b]	3.3	2.6	1.6
Pct. Any Religion in 1936[a,b,c]	37.4	30.4	26.5
Pct. Baptist of All Religion in 1936[a,b]	44.5	46.2	54.5
Population in 1936 (1000's)[a,b,c]	22.1	27.4	16.6

Note: DEA = Drug Enforcement Agency, KSP = Kentucky State Police, and UCR = FBI Uniform Crime Report. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry). 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 calculated per 100,000 people in the county population. Equal means t-test at α=.05 are conducted for each pair of groups. Significant outcomes are indicated: a = wet vs dry, b = moist vs dry, c = wet vs dry.

Appendix 2: Synthetic Drug Arrest Total per 100,000 (KSP)

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-1.967	-12.34*	-5.482	-25.5††
	(9.275)	(7.409)	(9.083)	(16.83)
Moist	-8.686	-17.49**	-7.910	
	(7.036)	(7.067)	(6.605)	
R-squared	0.163		0.196	0.082
First Stage F - test				93.79
Hansen J (p-value)				0.6476
Pct. Pop. Wet	1.621		-2.706	-32.98*
	(9.211)		(9.121)	(18.34)
R-squared	0.149		0.187	0.146
First Stage F – test				49.23
Hansen J (p-value)				0.0009
Liquor Stores per cap	0.583		0.205	-1.660**
	(0.435)		(0.652)	(0.666)
R-squared	0.152		0.188	0.133
First Stage F - test				71.24
Hansen J (p-value)				0.0039
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).

† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.

†† Moist counties are included with dry counties in this estimation

Appendix 3: Synthetic Drug Arrest Total per 100,000 (UCR)

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-5.178	-1.272	-4.857	-24.25**††
	(4.242)	(4.347)	(4.535)	(9.825)
Moist	8.775	-0.223	8.605	
	(6.257)	(24.29)	(6.315)	
R-squared	0.324		0.331	0.320
First Stage F - test				93.79
Hansen J (p-value)				0.6476
Pct. Pop. Wet	-5.078		-5.091	-27.26**
	(4.225)		(4.581)	(11.11)
R-squared	0.320		0.327	0.312
First Stage F – test				87.32
Hansen J (p-value)				0.6378
Liquor Stores per cap	0.0493		-0.117	-1.032**
	(0.157)		(0.200)	(0.423)
R-squared	0.309		0.327	0.313
First Stage F - test				122.24
Hansen J (p-value)				0.7438
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).
† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.
†† Moist counties are included with dry counties in this estimation

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

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-0.938	4.731	-1.088	-11.71**††
	(2.472)	(3.449)	(2.636)	(5.654)
Moist	6.673**	5.094	6.634*	
	(3.385)	(9.697)	(3.422)	
R-squared	0.384		0.384	0.372
First Stage F - test				93.79
Hansen J test				0.5339
Pct. Pop. Wet	-1.579		-1.871	-13.14**
	(2.466)		(2.675)	(6.384)
R-squared	0.378		0.378	0.365
First Stage F – test				87.32
Hansen J test				0.5277
Liquor Stores per cap	-0.0139		-0.109	-0.504**
	(0.0795)		(0.110)	(0.246)
R-squared	0.378		0.378	0.370
First Stage F - test				122.24
Hansen J test				0.6024
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).

† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.

†† Moist counties are included with dry counties in this estimation

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

	Full Sample	Counties on Common Support		
VARIABLES	OLS	PS	OLS	IV
Wet	-4.240	-6.004***	-3.769	-12.54**††
	(2.689)	(2.237)	(2.783)	(6.052)
Moist	2.102	-5.317	1.970	
	(4.087)	(15.27)	(4.110)	
R-squared	0.358		0.363	0.358
First Stage F - test				93.79
Hansen J (p-value)				0.8880
Pct. Pop. Wet	-3.498		-3.220	-14.12**
	(2.658)		(2.778)	(6.838)
R-squared	0.356		0.362	0.355
First Stage F – test				87.32
Hansen J (p-value)				0.8774
Liquor Stores per cap	0.0996		-0.00804	-0.496*
	(0.121)		(0.136)	(0.259)
R-squared	0.356		0.361	0.352
First Stage F - test				120.85
Hansen J (p-value)				0.6547
Observations	840	655/445†	770	770

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The instrumental variable specifications use religious organization membership for 1936 as instruments. Full Sample results use the full sample of Kentucky counties between 2004 – 2010. Common Support restricts the sample to include counties with overlapping propensity scores of the Pr(dry).

† Propensity score estimates are constructed by comparing wet vs dry (n=655) and moist vs dry (n=445) separately.

†† Moist counties are included with dry counties in this estimation

Appendix 6: Poisson Count Model

VARIABLES	Meth Labs (DEA)	Meth Arrest (KSP)	Synthetic Drug Arrest (KSP)	ER Burn Visits
Wet County	-0.409***	-0.409***	-0.337**	-0.103***
	(0.0774)	(0.0774)	(0.139)	(0.0211)
Moist County	-0.519***	-0.519***	-0.134	-0.0325
	(0.103)	(0.103)	(0.241)	(0.0839)
Wet County	-0.582***	-0.582***	-0.668***	-0.110***
	(0.0873)	(0.0873)	(0.198)	(0.0354)
Moist County	-0.707***	-0.707***	-0.469***	-0.0379
	(0.0975)	(0.0975)	(0.156)	(0.0980)
Limited Sales by Drink	-0.269***	-0.269***	-0.513**	-0.0106
	(0.0868)	(0.0868)	(0.217)	(0.0541)
Pct of County Pop. Wet	-0.336***	-0.336***	-0.372**	-0.0729***
	(0.0747)	(0.0747)	(0.178)	(0.0140)
Liquor Stores per 100,000	-0.0284***	-0.0284***	-0.00784	-0.000343
	(0.00575)	(0.00575)	(0.0115)	(0.00160)
Observations	770	770	770	317
YEAR FE	YES	YES	YES	YES
Demo. Controls	YES	YES	YES	YES
Border Controls	YES	YES	YES	YES
Current Religion Controls	YES	YES	YES	YES
Highway & Commuter Controls	YES	YES	YES	YES
Common Support	YES	YES	YES	YES

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The sample size is restricted to include counties with overlapping propensity scores of the Pr(dry).

Appendix 7: Inverse Propensity Score Weighting of Main Dependent Variables

VARIABLES	Meth Labs (DEA)	Meth Arrest (KSP)	Non-Narcotic Drug Sale/Manuf. Arrest	Non-Narcotic Drug Possession Arrest	ER Burn Visits	Child Obesity	SYN. Drug Arrest (KSP)
Wet County	-3.74***	-42.18***	-62.52***	-69.45***	-28.11*	-0.029***	-29.56***
	(0.53)	(13.73)	(9.44)	(7.39)	(16.92)	(0.008)	(4.73)
Moist County	-2.488***	-19.81**	-12.13	-12.05	-30.26***	-0.00136	-16.72***
	(0.61)	(9.35)	(18.62)	(15.23)	(9.87)	(0.003)	(5.767)
Observations	767	767	767	767	316	746	767
YEAR FE	YES	YES	YES	YES	YES	YES	YES
Demo. Controls	YES	YES	YES	YES	YES	YES	YES
Border Controls	YES	YES	YES	YES	YES	YES	YES
Current Religion Controls	YES	YES	YES	YES	YES	YES	YES
Highway & Commuter Controls	YES	YES	YES	YES	YES	YES	YES
Common Support	YES	YES	YES	YES	YES	YES	YES
Observations	YES	YES	YES	YES	YES	YES	YES

Robust standard errors 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, interstate highway access, Census commuting patterns, as well as state border and dry county border dummies. The sample size is restricted to include counties with overlapping propensity scores of the Pr(dry).

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