Tutorial-04

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Exercise 1: DiD - paper discussion

Research question

Are supply-side drug control efforts effective? The study attempted to answer this question by focusing on the state and federal restrictions on OTC medicines containing methamphetamine precursors in the US.

Contribution

The study indicated that there is no consensus in the literature regarding the effectiveness of enforcement efforts in reducing drug use. As a result, the paper contributes to the existing literature by providing concrete empirical evidence on the effectiveness of enforcement efforts by using rich administrative records and the staggered implementation of state laws targeting over-the-counter medicines that can be used to produce methamphetamine.

More precisely, the authors indicated that their paper contributes to the literature by providing more credible estimates of the effect of analyzing the success of a smaller, but more typical enforcement effort.

Aim of the analyzed policy

The legislation's aim is preventing the diversion of ephedrine or pseudoephedrine (precursors of methamphetamine) to methamphetamine production and hence reduce its availability.

Methodology

- The authors examine the effect of the laws using a difference-in-difference model where the treatment is at the state level, with controls for state and month/year fixed effects and state-specific time trends.
- Additionally, event studies are used to support the validity of the main conclusions of the paper and to provide insight about the dynamic effects of the OTC restrictions.

Identifying variation

Geographic (states) as well as temporal variation in the implementation of the regulation: the paper exploited the variation in the timing of states' implementation of OTC regulations.

Key identifying assumption

As noted above, there is variation in the timing of state OTC regulations. The paper aimed at separately identifying the effects of the regulations from common changes in outcomes across all states. Thus, the identification assumption is once we control for state fixed and year/month effects (linear or nonlinear), there are no unmeasured state-level non-linear trends that are correlated with methamphetamine production and consumption and the introduction of the OTC restrictions.

Data

The study compiled data from multiple sources.

- Number of methamphetamine labs, from The National Clandestine Lab Seizure System (NCLSS),
- The price and purity of methamphetamine, from Drug Enforcement Agency's System to Retrieve Information (STRIDE),
- Positive drug tests for amphetamine among workers and hospital inpatients, from Quest Diagnostics and the Health Care Utilization Project (HCUP), and
- Drug-related arrests, from Uniform Crime Reports (UCR)

Results / findings

- The paper estimates that OTC restrictions reduced total methamphetamine production capacity within a state by 26%.
- The OTC restrictions significantly decreased within-state methamphetamine production—the estimate that the laws caused a reduction in the number of methamphetamine laboratories being 36%. The reduction in the number of labs was largest among the laboratories with the smallest production capacities, but it was relatively small in the number of larger laboratories.
- According to the paper's estimate, there is about 25% decline in overall domestic production of methamphetamine.
- However, the study found no evidence about the impact of the OTC restrictions on the purity, price and consumption of methamphetamine, and drug related arrests.
- Evidence for the spatial spillover effect of the intervention on border/neighboring counties/states.

Interpretation of the results / implications / policy relevance

I summarize the implications of the findings of the paper as follows.

- The OTC laws successfully disrupted local methamphetamine production; the number of meth-labs in the state has declined significantly (by about 40%). Reductions apply to laboratories of all sizes, but the largest and most significant reductions were among the smaller laboratories.
- Despite the large reduction in the production of methamphetamine within a state, the study finds no evidence of reductions in methamphetamine purity, consumption, or arrests. This is worrisome as the goal of the legislation was to cut the supply of methamphetamine so that people's drug consumption are curtailed or at least controlled.
- Highlighting the possible policy implications of the paper requires answering the question why the legislation's effectiveness (in significantly reducing methamphetamine supply) did not translate into reductions in drug consumption (in terms of price as well as quality) and drug related arrests. It would require providing broader insight about the interplay between the overall drug supply and demand markets in the US and neighboring countries, especially in Mexico. Because, for example having a bulk production of close substitutes to methamphetamine in the US and the possibility of import from Mexico and other Latin American countries would obscure the effects of the regulations. In fact, the study finds evidence that methamphetamine producers in border counties responded to the OTC laws by purchasing precursors in neighboring states that did not have a law in place. This reduced the effectiveness of the laws and as purchasing and transporting a legal product involves low if not no risk.

Limitations of the paper

One clear limitation of the paper is the data. While acknowledging the fact that the ideal data for measuring the effect of the laws on methamphetamine production would be a census of labs for each state spanning before and after the laws went into effect, the study relied on the number of labs discovered by law enforcement agents as a measure for the outcome variable(s). However, the number of labs discovered each month is just an unknown fraction of the total number of labs in operation that month. Thus, the outcome variable is clearly understated.

Moreover, the findings are based on the assumption that the probability of a lab being seized remains constant even after the introduction of the law. But following the regulation enactment, it is likely that the detection probability would change afterwards. For example, the investigation efforts of law enforcement agents may go down, reports from the public may increase as the public has now law protection due to the new regulations for exposing offenders. These possibilities are not considered in the paper.

The results on drug use might suffer from selection bias in the measurement of methamphetamine consumption as it is likely that only patients and workers with a previous record of drug use are subject to methamphetamine consumption tests.

In terms of the policy objective, the general problem of drug abuse and violence might remain unalleviated if the regulation restrictions do not also apply to the substitutes to methamphetamine

and other types of drugs. Special attention should also be accorded to producers that are more experienced and have widely established production and distribution networks since the detection likelihood of such firms is low. Moreover, the policy implications of the paper cannot be extrapolated to all drugs that are available for consumption for in the US since some drugs are mainly imported from neighboring countries. In addition, coordination among states and also with the federal government could have made the policy more effective.

Exercise 2: DiD - practical application

(a) **{Reproduce Figure (2) of (Dobkin, Nicosia, and Weinberg 2014)**

The two points mentioned in the paper corresponding to this figure can also be seen in this plot (see Figure (1)). First, for each group, there was a decrease in the average number of labs discovered beginning in early 2004. Second, by 2007 the average number of labs discovered in a state was less than half of what it was before 2004 for each of the three groups of labs. However, these declines in the number of labs from 2004 to 2007 were not solely due to the OTC regulations, as the declines began before states enacted the sales restrictions. This fact is further supported by Figure (2).

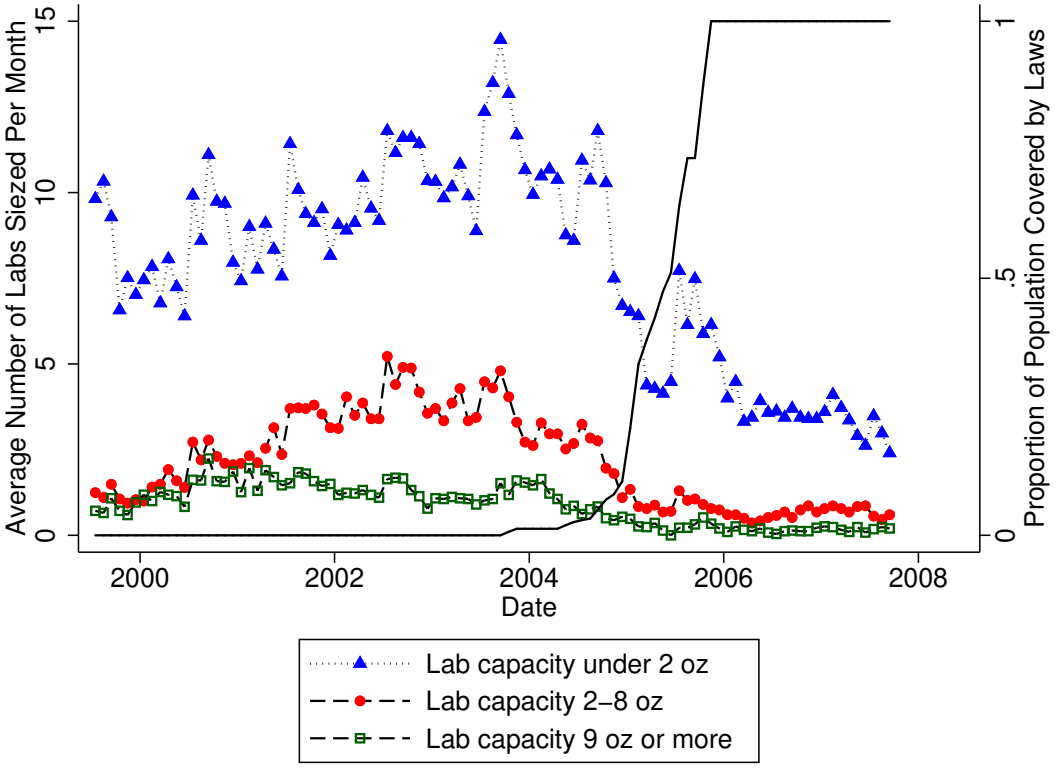

Figure 1: Methamphetamine labs discovered or seized by capacity.
The figure contains the average number of labs discovered in a state by month.

(b) **{Make a graph that shows the average number of the three different types of labs discovered in event time. Center the figure at time 0 (when the law went into effect in the state).**

The number of labs seized (in each group) started declining before the states implemented the regulations, roughly a year (12 months) before the law came into effect, as can be seen in Figure (2).

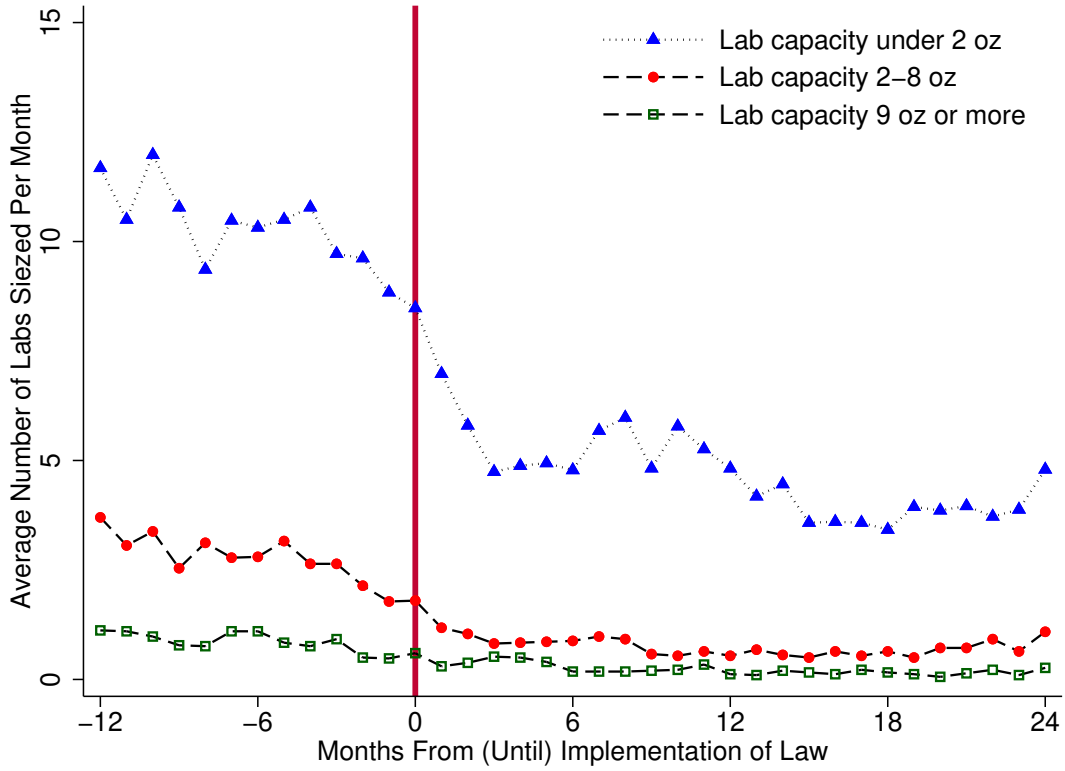

Figure 2: Methamphetamine labs discovered or seized by capacity in event time.
The figure contains the average number of labs discovered in a state by month.

(c) **Estimate a standard FE model to determine the effect of the law on the number of discovered labs of the three different sizes. Equation (1) of (Dobkin, Nicosia, and Weinberg 2014) serves as your reference point. Be sure to code the OTC_{st} indicator as defined in the paper. Use the appropriate standard errors and justify your choice. Do your coefficients coincide with what you see in your graphs and with the regression estimates of the paper?**

Following the paper's definition of the variable of interest OTC regulation, I coded OTC_{st} as follows.

$$OTC_{st} = \begin{cases} 0 & event.date_{month} < any.law_{month} \\ \frac{end.of.month - event.date - 1}{end.of.month} & event.date_{month} = any.law_{month} \\ 1 & event.date_{month} > any.law_{month} \end{cases}$$

I estimate the 4 models of the paper starting from model (1) and then by progressively adding state-specific linear time trend in (2), quadratic state-specific time trends in (3), and in the last one (4) adding two covariates, the unemployment rate and the number of households receiving food stamps. The results of the estimations are reported in Table (1). And, my coefficients look to

Table 1: Impact of OTC regulations on methamphetamine lab seizures.

	Number of Labs Seized				Lab capacity under 2 oz			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
OTC Restriction	-6.593**	-6.601**	-4.830**	-5.523***	-4.075**	-4.077**	-2.893**	-3.424***
Mean	10.90	10.90	10.90	10.90	7.834	7.834	7.834	7.834
Observations	4937	4937	4937	4937	4937	4937	4937	4937
States	50	50	50	50	50	50	50	50

	Lab capacity 2-8 oz				Lab capacity 9 oz or more			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
OTC Restriction	-2.251***	-2.258***	-1.752***	-1.940***	-0.266	-0.266	-0.185	-0.158
Mean	2.177	2.177	2.177	2.177	0.890	0.890	0.890	0.890
Observations	4937	4937	4937	4937	4937	4937	4937	4937
States	50	50	50	50	50	50	50	50

Notes: All regressions include state fixed effects and year/month fixed effects.

The dependent variable in the regressions is count of labs seized or discovered in a month in a particular state.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

roughly match the estimates reported in Table 1 of (Dobkin, Nicosia, and Weinberg 2014). They slight differences are due to the fact that we include the whole time period of the sample and the data for the state of Florida was missing.

The results of each of the models coincide with what we see on the plots. There is a statistically significant strong negative effect of the law on the number of labs seized for each category of labs, specially the effects are more pronounced in smaller labs. The magnitude of the slope coefficients increase as we add more and more controls to the baseline model (1) (exception being large labs). None of the coefficients are statistically significant when the outcome variable is `Lab capacity 9 oz or more`.

$$Y_{st} = \beta OTC_{st} + \alpha_s + \gamma_t + \epsilon_{st} \tag{1}$$

$$Y_{st} = \beta OTC_{st} + \alpha_s + \gamma_t + \delta_s \cdot t + \epsilon_{st} \tag{2}$$

$$Y_{st} = \beta OTC_{st} + \alpha_s + \gamma_t + \delta_s \cdot t + \Delta_s \cdot t^2 + \epsilon_{st} \tag{3}$$

$$Y_{st} = \beta OTC_{st} + \alpha_s + \gamma_t + \delta_s \cdot t + \Delta_s \cdot t^2 + \theta_1 FOOD_{st} + \theta_2 UNEMP_{st} + \epsilon_{st} \tag{4}$$

Comment on Cluster Standard Errors

Abadie et al. (2017) argue that clustering is in essence a design problem, either a sampling design or an experimental design issue. Since the states are not selected randomly, and since there are not clusters in the population of interest (the country United States) beyond the 50 (plus 1) clusters that are seen in the sample, the second design issue suitably applies to this paper. Clustering due to an experimental design is if the treatment is correlated within the clusters. I think that the treatment (OTC regulation) is correlated within clusters, i.e., states.

However, one may ask why do we care about cluster standard errors when we use fixed effects? Including fixed effects in the regression function to account for the clusters, thinking that the fixed effects completely eliminate the within-cluster correlation of the residuals, does not rule out the need for cluster standard errors adjustments. In case of fixed effects, cluster standard errors should be used if there is heterogeneity in the treatment effects.

States implemented the OTC regulations at different times, and this is in fact the motivation for the study. The timing of the treatment then depends which state we are referring to. Thus, I think unobserved components in outcomes (residuals) (and also observed ones-regressors) for individual units (lab seizures) within clusters are correlated.

Therefore, the existence of variation in the timing of state OTC regulations necessitates the use for cluster standard errors. Hence, there should be clusters at the state level—the highest level of aggregation in the sample.

(d) **Under what assumptions does equation (1) of the paper reveal consistent estimates? Do you think that these assumptions are met?**

- Unbiasedness of the DiD estimator (Assumption DID.2): which requires that the policy change not be systematically related to other factors that affect the outcome variables (lab seizures) (and are hidden in the error term). State and time invariant effects are not correlated with the error term. I think it's hardly true that this assumption is met, because the model does not account for state specific (time varying such as state unemployment rate) covariates.
- Consistency of the DiD estimator: which requires that there are no state specific trends that are correlated with the treatment—OTC restriction. Time fixed effects were included to account for aggregate common changes over time. **DiD common trend assumption** (Assumption DID.4 (Common Trend - CT)).
- No pre-trend (Assumption DID.3 (No Effect Prior to Treatment - NEPT)): This assumption has been tested in the paper through event study analysis. The paper indicated that event study analysis not only allows to examine any "pre-trend" that would raise concerns about the identification but also to determine exactly when the regulations had an impact and how persistent it might be.
- Broadly, assumptions DiD1-DiD5

(e) **What does equation (1) assume about the temporal evolution of the treatment effect? How does the regression equation (2) of the paper improve on this?**

Equation (1) (implicitly) assumes the treatment effect to be constant over time; β (the effect of the treatment) do not vary across states and time. In contrast, in equation (2) the treatment effect is allowed to vary over time, but still no variation across states. We can say this is an improvement over the baseline model, because equation (2) captures the temporary evolution of the treatment.

(f) **Similar to equation (2) of the paper, run a regression of the number of labs discovered on state FE, time dummies and event time dummies. Plot the estimates of the event time dummies and their confidence intervals. Interpret the figure and compare it with your previous findings. Did the laws reduce the number of labs? Does the effect look persistent?**

We estimate the following model:

$$Y_{st} = \sum_{j=-12}^{24} \pi_j 1\left(\tau_{st} = j\right) + \alpha_s + \gamma_t + \delta_s * t + \epsilon_{st} \tag{5}$$

The estimated π_j coefficients with their 95 percent confidence intervals are plotted below against event time dummies for $j \in [-12, 24]$ for each category of lab sizes.

In terms of the effects of the treatment, what the confidence interval plots show is consistent with the previous findings (cf. Table 1). The reductions in the number of small labs are substantial due to the regulation. The effect on large labs is not significant since the 95 percent confidence intervals of the π_j coefficients include zero (see 6)—consistent with the findings in the above regression models (see (c)). Yes, the effect looks persistent to me.

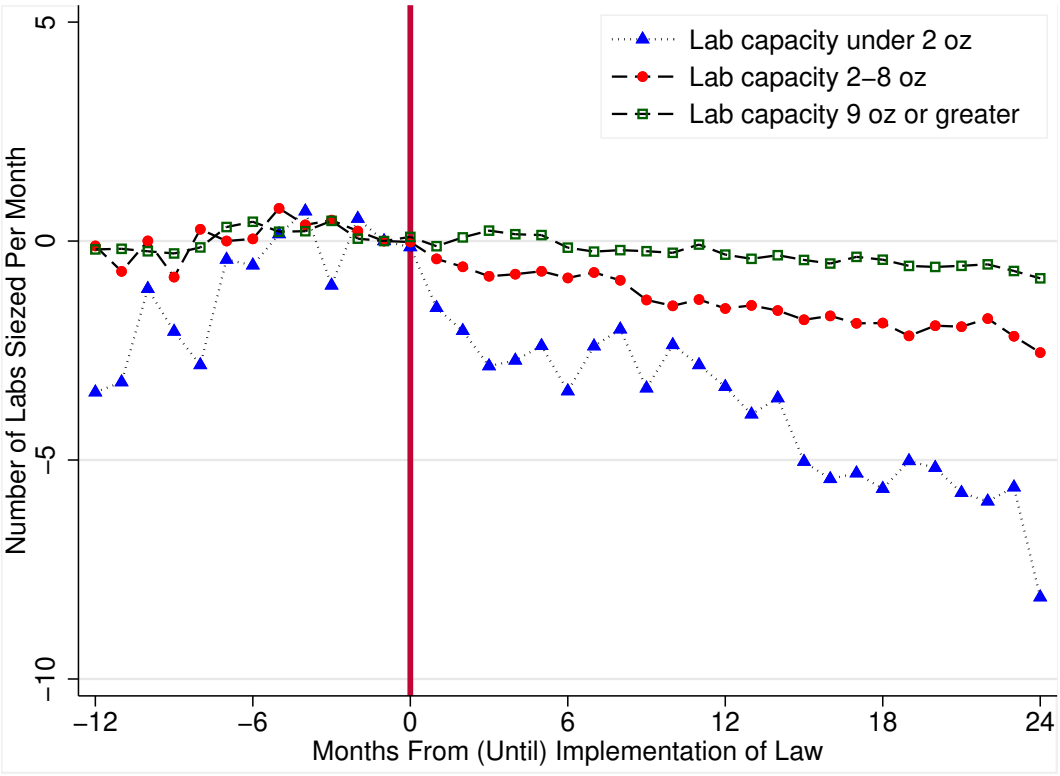

Figure 3: Methamphetamine labs discovered or seized by capacity, event study.

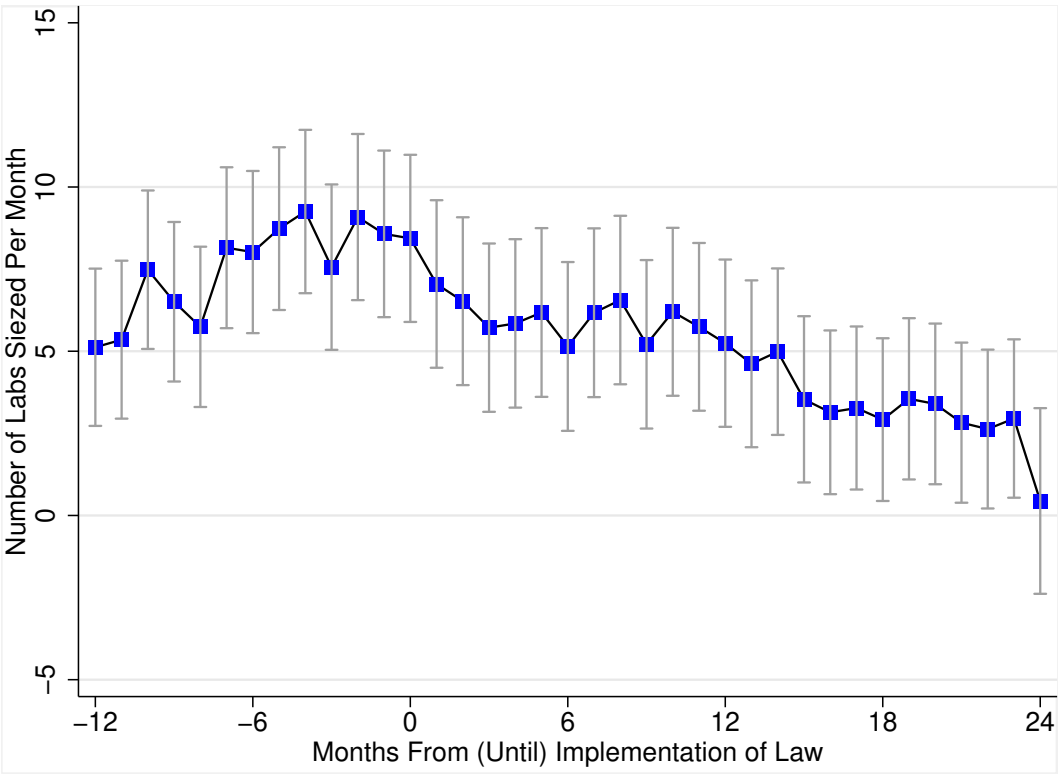

Figure 4: Event Study: Methamphetamine Labs Discovered or Seized With Capacity Under 2 oz

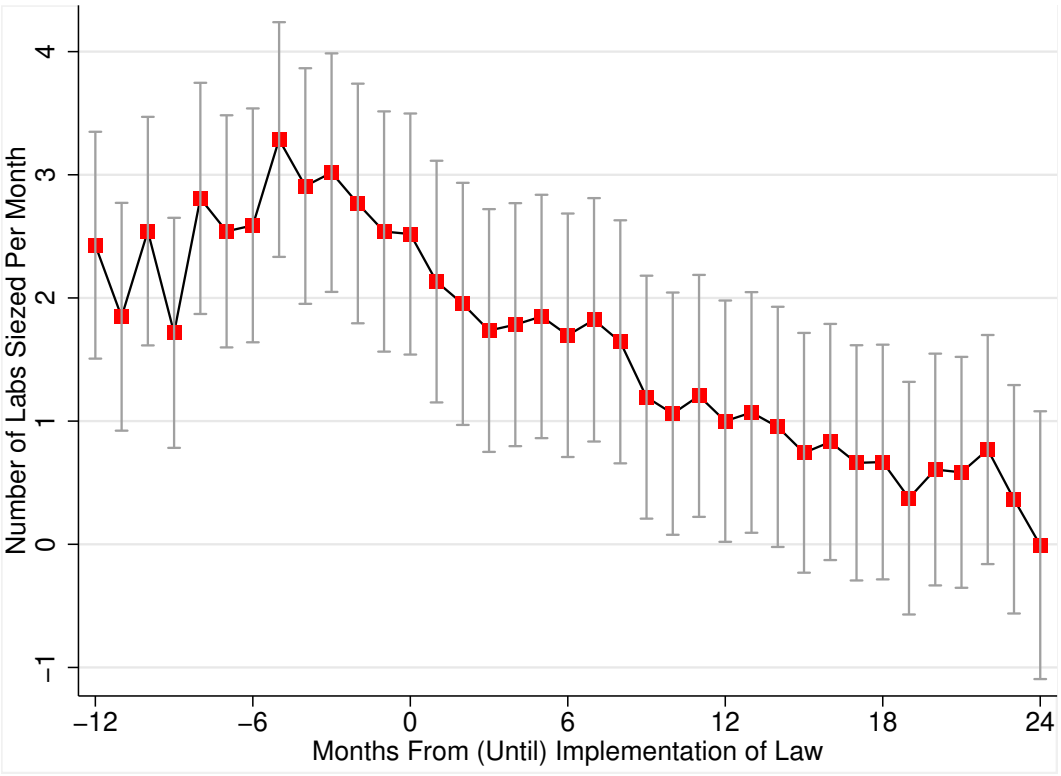

Figure 5: Event Study: Methamphetamine Labs Discovered or Seized With Capacity Between 2 and 8 oz

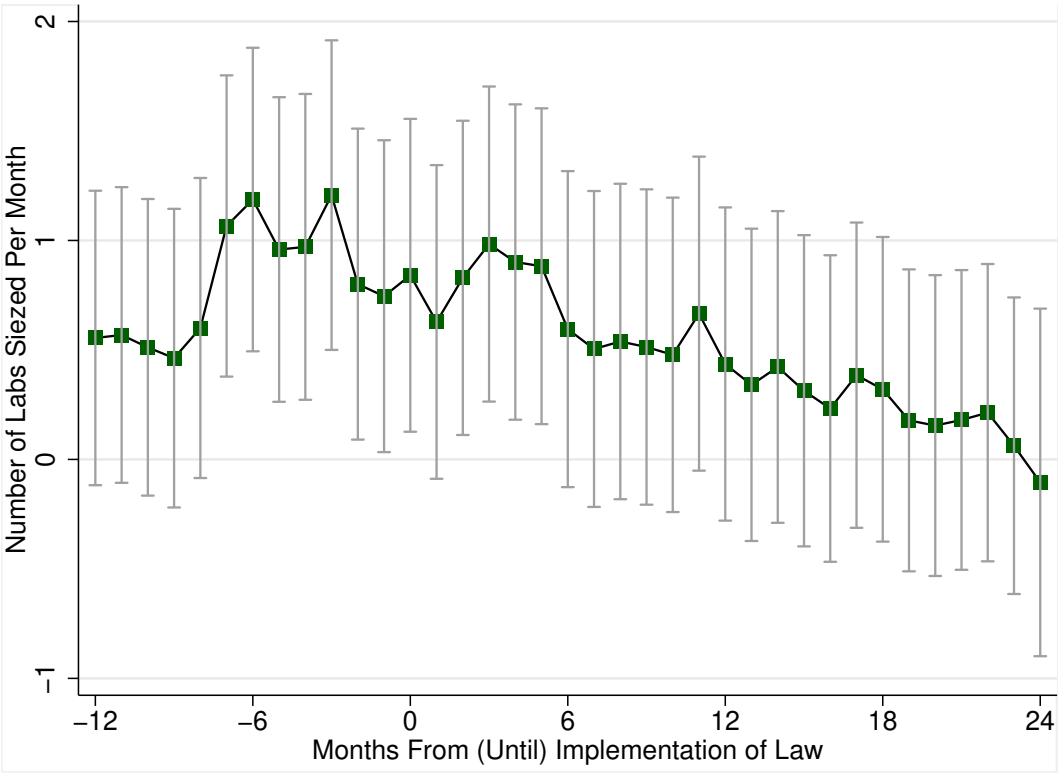

Figure 6: Event Study: Methamphetamine Labs Discovered or Seized With Capacity Greater than 9 oz

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge. 2017. "When Should You Adjust Standard Errors for Clustering?" Working Paper 24003. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w24003.

Dobkin, Carlos, Nancy Nicosia, and Matthew Weinberg. 2014. "Are Supply-Side Drug Control Efforts Effective? Evaluating Otc Regulations Targeting Methamphetamine Precursors." *Journal of Public Economics* 120: 48–61. https://doi.org/https://doi.org/10.1016/j.jpubeco.2014.07.011.