Replication
Bargaining in the Shadow of the Law: Divorce Laws and Family Distress (From B. Stevenson and J. Wolfers)

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April 2020

1 Discussion

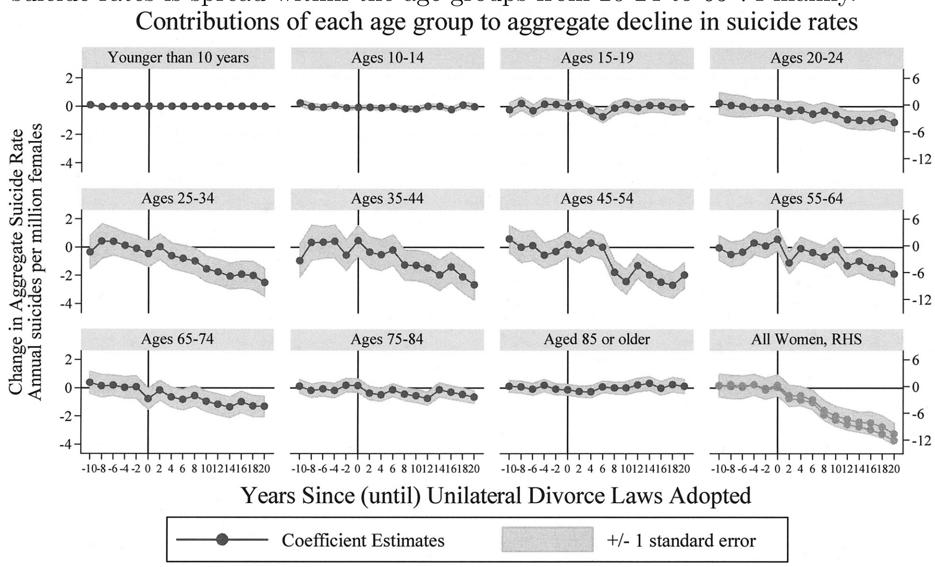
1.1 Brief Summary

In this paper, Stevenson and Wolfers address a question concerning whether allowing unilateral divorce benefited individuals in violent relationships, and by how much. They exploited the fact that multiple states across the US passed unilateral divorce laws, with a considerable variation occurring from the different timing of approval, to use a Differences-in-Differences design in order to isolate the causal effect of the reformed divorce legislation on family violence from the state fixed effects and the trend.

The authors used data on suicide, domestic violence and homicide rates for women and men as proxies for family violence. Data on suicide was obtained from a census of death certificates from the National Center for Health Statistics (NCHS). For domestic violence, they used data from the landmark Family Violence Surveys, which was gathered by way of household interviews rather than police reports because of under-reporting phenomena. Lastly, data on homicide came from the FBI Uniform Crime Reports (UCR).

Stevenson and Wolfers found evidence that changes in divorce laws allowing unilateral divorce ended up decreasing female suicide and domestic violence. Additionally, they found suggestive, but less convincing, evidence of decline in females murdered by intimates.

The figure they present to illustrate their findings I found is the most compelling is the one shown below. It shows the contribution of each age group to the coefficient estimates and allows the reader to observe that the decline in suicide rates is spread within the age groups from 20-24 to 65-74 mainly.



When I first read the paper, I found the analysis convincing. However, after analyzing Andrew Goodman-Bacon's reasoning about possible sources of bias in Diff-in-Diff with variation in treatment timing, I saw that time-varying treatment effects can lead to biased Diff-in-Diff estimators. One thing that the authors could have done that would address that issue would be to explicitly decompose the estimator in groups (Earlier vs Later Treated, Later vs Always Treated, Later vs Earlier Treated and Treaded vs Untreated), which would allow them to identify and address possible sources of bias.

1.2 What is no fault divorce and why do Stevenson and Wolfers think it's relevant to suicide and homicide? Briefly explain their theory and what it has to do with the Coase theorem.

No fault divorce is a legal concept that allows married individuals to file for divorce without having to prove fault or persuade their spouse to reach a mutual agreement. It is relevant to domestic violence because it shifts bargaining power towards the person that is most eager to end the marriage.

In a sense, this mechanism provides the person in a violent relationship a viable way to exit, and it can affect the nature of the abuse in two ways. First, it allows the marriage, and therefore the violence, to end. Secondly, the mere fact that filing for unilateral divorce becomes a credible threat might be sufficient to hinder future abuse actions in the relationship without the marriage having to end.

Applying the Coase Theorem in this context, unilateral divorce laws will transfer the right to remarry from the spouse who wants to stay in the relationship to the one that doesn't want to. Under center requirements, the Theorem's results imply that the marriages only dissolve if relationship is sub-optimal for both spouses, and the result of the bargaining will be the same no matter what the initial assignment of the right to remarry was. Hence, it predicts that allowing unilateral divorce wouldn't affect the divorce rate and, therefore, the first effect previously described will be neutral (as long as the requirements are satisfied).

1.3 Write down and explain their estimation equation. Explain what each variable means, what each coefficient means, what each summation sign means, what each subscript means, what the epsilon means. What is the main parameter of interest?

$$\begin{aligned} Suicide\,rate_{s,t} = \sum_k \beta_k Unilateral^k_{s,t} + \sum_s \eta_s State_s \\ + \sum_t \lambda_t Year_t + Controls_{s,t} + \varepsilon_{s,t} \end{aligned}$$

Where $Unilateral$ is a series of dummy variables indicating whether the state had adopted unilateral divorce k years ago or not, $State$ is a series of dummy variables for each of the s states listed in Table 1, $Year$ is a series of dummy variables for each of the t years in the time period of the analysis, and $Controls$ are economic, demographic and social policy controls such as state income, unemployment rate, age composition of the population, race, etc.

The coefficient β_k denotes the effect of Unilateral Divorce Law on Suicide Rate in each of the k years after the legislation changed, and $\sum_k \beta_k$ denotes the sum of the effects for all k. The coefficient η_s denotes the fixed effects of each of the s states, while $\sum_s \eta_s$ denotes the sum of all states effects. The coefficient λ_t denotes the fixed effects of each of the t years, while $\sum_t \lambda_t$ denotes the sum of all annual effects. Finally, $\varepsilon_{s,t}$ denotes the error term, which is consisted by the variation of Suicide rate that isn't explained by the variables included in the model.

Equivalently, the model below includes the same variables to estimate the change in Suicide Rate.

$$\begin{aligned} Homicide\,rate_{s,t} = \sum_k \beta_k Unilateral^k_{s,t} + \sum_s \eta_s State_s \\ + \sum_t \lambda_t Year_t + Controls_{s,t} + \varepsilon_{s,t} \end{aligned}$$

The main parameter of interest in the model is $\sum_k \beta_k$, which shows Diff-in-Diff estimator for the causal effect of Unilateral Divorce Law on Suicide and Homicide rates.

2 Pre-Analysis

2.1 Create a table of states and treatment dates.

Table 1: STATES AND TREATMENT DATES

Treatment		Control	
Year	State	Never treated	Pre treated
1969	Kansas	Arkansas	Louisiana
	South Carolina	Delaware	Maryland
1970	California	Mississippi	North Carolina
	Iowa	New York	Oklahoma
1971	Alabama	Tennessee	Utah
	Colorado		Vermont
	Florida		Virginia
	Idaho		West Virginia
	New Hampshire		
	New Jersey		
	North Dakota		
1972	Kentucky		
	Michigan		
	Nebraska		
1973	Arizona		
	Connecticut		
	Georgia		
	Indiana		
	Maine		
	Missouri		
	Nevada		
	New Mexico		
	Oregon		
	Washington		
1974	Minnesota		
	Ohio		
	Texas		
1975	Massachusetts		
	Montana		
1976	Rhode Island		
1977	District of Columbia		
	Wisconsin		
	Wyoming		
1980	Pennsylvania		
1984	Illinois		
1985	South Dakota		
	Total: 37	Total: 5	Total: 8

3 Empirical Work

3.1 First estimate a simple Diff-in-Diff model with a static post-treatment dummy variable for the ATT. To do this, regress Homicide rates (asmrh) and Suicide rates (asmrs) against a treatment dummy (post), state fixed effects, and year fixed effects.

Table 2

	Dependent variable:			
	Homicide Mortality		Suicide Mortality	
	(1)	(2)	(3)	(4)
Unilateral Divorce Law	−0.150	−0.172	−3.080	0.593
	(0.150)	(0.255)	(2.431)	(2.009)
State Fixed effects	Yes	Yes	Yes	Yes
Year Fixed effects	Yes	Yes	Yes	Yes
State Specific Time Trend		Yes		Yes
Observations	1,617	1,617	1,617	1,617
Adjusted R^2	0.784	0.805	0.685	0.775
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors clustered by State			

Columns 1 and 3 show the Diff-in-Diff estimator for the effect caused by Unilateral Divorce Law on female Homicide and Suicide, with year and state fixed effects. Columns 2 and 4 include state specific time trends.

3.2 What is the identifying assumption needed to estimate the variance weighted ATT when there is differential timing and using OLS? Test for the plausibility of this assumption in the pre-treatment period by estimating pre-treatment leads.

The main identifying assumption in a regular Diff-in-Diff research design is the parallel trends assumption. The table below illustrates why it is necessary. By decreasing the outcome after treatment from the outcome before treatment for a treated state, the difference (D1) is going to be the effect caused by the treatment (E) plus a trend (T). For a state that wasn't treated, the difference (D1) before and after treatment is the trend (T) only. So, if we assume that

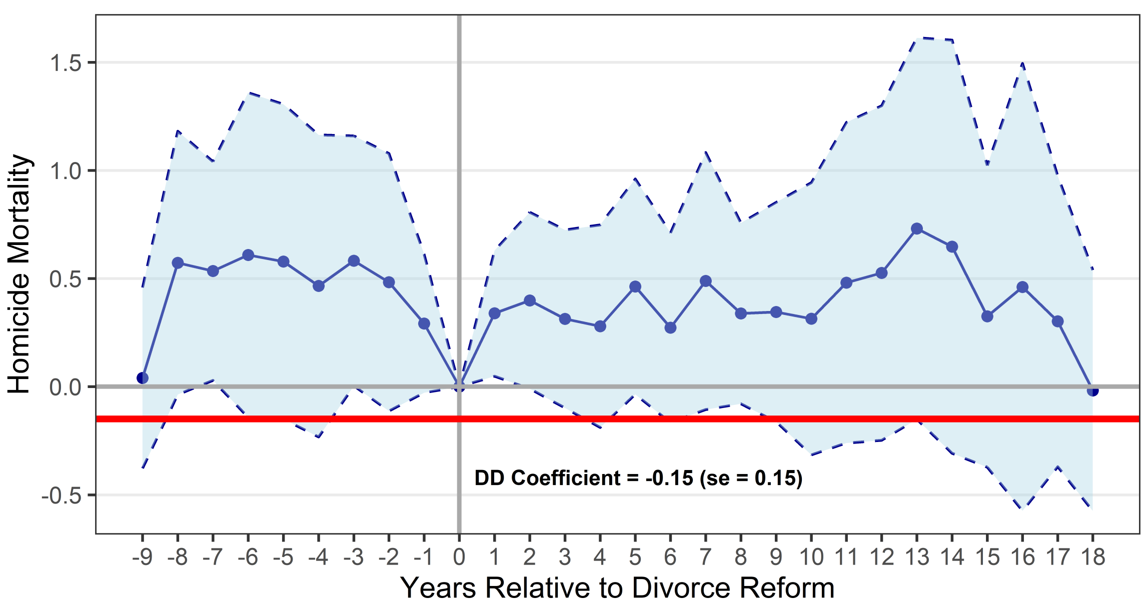
T is the same for both states, we can decrease T, that was measured from the control state, from T + E in order to isolate the causal effect E.

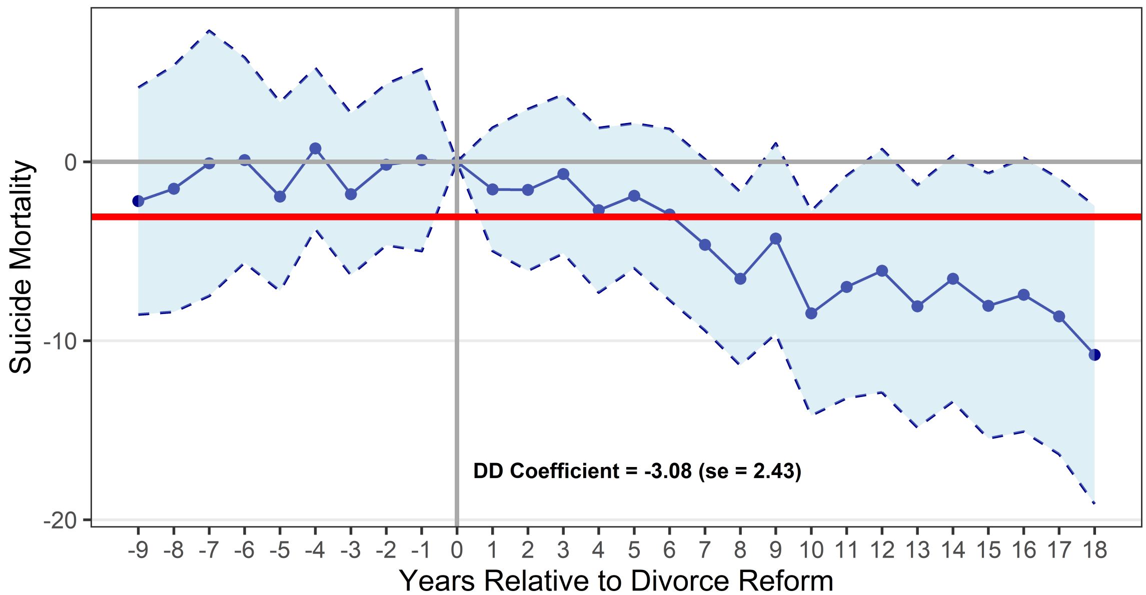
When dealing with differential timing and using OLS, the identifying assumption is a variance-weighted version of common trends between all groups (as long as treatment effects do not vary over time).

This assumption is not testable because we don't know what would've happened to the treatment state had it not been treated. What we can do is to test whether the trends were parallel before the treatment and argue that, if the assumption holds for the pre-treatment period, there might be no reason for it not hold in the post-treatment too.

State	**Time**	**Outcome**	**D1**	**D2**
Treated State	Before	Y = S_t	T + E	
	After	Y = S_t + T + E		
				E
Control State	Before	Y = S_c	T	
	After	Y = S_c + T		

The figures below illustrate the results of the test for the plausibility of this assumption in the pre-treatment for both the dependent variables. The coefficients to the left of the grey vertical line are the pre-treatment leads, would have to be 0 to support the parallel trends assumption. In both cases, the point estimates are close 0 to in the pre-treatment period, with 0 being in the confidence interval range except for lead 7 in Homicide Mortality.





3.3 Interpret the coefficients on the leads and lags. How convincing is it that the treatment units were not statistically different from the control units in the pre-treatment period?

The coefficients capture how the treatment group differs from the control group when controlling for multiple factors and when considering state and year fixed effects. Therefore, there should be less to be explained by the leads coefficients since the only difference should be the treatment itself, and it doesn't occur in the previous years. The lags coefficients would be the causal effect of the treatment in each of the years after the treatment.

As stated in the previous question the point estimates for the leads in both regressions are close 0 to in the pre-treatment period, with 0 being in the confidence interval range except for lead 7 in Homicide Mortality. A test of joint significance of the leads coefficients, as in Kearney and Levine (2015), fail to reject the null hypothesis that they are jointly equal to zero (p-value = 0.311 for Homicide; p-value = 0.775 for Suicide).

Table 3: Test of joint significance of leads coefficients

F-Test	Res.Df	Df	Chisq	Pr(>Chisq)
Leads = 0 (Homicide)	52.500	9.000	10.502	0.311
Leads = 0 (Suicide)	52.500	9.000	5.648	0.775

For the Homicide regression, we can observe that after the approval of Unilateral Divorce Laws, the lag coefficients turn out to be positive, but still close to 0, for all but the last period after the treatment. On the other hand, for the Suicide regression we can observe that all lags coefficients are negative, and show a downward slope trend.

3.4 Decompose the treatment effect into individual 2x2 diff-in-diff numbers. Plot the figure scattering the weights against their respective 2x2 numbers. Show that the DD coefficient you estimated using your regression is equal to the weighted average of all DD comparison groups.

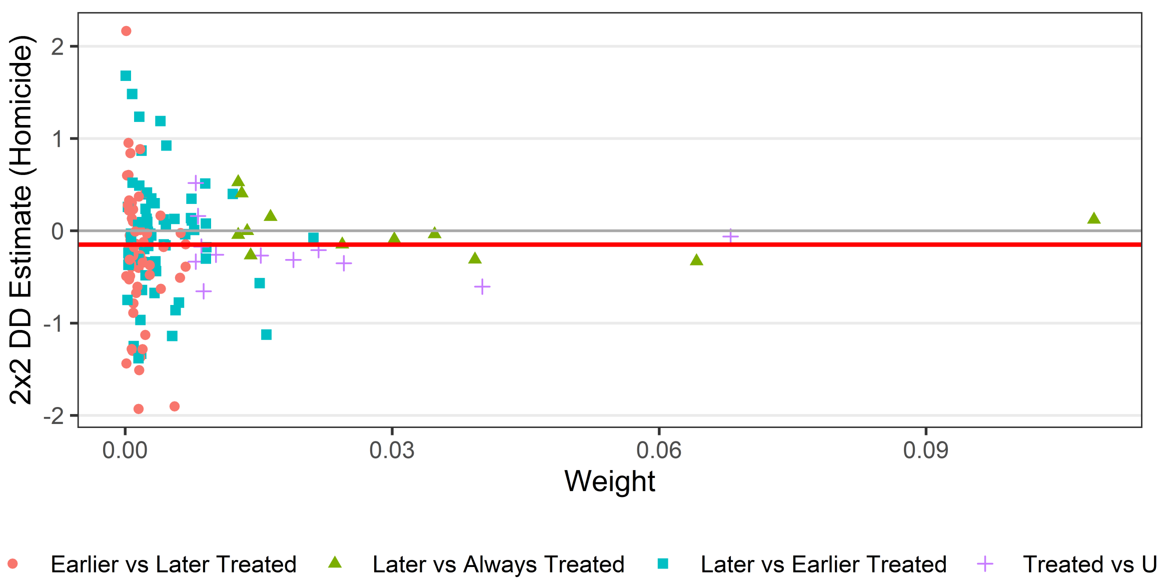


Table 4: DD Estimate Bacon Decomposition for Homicide

	Weigth	Avg. DD Estimate	DD Estimate
Earlier vs Later Treated	0.11	-0.38	-0.04
Later vs Always Treated	0.38	-0.05	-0.02
Later vs Earlier Treated	0.26	-0.12	-0.03
Treated vs Untreated	0.24	-0.24	-0.06
		Total	-0.15
		DD Estimate[1]	-0.15

Note: [1] From Table 2, Column (1)

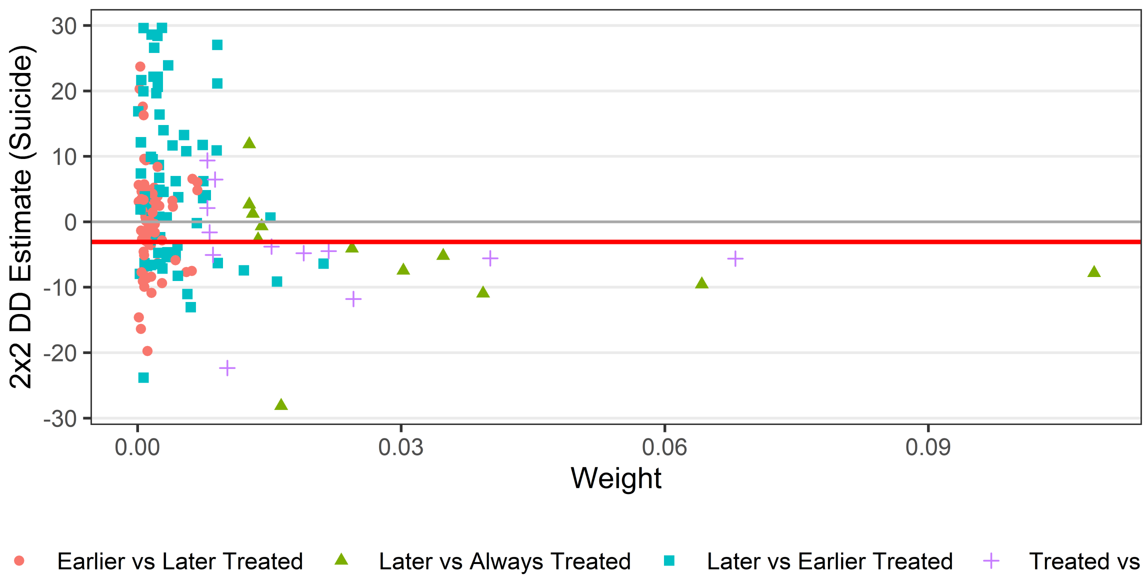


Table 5: DD Estimate Bacon Decomposition for Suicide

	Weigth	Avg. DD Estimate	DD Estimate
Earlier vs Later Treated	0.11	-0.19	-0.02
Later vs Always Treated	0.38	-7.04	-2.71
Later vs Earlier Treated	0.26	3.51	0.93
Treated vs Untreated	0.24	-5.33	-1.28
		Total	-3.08
		DD Estimate[1]	-3.08

Note: [1] From Table 2, Column (3)

From Tables 3 and 4, we can see that the Diff-in-Diff coefficient estimated in Table 2 is a weighted average of all Diff-in-Diff comparison groups.

3.4.1 Name two situations under which the static DD parameter is a biased estimate of the true ATT? Which one is testable and which one is not testable? How concerned should we be, and why?

There are two potential sources of bias when estimating a Diff-in-Diff parameter with variation in treatment timing: from variance weighted (non)common trends and from time-varying (heterogeneous) effects.

For the common trend, we can test whether it is present in the pre-treatment period, but can't test it in post-treatment period since it requires us to know what would've happened to the outcome had the state not been treated (which is counterfactual). Additionally, if we add up unequal trends it is possible that the differences end up being neutralized by the weights. Hence, it is a slightly weaker assumption then the regular parallel trends assumption.

For heterogeneity in time-varying effects, we can decompose the Diff-in-Diff estimator to check weights and values, which allows us to identify and correct possible sources of bias.

Since both situations can introduce bias to our estimator, we should be concerned about both of them. Given that the first will only be present in case of a violation of a slightly weaker assumption than the general parallel trends, it turns out that we shouldn't be more concerned than we already were before. The second one, as we saw in Table 4 and 5 above, adds an extra source of bias that we should be concerned with.