Table 1: DDD estimates of the impact of state mandates on hourly wages

Location/year	Before law change	After law change	Time difference for location
A. Treatment Individuals: Married Women, 20-40 Years Old:			
Experimental states	1.114605 (0.407177) [722]	1.323925 (0.4088345) [920]	0.20932
Nonexperimental states	1.028503 (0.3451536) [997]	1.253724 (0.3762843) [1,113]	0.181095
Location difference at a timepoint:	0.086102 (0.019)	0.070201 (0.017)	
Difference-in-difference:	-0.015901 (0.025)		

Codes are written in stata 14.1. It can be accessed here

After downloading the Current Population Survey data from the NBER website, I appended the datasets for 1974, 1975, 1977, 1978.

```
. use "cpsmay74.dta", clear
. append using "cpsmay75.dta"
. append using "cpsmay77.dta"
. append using "cpsmay78.dta"
```

Then I dropped irrelavant variables and kept age, state, marrital status, sex, year and wage (in cents). Since we will be using only 3 states as treatment (New York, New Jersey, Illinois) and 5 as control (Ohio, Indiana, Connecticut, Massachusetts, North Carolina), I have dropped all the other observations from other states.

```
. keep x9 x67 x68 x70 x200 x188
. keep if (x9 == 33 | x9 == 31 | x9 == 32 | x9 == 22 | x9 == 21
| x9 == 12 | x9 == 11 | x9 == 53)
```

Then I renamed the variables and dropped any unwanted observations such as age below 20 and over 40, males and unmarried people.

```
. rename x9 state
. rename x67 age
. rename x68 married
. rename x70 sex
```

```
. rename x200 year
. rename x188 wage
. drop if wage == -99
. keep if (age > 19 & age < 41)
. keep if sex==2
. drop if (married==4 | married==5)
```

Since the wages are in cents, I converted it into dollar and then generated a natural logarithmic variable of wages. I generated a experimental states (state_treat) variable and treatment year (yr_treat) variable.

```
. gen lnwage= ln(wage/100)
. gen state_treat = 0
. replace state_treat = 1 if (state == 21 | state == 22 | state == 33)
. gen yr_treat = 0
. replace yr_treat = 1 if (year == 1977 | year == 1978)
```

After this, generating diff-in-diff estimator is relatively straightforward.

```
. diff lnwage, treated(state_treat) period(yr_treat)
```

DIFFERENCE-IN-DIFFERENCES ESTIMATION RESULTS

Number of observations in the DIFF-IN-DIFF: 3752

	Before	After	
Control:	997	1113	2110
Treated:	722	920	1642
	1719	2033	

Outcome var.	lnwage	S. Err.	|t|	P>|t|
Before				
Control	1.029			
Treated	1.115			
Diff (T-C)	0.086	0.019	4.60	0.000***
After				
Control	1.254			
Treated	1.324			
Diff (T-C)	0.070	0.017	4.12	0.000***
Diff-in-Diff	-0.016	0.025	0.63	0.530

R-square: 0.08
* Means and Standard Errors are estimated by linear regression
**Inference: *** p<0.01; ** p<0.05; * p<0.1

```
. sum lnwage if (state_treat == 1 & yr_treat == 0)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
lnwage	722	1.114605	.407177	-.6931472	3.135494

```
. sum lnwage if (state_treat == 1 & yr_treat == 1)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
lnwage	920	1.323925	.4088345	-.6931472	3.518981

```
. sum lnwage if (state_treat == 0 & yr_treat == 0)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
lnwage	997	1.028503	.3451536	-.2876821	3.218876

```
. sum lnwage if (state_treat == 0 & yr_treat == 1)
```

Variable	Obs	Mean	Std. Dev.	Min	Max
lnwage	1,113	1.253724	.3762843	-1.203973	2.70805

The values used in the table 3 are shown in blue square in the results. If we compare it with the Gruber (1994) results, we can see that observations and the DiD are less than the original. However the DiD result is still negative.

Why is this an important research question to study?

In recent decades there has been an increase in the implementation of different mandated benefits to incentivize employment. These kinds of social policies are both politically attractive and efficient in some cases. Public financing might result in a large deadweight loss, which can be avoided if the benefits are mandated. However, in some cases where it is easier for the employer to demographically identify a certain group of people, (in this paper, it is married women of age group 20-40) the efficiency of these policies are dependent on how much the costs are shifted in their group-specific-wage. Also, it is important to figure out if these kinds of mandated benefits lead to any perverse incentives or not.

What is the identification strategy? What are the identifying assumptions? What evidence is provided to support the identifying assumptions? What are the strengths and weakness of the empirical approach?

This paper uses difference-in-difference-in-difference (DDD) design to find the causal effect of treatment (mandated maternity benefits in certain states) on outcome (shifting of costs to the targeted group, captured by the lower wages). The identifying assumption required in this design is *no contemporaneous shock* which will impact the relative outcomes of the treatment group. Using this methodology, this paper will be able to tell whether there is a shift of the cost to the employees and if not, then either the employees have problems evaluating the benefits or there is wage rigidity. This paper focuses on the efficiency part of the mandated benefits, but ignores the equity considerations; whether these benefits are there as a redistributive policy or not.

What can you learn about current policy questions by studying the effect of this mandate? What limitations are there to applying these findings to other settings?

Because the wages of the targeted group were allowed to correspond to the value placed on these benefits, it is possible that group-specific mandates do not alter the relative cost of employing the targeted group of workers, which helps us to use the mandates as a policy tool. However, there are some caveats to that approach. We have to evaluate whether the goals of policies that are implemented addresses the problem (market failure) that they are designed for. In some cases this may lead to moral hazard (excessive use of medical services) and in some cases it may undo some other policy or social outcome (reduction in the employment). If there are information delays regarding identifying the demographically identifiable group, then this may delay the original outcome, without changing the overall scenario (Ban the box law).