

STATA Exercise 2: The effect of limiting employment at will: applying a difference-in-difference estimator

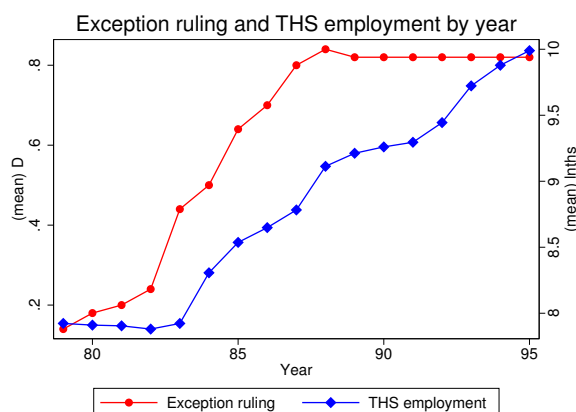
SUGGESTED ANSWERS

March 20, 2019

1. Initial descriptive statistics:

- (a) The data set includes observations for 50 states for the years 1979 - 1995. In total there are 850 records in the data set.
- (b) Figure 1 displays log THS employment and the fraction of states with exception rulings against year.

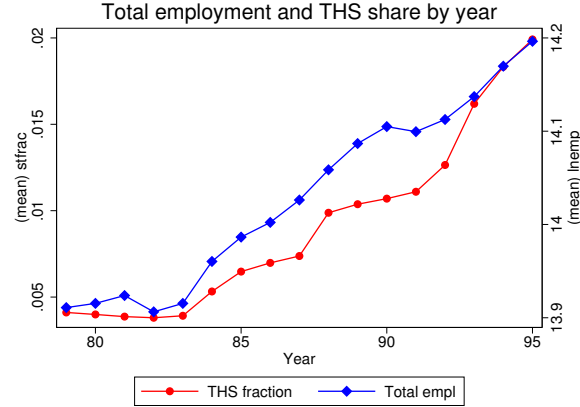
Figure 1: log THS employment and the fraction of states with exception rulings against year



The figure shows that exception rulings increased gradually starting in 1983. The fraction of states with exception ruling reached its maximum by 1988 where approximately 80 percent of all states had exception rulings. The blue line show log THS employment. THS employment increased starting in 1984 and continued to increase throughout the observation period. The THS employment increase appears with a lag relative to the exception rulings.

- (c) Figure 2 plots log total employment and log THS fraction out of total employment against year

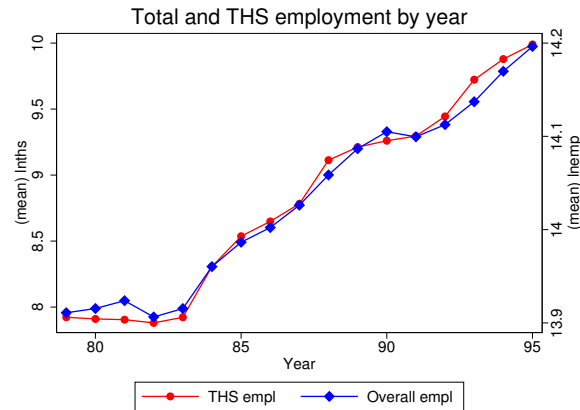
Figure 2: log total employment and log THS employment fraction against year against year



The figure illustrates that both total employment and the THS share are increasing over the period considered. Also here the THS employment share appears to increase with a lag relative to total employment, and it is thus not clear how the exception ruling rate drives THS employment.

(d) Figure 3 plots log THS and log total employment against year

Figure 3: log total employment and log THS employment against year against year



This figure shows that the log employment in the THS industry is very closely correlated with overall employment over the period considered.

(e) Based on the numbers presented in Figure 1-3 it is clear that THS employment has grown in the same period as the exception rulings appeared across US states. However, there is a very close connection between THS employment and total employment, both of which increased in the same period as the exception rulings swept across the country. It is therefore not possible to

conclude based on the graphical evidence whether exception rulings has caused THS employments.

2. Estimation of the basic Differences-in Differences model. The task is to estimate different versions of the following model

$$lnths_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 lnemp_{it} + \mu_i + \lambda_t + (\mu_i \times \tau) + u_{it} \quad (1)$$

where $lnths$ is the log of total number of workers on THS payrolls and $lnemp$ is the log of total employment in each state in each year. μ_i is a state fixed effect, λ_t is a vector of year dummies, τ is a time trend, and so $\mu_i \times \tau$ are state specific time trends.

- (a) First, we estimate a simple version of the model that does not include the terms $\mu_i, \lambda_t, (\mu_i \times \tau)$. The result is in column 1 of Table 1, and it shows that the effect of introducing an exception ruling is to increase THS employment by 64 percent. However, the regression does not include any of the fixed effects.
- (b) In column 2 of Table 1 the previous regression is repeated while controlling for year fixed effects. Including year FEs changes the parameter estimate of interest dramatically to -0.0402. The standard error is also reduced, but the estimate of β_1 is insignificant in spite of this. In column 3 state fixed effects are included and this reverses back the sign of the estimate of β_1 and reduces the standard error further, but the estimate is still not significantly different from zero. Finally, in column 4 $state \times year$, i.e. state specific trends, are included, and this reduces the standard error further, so that β_1 is now significant. This result suggests that having an exception ruling increases THS employment by about 15 percent. Including $\mu_i, \lambda_t, (\mu_i \times \tau)$ is thus critical for obtaining this result.

Table 1: Results from estimating equation 1 with different sets of control variables

| VARIABLES | (1) OLS | (2) OLS | (3) OLS | (4) OLS |
|---------------|-------------------------|-------------------------|-------------------------|------------------------|
| D | 0.5411*** (0.1439) | -0.0402 (0.1363) | 0.1280 (0.0915) | 0.1451** (0.0584) |
| lnemp | 1.4889*** (0.0789) | 1.4438*** (0.0676) | 2.0137*** (0.4366) | 1.4999*** (0.4272) |
| Constant | -12.4132*** (1.1996) | -12.1563*** (1.0068) | -19.5900*** (5.6487) | -13.3255** (5.5256) |
| Observations | 850 | 850 | 850 | 850 |
| R-squared | 0.8208 | 0.9136 | 0.9727 | 0.9885 |
| State FE | NO | NO | YES | YES |
| Year FE | NO | YES | YES | YES |
| StateXyear | NO | NO | NO | YES |
| Clustered err | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3. On the importance of clustered errors. In Table 2 the regression from Table 1, column 4 is repeated while calculating different types of standard errors: OLS, robust errors, and errors clustered at the state level. The table reveals how important the choice of standard errors is. Standard errors almost double going from OLS to clustered errors. In particular, it is the step where moving from robust errors to clustered errors that increases the standard errors. This suggests that it is important to take into account within-state autocorrelation of the error terms.

Table 2: Results from estimating equation 2 with different types of standard errors

| VARIABLES | (1) OLS | (2) OLS | (3) OLS |
|--------------|-------------------------|-------------------------|------------------------|
| D | 0.1451*** (0.0340) | 0.1451*** (0.0344) | 0.1451** (0.0584) |
| lnemp | 1.4999*** (0.2162) | 1.4999*** (0.2745) | 1.4999*** (0.4272) |
| Constant | -13.3255*** (2.8058) | -13.3255*** (3.5598) | -13.3255** (5.5256) |
| Observations | 850 | 850 | 850 |
| R-squared | 0.9885 | 0.9885 | 0.9885 |
| State FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| StateXyear | YES | YES | YES |
| Errors | Simple | Robust | Cluster |

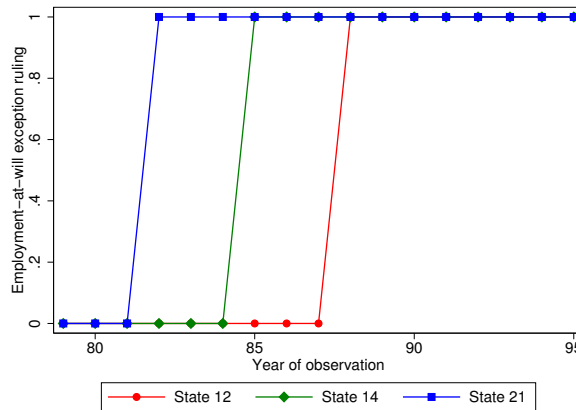
Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4. Event study.

- (a) David Autor emphasizes that law changes are discrete, and that the timing of the law changes is in part unanticipated. These two features may generate discontinuous impacts on THS employment. This motivates an event analysis. Figure 4 illustrates the discreteness of the exception rulings in the data by plotting D_{it} against year for state number 12, 16, and 21.

Figure 4: D_{it} against year for state number 12, 16, and 21



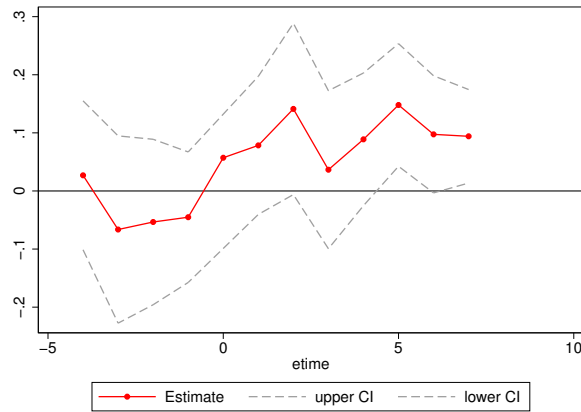
- (b) In order to conduct the event study a set of event dummies are created in order to estimate the following model

$$\ln ths_{it} = \beta_0 + \beta_1 \ln emp_{it} + \sum_k D_{it}^k \delta_k + \mu_i + \lambda_t + \mu_i \times \lambda_t + u_{it}$$

where μ_i is a fixed effect, λ_t is a (calendar) time effect, and D_{it}^k is a dummy variable taking the value 1 if treatment took place k periods ago, so that δ_k measures the effect k periods after treatment. The event analysis is to be conducted for the period from four periods before treatment and until seven periods after. $k = -4, \dots, -1$ are thus the four periods before treatment took place and $k = 1, \dots, 7$ the seven periods following treatment.

Figure 5 presents the estimated parameters from an event study regression together with state-clustered standard errors.

Figure 5: Estimated effects around the time of the exception ruling



The estimated parameters presented in the graph suggest that there is no effect before the exception rulings and there appears to be an increase in THS employment after the ruling has taken place. However, the effect is small and the estimated effects vary a lot. For example, in period 2 after the ruling there appears to be an effect of about 14 percent, but for the period after the effect is estimated to be only 4 percent. In other words, the effect is estimated very imprecisely and is only significantly different from zero in year 5 after the law change. The pre-law effect is never significantly different from zero

- (c) In order to test formally whether the pre-ruling parameters are jointly insignificant we test the following hypothesis $H_0 : \delta_{-4} = \delta_{-3} = \delta_{-2} = \delta_{-1} = 0$ against $H_1 : \delta_{-4} \neq 0 \vee \delta_{-3} \neq 0 \vee \delta_{-2} \neq 0 \vee \delta_{-1} \neq 0$ by applying a cluster robust F (or Wald) test. The test statistic is 0.68. It is $F(4, 49)$ distributed and the null hypothesis cannot be rejected at the 5% level. We thus conclude that the pre-ruling trends among the treated and the untreated are parallel.
- (d) In order to test whether there is an effect of an exception ruling on THS employment we test hypothesis $H_0 : \delta_1 = \delta_2 = \dots = \delta_7 = 0$ against $H_1 : \delta_1 \neq$

$0 \vee \delta_2 \neq 0 \vee \dots \vee \delta_7 \neq 0$ by applying a cluster robust F (or Wald) test. The test statistic is 1.99. It is $F(7, 49)$ distributed. The null hypothesis is rejected at the 7.6% level. This means that the post exception ruling dummies are jointly borderline significant. The event analysis does hence not deliver a clear conclusion.

5. The overall conclusion is that the data does not give a clear indication about the effect of the exceptions. When estimating a simple static model there is some evidence, but when estimating a full-blown event model the effect is only borderline significant. The results depend a lot on the specification of the error structure and on the modelling of the effects (dynamic vs static) and the effects are never very precisely estimated. The evidence is thus too weak to conclude anything decisively about the effect of employment-at-will-exceptions