

Replicating Card and Krueger's Minimum Wages and Employment study on R

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Abstract

In this report we replicate the study by Card and Krueger (1994) on the impact of a minimum wage increase on employment in the fast-food industry. The original study exploited the 1992 policy change in New Jersey, where the minimum wage rose from \$4.25 to \$5.05 per hour. Pennsylvania, which kept its minimum wage constant, is used as a control group. Using survey data from 410 fast-food restaurants (Burger King, KFC, Roy Roger's, Wendy's), Card and Krueger found that the minimum wage increase did not reduce employment.

Here's the [Colab notebook](#) with the R code.

Data and methodology

We used the original dataset (downloaded from https://davidcard.berkeley.edu/data_sets.html), which contains 410 observations on 47 variables. The statistical unit is a fast-food restaurant. The dependent variable is employment measured in full-time equivalent employees (FTE). Following Card and Krueger's approach, we calculated FTE as:

$$\text{FTE} = \text{Full time employees} + \text{Managers} + 0.5 \cdot \text{Part-time employees}$$

This conversion allows comparability across restaurants with different mixes of full-time and part-time staff. We constructed two separate measures of full-time equivalent employment (FTE): one before and one after the minimum wage increase. We then computed the change in employment (ΔFTE) as the difference between post- and pre-treatment FTE for each restaurant, which provides a direct measure of how employment evolved following the policy.

$$\Delta\text{FTE}_i = \text{FTE}_i^{\text{after}} - \text{FTE}_i^{\text{before}}$$

We then applied a difference-in-differences (DiD) estimation to compare the change in employment between New Jersey (the treated group) and Pennsylvania (the control group) before and after the policy. This allowed us to isolate the causal effect of the minimum wage increase on employment levels.

$$\text{DiD} = \Delta X - \Delta Y, \quad \Delta X = X_1 - X_0, \quad \Delta Y = Y_1 - Y_0$$

Where X is the average FTE in New Jersey and Y the average FTE in Pennsylvania, 1 indicates the second wave (November 1992) and 0 the first (February 1992). To assess whether the difference-in-differences results indicated any negative impact of the minimum wage increase on employment, we complemented the analysis with t-tests comparing mean FTE levels before and after the policy.

In addition, we estimated several regression models, replicating those by Card and Krueger, to test the robustness of the DiD results and to verify whether the observed changes in employment were statistically significant.

Graphical Analysis

First, let's look at the data. We produced a series of graphical analyses that allowed us to inspect the distribution of employment levels and compare pre- and post-treatment differences across states.

Figure 1 shows how the distribution of starting wage changed between February and November 1992. This is our replica of figure 1 in Card and Krueger's paper.

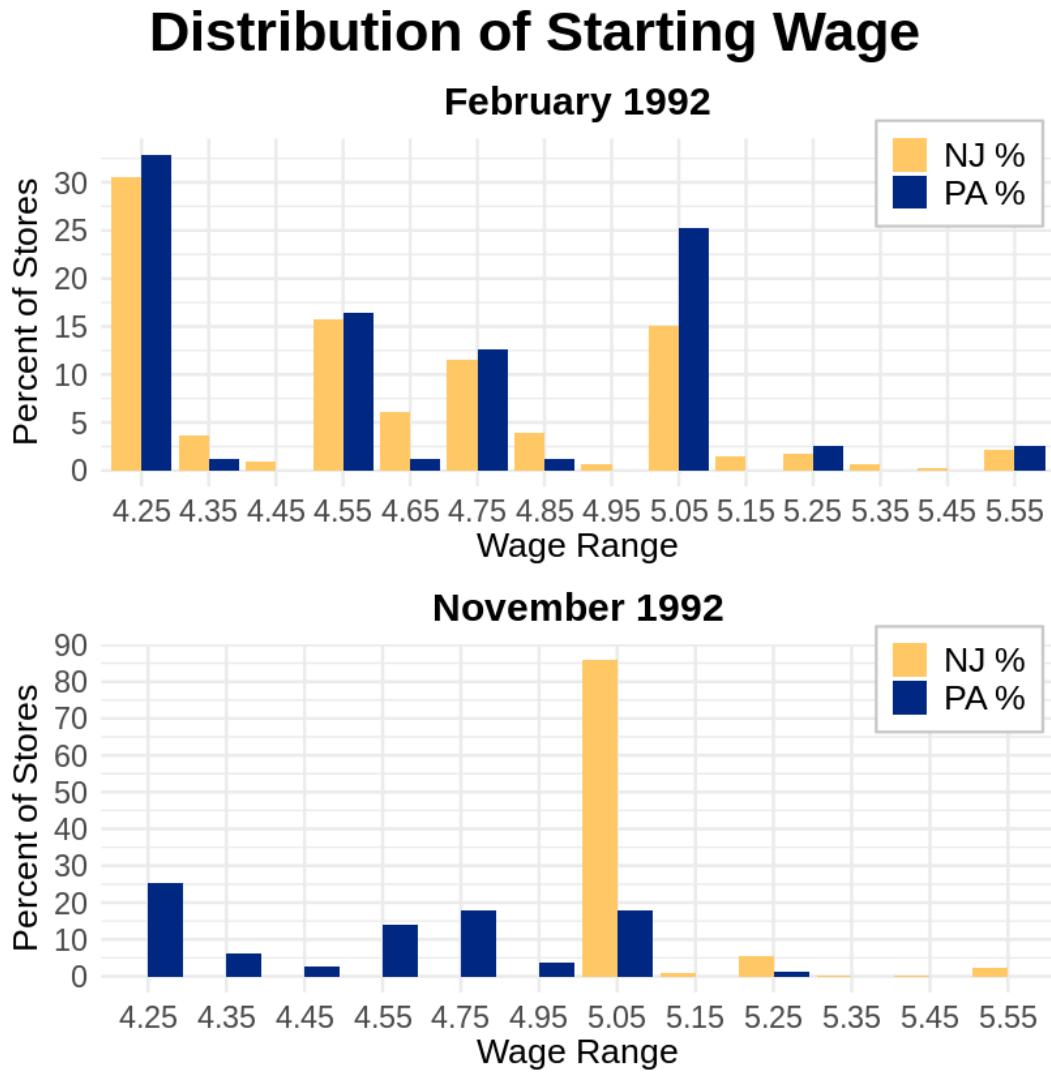


Figure 1 - Starting Wage distribution, by state.

The barplot illustrates a clear upward shift in the wage distribution among New Jersey fast-food restaurants, reflecting compliance with the new minimum wage law. In contrast, the distribution for Pennsylvania remains largely unchanged, as the minimum wage there did not increase during the same period.

Figure 2 is a scatter plot comparing employment levels before (FTE1) and after (FTE2) the minimum wage increase for each restaurant. The 45-degree line indicates no change in employment between the two periods. Figure 3 displays a boxplot of the change in full-time equivalent employment (ΔFTE) by state and fast-food chain.

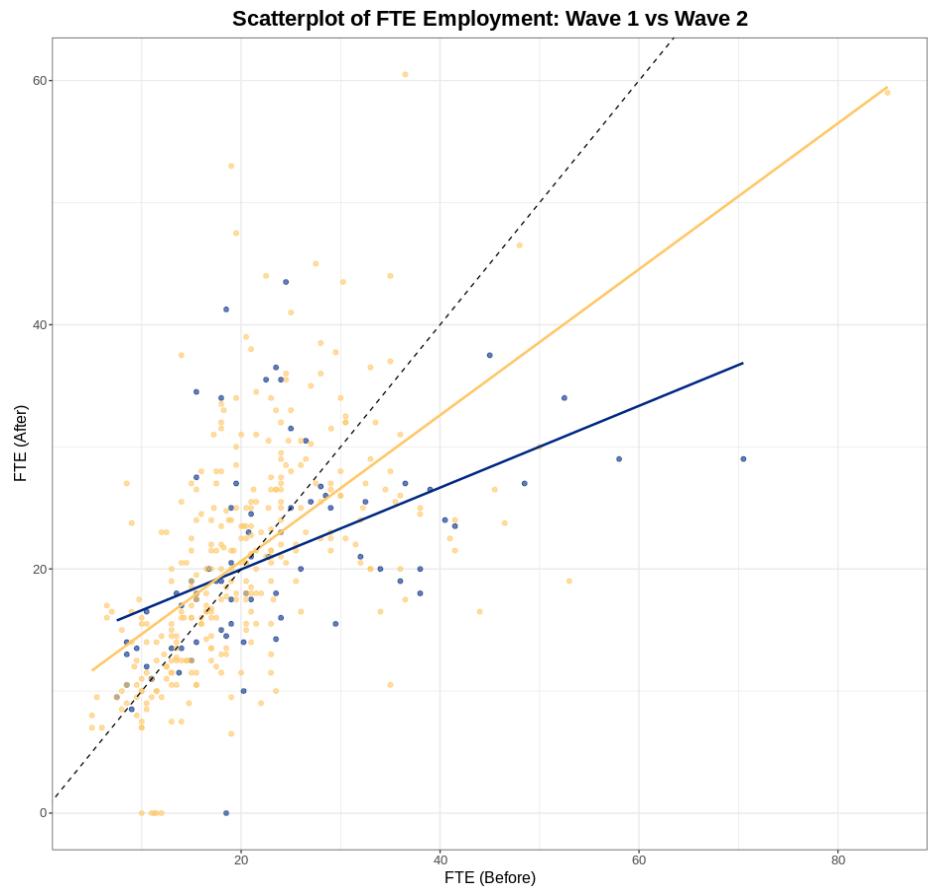


Figure 2 - Scatterplot FTE before vs after.

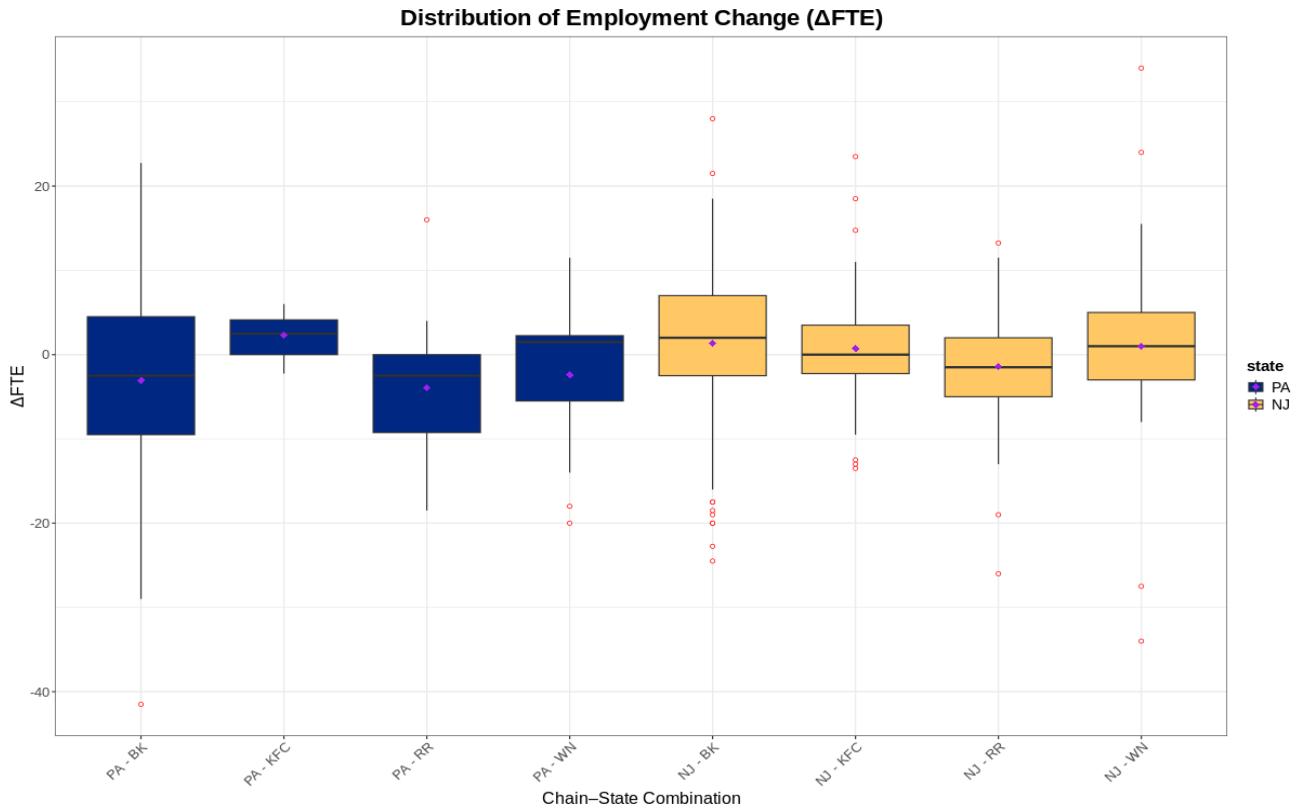


Figure 3 - Boxplot of ΔFTE by chain and state.

We computed the mean, median, and standard deviation of the FTE distributions for each state and period.

Table: FTE Before Wage Increase

State	mean	median	sd	State	mean	median	sd
PA	23.33117	20.50	11.856283	PA	21.16558	20.0	8.276732
NJ	20.43941	19.25	9.106239	NJ	21.02743	20.5	9.293024

Table: FTE After Wage Increase

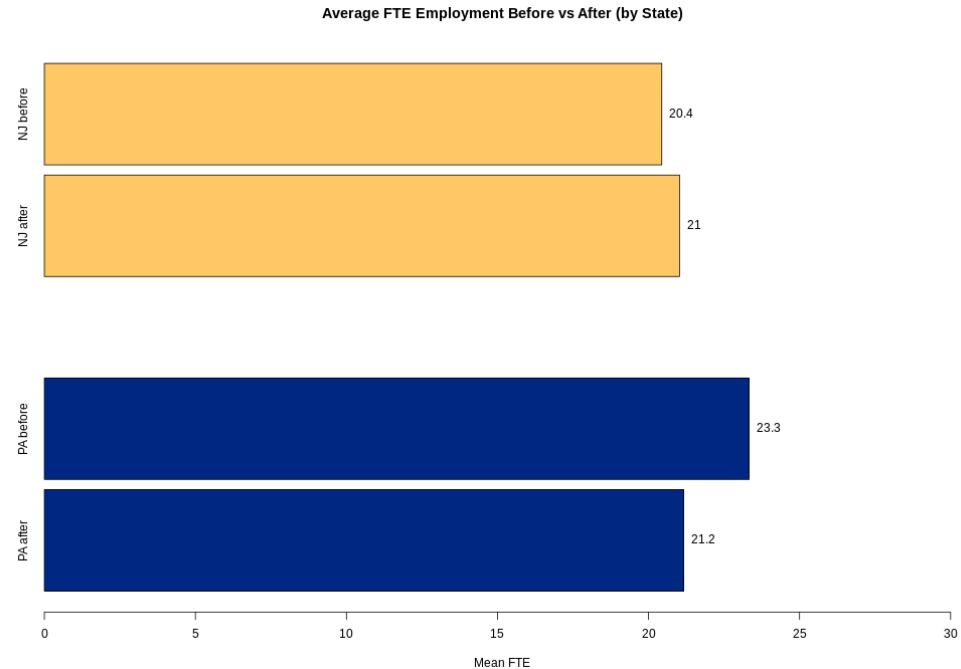


Figure 4 - Barplots of FTE mean distribution.

Figure 4 is a barplot of the average FTE for each state before and after the policy. To visualize the distribution of FTE across the states we also show a histogram in Figure 5.

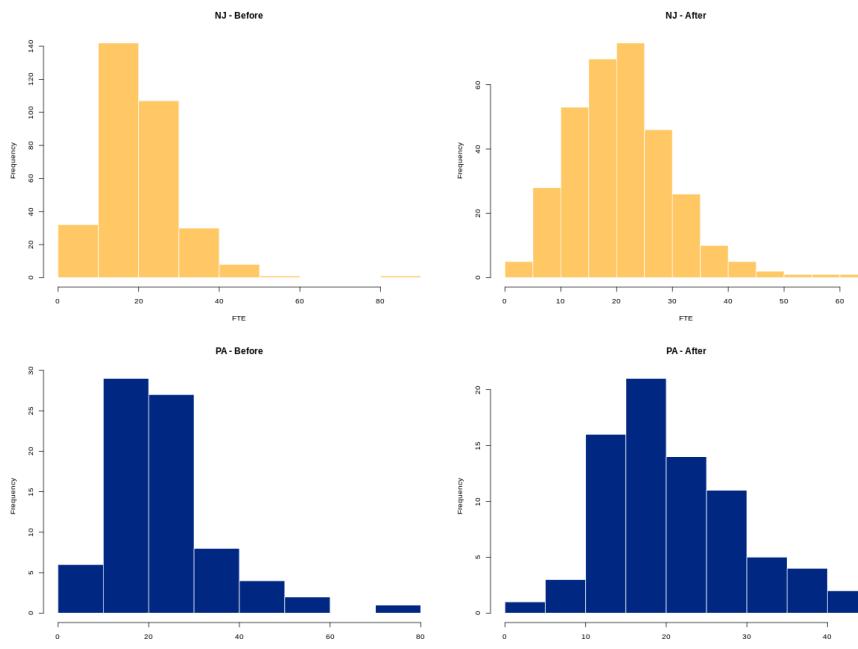


Figure 5 - Histograms of FTE distribution.

Price of a full meal: analysis

We investigated whether the increase caused inflation in full meal prices. We analyzed the percentage change in price for each restaurant and state and constructed the variable aggregating `df$pricefm = df$psoda+df$pfry+df$pentree`, for each survey wave. Figure 6 compares the increase of a full price meal across the two waves:

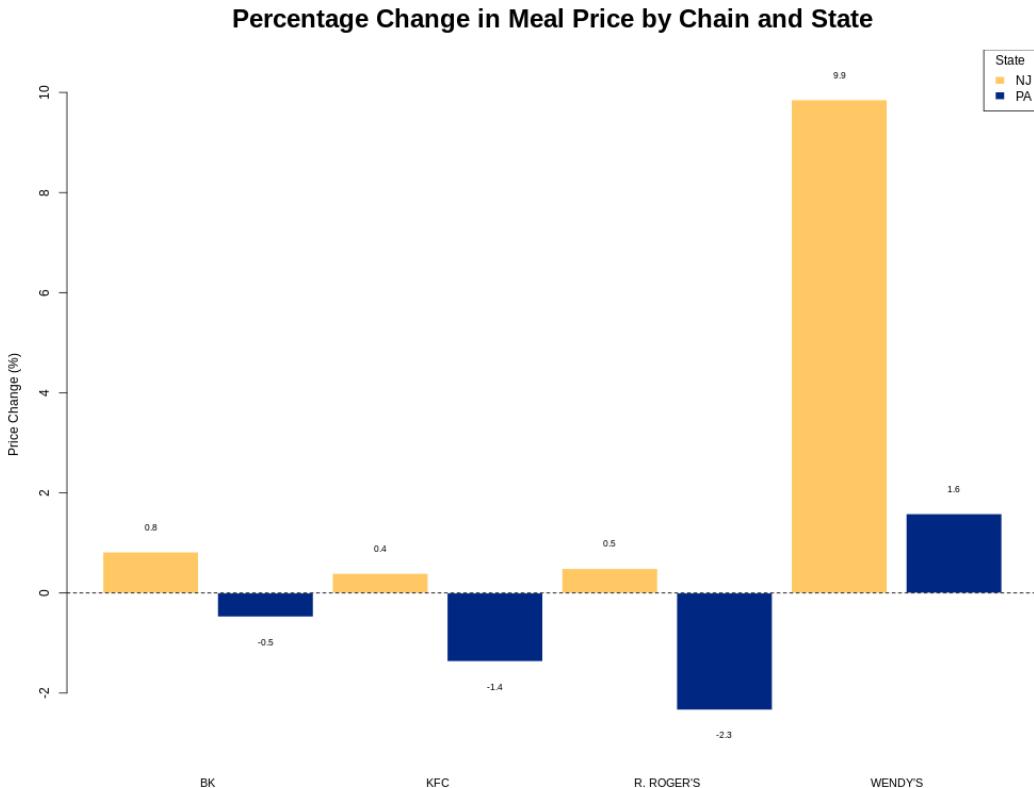


Figure 6 - Barplot of a full meal percentage change.

To assess whether the observed price increase is statistically significant, we conducted both a regression and a t-test. The regression model relates the percentage change in full meal price to a New Jersey dummy variable:

$$\Delta \text{price}_i = \beta_0 + \beta_1 I(\text{NJ}_i) + \varepsilon_i,$$

Call:

```
lm(formula = perch ~ I(state == "NJ"), data = tab)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.4967	-2.1521	-1.2020	0.6871	6.9651

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.6493	1.7458	-0.372	0.723
I(state == "NJ")TRUE	3.5359	2.4690	1.432	0.202

Residual standard error: 3.492 on 6 degrees of freedom

Multiple R-squared: 0.2548, Adjusted R-squared: 0.1306

F-statistic: 2.051 on 1 and 6 DF, p-value: 0.2021

The regression results indicate a high p-value for the New Jersey dummy, suggesting that the observed difference in full meal price changes between New Jersey and Pennsylvania is not statistically significant.

Welch Two Sample t-test

```
data: perch by state
t = 1.4322, df = 3.7622, p-value = 0.1148
alternative hypothesis: true difference in means between group NJ and group PA is
greater than 0
95 percent confidence interval:
-1.824577      Inf
sample estimates:
mean in group NJ mean in group PA
2.8866257     -0.6493124
```

The one-sided t-test, with the alternative hypothesis that New Jersey experienced a greater increase in full meal prices than Pennsylvania, yielded a p-value of 0.11. Since this p-value exceeds the 0.05 significance level, we fail to reject the null hypothesis, indicating that there is not enough evidence that the minimum wage increase led to higher prices in New Jersey relative to Pennsylvania.

Difference-in-Differences estimation

We aim to test whether the difference-in-differences in full-time equivalent employment (FTE) between New Jersey and Pennsylvania is equal to zero, against the alternative hypothesis that the change in New Jersey is less than in Pennsylvania. Formally:

$$H_0 : \Delta FTE_{NJ} - \Delta FTE_{PA} = 0 \quad \text{vs.} \quad H_1 : \Delta FTE_{NJ} - \Delta FTE_{PA} < 0$$

We performed a one-sided t-test comparing the average change between the two states. Both versions of the t-test were used: one assuming equal (pooled) variances across states, and another allowing for unequal variances, to ensure robustness of the results.

```
data: delta_nj and delta_pa
t = 2.0487, df = 96.884, p-value = 0.9784
alternative hypothesis: true difference in means is less than 0
95 percent confidence interval:
-Inf 4.979271
sample estimates:
mean of x mean of y
0.4666667 -2.2833333

Two Sample t-test

data: delta_nj and delta_pa
t = 2.3823, df = 382, p-value = 0.9912
alternative hypothesis: true difference in means is less than 0
95 percent confidence interval:
-Inf 4.653362
sample estimates:
mean of x mean of y
0.4666667 -2.2833333
```

The p-values from both versions of the one-sided t-test are very high, indicating no statistically significant difference in the change of FTE between New Jersey and Pennsylvania. The evidence does not support the hypothesis that the minimum wage increase led to a reduction in employment in New Jersey relative to the control state.

In addition to the t-tests, we also used the normal approximation to compute p-values for the difference in FTE changes. All approaches—t-tests assuming equal and unequal variances, as well as the normal approximation—produced consistently high p-values.¹

```
Two-sided p-value (t): 0.0377697
Two-sided p-value (normal approx): 0.0353057

One-sided p-value H1: DiD < 0 (t): 0.981115
One-sided p-value H1: DiD < 0 (normal approx): 0.982347

One-sided p-value H1: DiD > 0 (t): 0.0188849
One-sided p-value H1: DiD > 0 (normal approx): 0.0176529
```

Finally, we compared these results with the t-test obtained from regressing ΔFTE on the state dummy, testing whether the coefficient β_1 is significantly different from zero.

```
Call:
lm(formula = (fte_after - fte_before) ~ state, data = data2)

Residuals:
    Min      1Q  Median      3Q     Max 
-39.373 -3.873  0.551  4.301 27.801 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -2.127     1.074  -1.980  0.0484 *  
state1       2.326     1.192   1.952  0.0517 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.791 on 355 degrees of freedom
Multiple R-squared:  0.01062, Adjusted R-squared:  0.007831 
F-statistic: 3.81 on 1 and 355 DF,  p-value: 0.05174
```

The t-tests from the regression yield results similar to those obtained from the previous one-sided and two-sided t-tests, reinforcing the conclusion that there is no statistically significant difference in ΔFTE between New Jersey and Pennsylvania.

We summarized the results of all tests in a single table, including the type of test (Welch t-test, pooled t-test, normal approximation, and regression), the corresponding t-values, degrees of freedom, and p-values.

¹The p-values reported in the table differ slightly from those of the t-tests because the t-tests were computed using R's `t.test()` function, while the table reports p-values were calculated manually based on the sample statistics. The difference arises from minor variations in the computation methods.

Test	t value	df	p-value
Welch	2.105	101.7	0.038
Pooled	2.451	408.0	0.015
Normal	2.105	Inf	0.035
Regression	1.952	355.0	0.052

Introducing the GAP variable

We introduced the GAP variable to measure the relative wage shortfall before the minimum wage increase.

$$GAP_i = \begin{cases} \frac{5.05 - wage_st_i}{wage_st_i} & \text{if store in NJ and } wage_st_i \leq 5.05, \\ 0 & \text{otherwise} \end{cases}$$

By definition, gap variable is greater than zero only in New Jersey restaurants that had a starting wage lower than \$5.05 in February 1992.

Was there the GAP?

	FALSE	TRUE
PA	79	0
NJ	45	286

Gap variable has distribution:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.00000	0.00000	0.06316	0.08036	0.16092	0.18824

We see that the gap is 8% on average with values up to 19%. Figure 7 is a scatterplot of this gap variable against ΔFTE . The red line indicates the average.

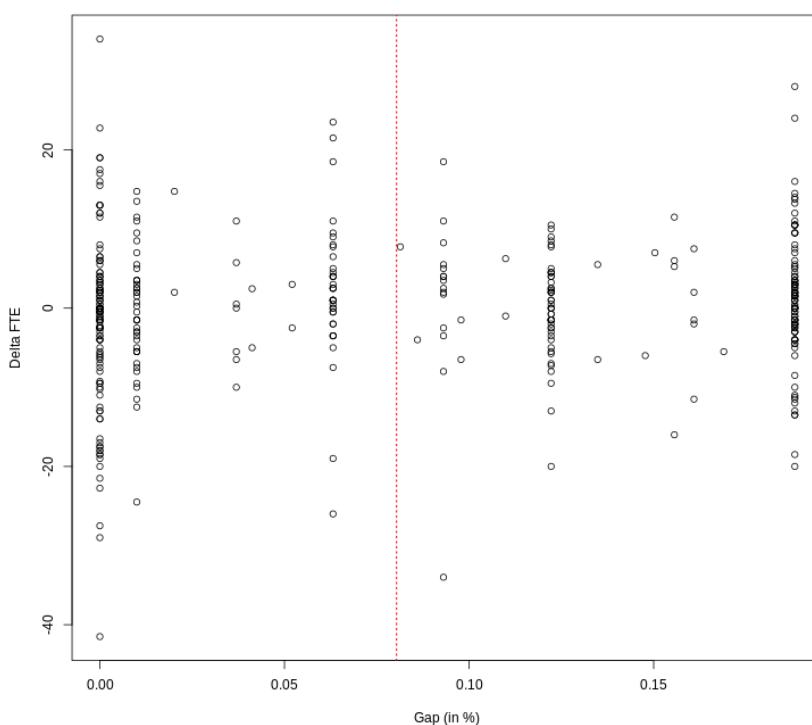


Figure 7 - Scatterplot of the gap variable.

Regression Models

We tried to replicate the results of the table below by replicating the five models proposed by Card and Krueger. We wrote down the formulas:

$$\text{Model 1: } \Delta FTE_i = \beta_0 + \beta_1 \times I(NJ)_i + \varepsilon_i$$

$$\text{Model 2: } \Delta FTE_i = \beta_0 + \beta_1 \times I(NJ)_i + \sum_{k=1}^{K-1} \beta_{2k} \times I(CH_{k,i}) + \gamma \times I(OWN)_i + \varepsilon_i$$

$$\text{Model 3: } \Delta FTE_i = \beta_0 + \beta_1 \times GAP_i + \varepsilon_i$$

$$\text{Model 4: } \Delta FTE_i = \beta_0 + \beta_1 \times GAP_i + \sum_{k=1}^{K-1} \beta_{2k} \times I(CH_{k,i}) + \gamma \times I(OWN)_i + \varepsilon_i$$

$$\text{Model 5: } \Delta FTE_i = \beta_0 + \beta_1 \times GAP_i + \sum_{k=1}^{K-1} \beta_{2k} \times I(CH_{k,i}) + \sum_{r=1}^{R-1} \beta_{3r} \times I(REG_{r,i}) + \gamma \times I(OWN)_i + \varepsilon_i$$

and we see that we have already run the first model. We also see that we need to build the Region factor for model 5. Here's the R code:

```
data2$region[data2$state == 1 & data2$northj == 1] <- "North_NJ"
data2$region[data2$state == 1 & data2$centralj == 1] <- "Central_NJ"
data2$region[data2$state == 1 & data2$southj == 1] <- "South_NJ"
data2$region[data2$state == 1 & data2$shore == 1] <- "Shore_NJ"

data2$region[data2$state == 0 & data2$pa1 == 1] <- "North_PA"
data2$region[data2$state == 0 & data2$pa2 == 1] <- "South_PA"

region <- factor(data2$region)
```

In model 2, we regress on the state dummy plus control variables for the chains (1,2,3) and co_owned factor.

```
Call:
lm(formula = (fte_after - fte_before) ~ state + contr_bk + contr_kfc +
contr_roys + co_owned, data = data2)

Residuals:
    Min      1Q  Median      3Q     Max 
-39.803 -3.903  0.606  4.106  27.393 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -2.209      1.613   -1.369   0.1717    
state1       2.304      1.196    1.927   0.0548 .  
contr_bk      0.512      1.498    0.342   0.7328    
contr_kfc     1.004      1.686    0.595   0.5519    
contr_roys   -1.705      1.682   -1.014   0.3114    
co_owned      0.308      1.094    0.282   0.7785    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.785 on 351 degrees of freedom
Multiple R-squared:  0.02315,    Adjusted R-squared:  0.009231 
F-statistic: 1.663 on 5 and 351 DF,  p-value: 0.1427
```

In model 3 we regress only on the gap variable.

```
Call:  
lm(formula = (fte_after - fte_before) ~ gapp, data = data2)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-39.924 -3.870   0.380   4.588  26.630  
  
Coefficients:  
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -1.5764    0.6966  -2.263   0.0242 *  
gapp         15.6529    6.0802   2.574   0.0104 *  
---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1  
  
Residual standard error: 8.757 on 355 degrees of freedom  
Multiple R-squared:  0.01833, Adjusted R-squared:  0.01556  
F-statistic: 6.627 on 1 and 355 DF, p-value: 0.01045
```

In model 4 we regress on gap variable plus controls for chain and co_owned.

```
Call:  
lm(formula = (fte_after - fte_before) ~ gapp + contr_bk + contr_kfc +  
    contr_roys + co_owned, data = data2)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-40.185 -4.152   0.268   4.373  26.507  
  
Coefficients:  
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -1.30141   1.37389  -0.947   0.3442  
gapp         14.91567   6.20533   2.404   0.0167 *  
contr_bk     -0.01362   1.51518  -0.009   0.9928  
contr_kfc     0.64534   1.69594   0.381   0.7038  
contr_roys   -1.92582   1.68287  -1.144   0.2532  
co_owned      0.40891   1.09233   0.374   0.7084  
---  
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1  
  
Residual standard error: 8.759 on 351 degrees of freedom  
Multiple R-squared:  0.0288, Adjusted R-squared:  0.01496  
F-statistic: 2.082 on 5 and 351 DF, p-value: 0.06717
```

In model 5 we compute the model on the same output of model 4 plus the region factor.

```
Call:  
lm(formula = (fte_after - fte_before) ~ gapp + contr_bk + contr_kfc +  
    contr_roys + co_owned + region, data = data2)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-41.247 -4.055   0.470   4.184  26.373  
  
Coefficients:  
              Estimate Std. Error t value Pr(>|t|)  
(Intercept) -0.29268   1.92514 -0.152   0.879  
gapp         11.95220   7.45590  1.603   0.110  
contr_bk      -0.40183   1.53404 -0.262   0.794  
contr_kfc      0.34249   1.71462  0.200   0.842  
contr_roys     -2.60696   1.72487 -1.511   0.132  
co_owned       0.27383   1.11650  0.245   0.806  
regionNorth_NJ 0.22991   1.50363  0.153   0.879  
regionNorth_PA -3.44055   2.27539 -1.512   0.131  
regionShore_NJ -2.27062   2.04790 -1.109   0.268  
regionSouth_NJ  0.07161   1.71418  0.042   0.967  
regionSouth_PA  0.44139   2.07203  0.213   0.831  
  
Residual standard error: 8.751 on 346 degrees of freedom  
Multiple R-squared:  0.04445,   Adjusted R-squared:  0.01683  
F-statistic:  1.61 on 10 and 346 DF,  p-value: 0.1021
```

To conclude, we summarized the results we have achieved in this table, that matches completely the table 4 of the original paper, except for some decimal change in model 5.

	(i)	(ii)	(iii)	(iv)	(v)
1. New Jersey dummy	2.33	2.30			
	(1.19)	(1.20)			
2. Initial wage gap		15.65	14.92	11.95	
		(6.08)	(6.21)	(7.46)	
3. Controls for chain and ownership	no	yes	no	yes	yes
4. Controls for region	no	no	no	no	yes
5. Standard error of regression	8.79	8.78	8.76	8.76	8.75

The table 4, for reference:

TABLE 4—REDUCED-FORM MODELS FOR CHANGE IN EMPLOYMENT

Independent variable	Model				
	(i)	(ii)	(iii)	(iv)	(v)
1. New Jersey dummy	2.33 (1.19)	2.30 (1.20)	—	—	—
2. Initial wage gap ^a	—	—	15.65 (6.08)	14.92 (6.21)	11.91 (7.39)
3. Controls for chain and ownership ^b	no	yes	no	yes	yes
4. Controls for region ^c	no	no	no	no	yes
5. Standard error of regression	8.79	8.78	8.76	8.76	8.75
6. Probability value for controls ^d	—	0.34	—	0.44	0.40

Notes: Standard errors are given in parentheses. The sample consists of 357 stores with available data on employment and starting wages in waves 1 and 2. The dependent variable in all models is change in FTE employment. The mean and standard deviation of the dependent variable are -0.237 and 8.825, respectively. All models include an unrestricted constant (not reported).

^aProportional increase in starting wage necessary to raise starting wage to new minimum rate. For stores in Pennsylvania the wage gap is 0.

^bThree dummy variables for chain type and whether or not the store is company-owned are included.

^cDummy variables for two regions of New Jersey and two regions of eastern Pennsylvania are included.

^dProbability value of joint *F* test for exclusion of all control variables.

One more regression

We also run the regression

$$E_{it} = \beta_0 + \beta_1 S_i + \beta_2 W_t + \gamma(S_i \cdot D_t) + \varepsilon_{it}$$

where the dependent variable is FTE employment in the *i*-th restaurant in wave *t* = 1, 2, *S_i* is the state dummy, taking value 1 if the restaurant is in New Jersey, 0 otherwise, *W_t* is the wave dummy, taking value 1 if the observation is after April 1992 (second wave), 0 otherwise. The interaction of state and wave, *S_i* * *D_t*, takes value 1 for NJ restaurants in wave 2 and 0 otherwise. In other words, *S_i* * *D_t* is a dummy variable that asks: "was introduced minimum wage (yet)?" If the answer is yes, it is 1, otherwise (PA or NJ in wave 1), it's zero.

Under the assumption of weak exogeneity of the error term, the coefficient γ measures the minimum wage effect. The least squares estimate of γ is the DiD estimate of the effect of the minimum wage.

In practice, if we want to prove that the minimum wage affects negatively the employment, we shall observe a significative estimate of $\gamma < 0$. Let's look at the data.

```

Call:
lm(formula = fte ~ state + wave + state * wave, data = data_did)

Residuals:
    Min      1Q  Median      3Q     Max 
-21.500 -6.514 -1.014  4.715 64.486 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 23.627     1.159   20.387 <2e-16 ***  
state1       -3.113     1.286   -2.421   0.0157 *    
wave         -2.127     1.639   -1.298   0.1948    
state1:wave   2.326     1.818   1.279   0.2013    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.486 on 710 degrees of freedom
Multiple R-squared:  0.008861, Adjusted R-squared:  0.004673 
F-statistic: 2.116 on 3 and 710 DF,  p-value: 0.09687

```

We see that the estimated parameter for the interaction, `state1:wave`, is not significant (also, it is larger than zero). We also see that the whole model is not a good fit (`F-statistic: 2.116 on 3 and 710 DF, p-value: 0.09687`).

Conclusions

Despite applying several econometric methods and robustness checks, our results consistently fail to show that higher minimum wages reduce employment. Even when extending the original Card and Krueger framework, we find no support for a negative employment effect.

References

Card D., & Krueger, A. (1994). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. *American Economic Review*, 84(4), pp. 772-793.

Rodrigues, B. (2019). Fast food, causality and R packages, part 2.

https://brodrigues.co/posts/2019-05-04-difindiff_part2.html

Appendix

In this appendix we provide additional results and procedures that complement the results presented in the main text.

1. Getting the data and processing

```
tempfile_path <- tempfile()
download.file("http://davidcard.berkeley.edu/data_sets/njmin.zip", destfile = tempfile_path)
tempdir_path <- tempdir()
unzip(tempfile_path, exdir = tempdir_path)

codebook <- read_lines(file = paste0(tempdir_path, "/codebook"))
```

(full code in the Colab notebook)

With this lean approach we avoid manually reloading the Excel dataset at each iteration, ensuring both computational efficiency and full replicability of the analysis.

During data processing, we found that the way the dataset is structured — particularly in terms of filtering and variable declaration — substantially affects the regression results.

When relying on R's default handling of missing values and data types (e.g., simply running `df <- as.data.frame(dataset)` and estimating models on `df`), the estimated coefficients differ significantly from those obtained using a controlled data pipeline.

By explicitly filtering and mutating variables through a structured workflow (as in our `data2` pipeline), we ensure consistent variable definitions, preserve relevant observations, and obtain more reliable and interpretable model estimates.

```
data2 <- dataset %>%          # proceeding this way we can compute better models
  select(co_owned, empft, emppt, nmgrs, empft2, emppt2, nmgrs2,
         state, chain, status2, wage_st, wage_st2, northj, centralj, southj, shore, pa1,
         pa2) %>%
  mutate(
    state = as.character(state),
    fte_before = empft + nmgrs + emppt * 0.5,
    fte_after = empft2 + nmgrs2 + emppt2 * 0.5,
    # dummy per le catene, più pulito
    contr_bk = ifelse(chain == "1", 1, 0),
    contr_kfc = ifelse(chain == "2", 1, 0),
    contr_roys = ifelse(chain == "3", 1, 0),
    contr_wend = ifelse(chain == "4", 1, 0),
    #gap variable
    gapp = ifelse(state == 1 & wage_st <= 5.05, (5.05 - wage_st) / wage_st, 0),
  ) %>%
  filter(complete.cases(fte_before, fte_after, wage_st, wage_st2) | status2 == 3)
```

!!If you run the regression as stated in Model 1 (only state dummy) using the `data2` dataset you get the exact result reported by the authors. If you use `df <- as.data.frame(dataset)` you get the model as shown below:

```

Call:
lm(formula = dfte ~ state, data = df)

Residuals:
    Min      1Q  Median      3Q     Max 
-39.217 -3.967  0.533  4.533 33.533 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -2.283     1.036  -2.205  0.0280 *  
stateNJ       2.750     1.154   2.382  0.0177 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.968 on 382 degrees of freedom
(26 observations deleted due to missingness)
Multiple R-squared:  0.01464, Adjusted R-squared:  0.01206 
F-statistic: 5.675 on 1 and 382 DF,  p-value: 0.01769

```

However, to perform a complete and deepened data analysis - we'll see just below - we need both the whole (`df`) and the filtered dataset (`data2`) .

2. Differences in Standard Errors

We can estimate the difference between two means by direct confrontation or regressing on a dummy (like model 1).

$$Y = \beta_0 + \beta_1 I(NJ)_i + \varepsilon_i$$

$$\hat{\beta}_1 = \bar{Y}_{NJ} - \bar{Y}_{PA}$$

The two point estimations match, but their standard errors don't.

Let's see that. If we regress `Fte_1` (wave 1) on the NJ dummy: `lm(df$fte~df$state)`, we get:

```

Call:
lm(formula = fte1 ~ state, data = df)

Residuals:
    Min      1Q  Median      3Q     Max 
-15.831 -6.439 -1.439  3.561 64.561 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  23.331     1.105  21.118 <2e-16 ***
stateNJ     -2.892     1.230  -2.351  0.0192 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.695 on 396 degrees of freedom
(12 observations deleted due to missingness)
Multiple R-squared:  0.01376, Adjusted R-squared:  0.01127 
F-statistic: 5.525 on 1 and 396 DF,  p-value: 0.01923

```

!! In this case we use the full dataset (`df`): we need all data, not only the filtered ones.

The intercept of this model is exactly the average FTE employment before policy, in Pennsylvania. The standard error is 1.105. We also see that $23.331 + (-2.892) * 1 = 20.439$ that is exactly the average FTE_1 in New Jersey. Now look at the first line of table 3 of the authors' paper:

TABLE 3—AVERAGE EMPLOYMENT PER STORE BEFORE AND AFTER THE RISE
IN NEW JERSEY MINIMUM WAGE

Variable	Stores by state			Stores in New Jersey ^a			Differences within NJ ^b	
	PA (i)	NJ (ii)	Difference, NJ – PA (iii)	Wage = \$4.25 (iv)	Wage = \$4.26–\$4.99 (v)	Wage ≥ \$5.00 (vi)	Low– high (vii)	Midrange– high (viii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	-2.89 (1.44)	19.56 (0.77)	20.08 (0.84)	22.25 (1.14)	-2.69 (1.37)	-2.17 (1.41)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	-0.14 (1.07)	20.88 (1.01)	20.96 (0.76)	20.21 (1.03)	0.67 (1.44)	0.75 (1.27)
3. Change in mean FTE employment	-2.16 (1.25)	0.59 (0.54)	2.76 (1.36)	1.32 (0.95)	0.87 (0.84)	-2.04 (1.14)	3.36 (1.48)	2.91 (1.41)
4. Change in mean FTE employment, balanced sample of stores ^c	-2.28 (1.25)	0.47 (0.48)	2.75 (1.34)	1.21 (0.82)	0.71 (0.69)	-2.16 (1.01)	3.36 (1.30)	2.87 (1.22)
5. Change in mean FTE employment, setting FTE at temporarily closed stores to 0 ^d	-2.28 (1.25)	0.23 (0.49)	2.51 (1.35)	0.90 (0.87)	0.49 (0.69)	-2.39 (1.02)	3.29 (1.34)	2.88 (1.23)

Notes: Standard errors are shown in parentheses. The sample consists of all stores with available data on employment. FTE (full-time-equivalent) employment counts each part-time worker as half a full-time worker. Employment at six closed stores is set to zero. Employment at four temporarily closed stores is treated as missing.

^aStores in New Jersey were classified by whether starting wage in wave 1 equals \$4.25 per hour ($N = 101$), is between \$4.26 and \$4.99 per hour ($N = 140$), or is \$5.00 per hour or higher ($N = 73$).

^bDifference in employment between low-wage (\$4.25 per hour) and high-wage ($\geq \$5.00$ per hour) stores; and difference in employment between midrange (\$4.26–\$4.99 per hour) and high-wage stores.

^cSubset of stores with available employment data in wave 1 and wave 2.

^dIn this row only, wave-2 employment at four temporarily closed stores is set to 0. Employment changes are based on the subset of stores with available employment data in wave 1 and wave 2.

We see that the means match, but the standard errors don't. In the regression, standard error of estimates depends on the variance of the model and the design matrix. This is built upon the assumption that

$$\varepsilon|X \sim N(0, \sigma^2) \Rightarrow \hat{\beta} \sim N(\beta, \hat{\sigma}^2(X'X)^{-1})$$

Outside the linear regression framework, the standard error of mean is just the square root of variance of the estimator, that is $\frac{\sigma^2}{n}$. Proof:

Assuming $\text{Var}(Y_i) = \sigma^2$ and Y_i iid:

$$\begin{aligned} \text{Var}(\bar{Y}) &= \text{Var}\left(\frac{1}{n} \sum_i Y_i\right) = \frac{1}{n^2} \text{Var} \sum_i Y_i \\ \frac{1}{n^2} \sum_i \text{Var}(Y_i) &= \frac{1}{n^2} \cdot n\sigma^2 = \frac{\sigma^2}{n} \quad \square \end{aligned}$$

Let's see this on data:

```
mean(df$fte1[df$state=="PA"], na.rm=TRUE)
v_pa_f1 <- var(df$fte1[df$state=="PA"], na.rm=TRUE)
n_pa_f1 <- sum(df$state == "PA" & !is.na(df$fte1))

se_mean_pa_f1 <- sqrt(v_pa_f1/n_pa_f1)
se_mean_pa_f1
```

23.3311688311688
1.35114886147513

3. Some other graphs

We conclude the appendix adding some extra graphs.

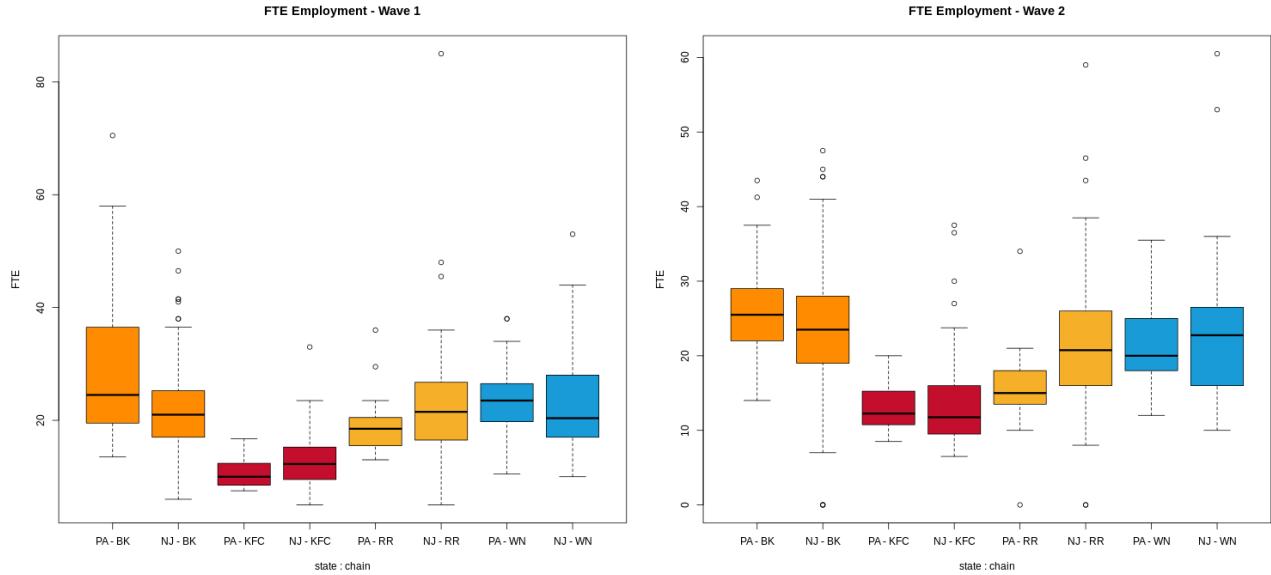


Figure 8 - Boxplot of FTE by state and chain, wave 1 (left) vs wave 2 (right).

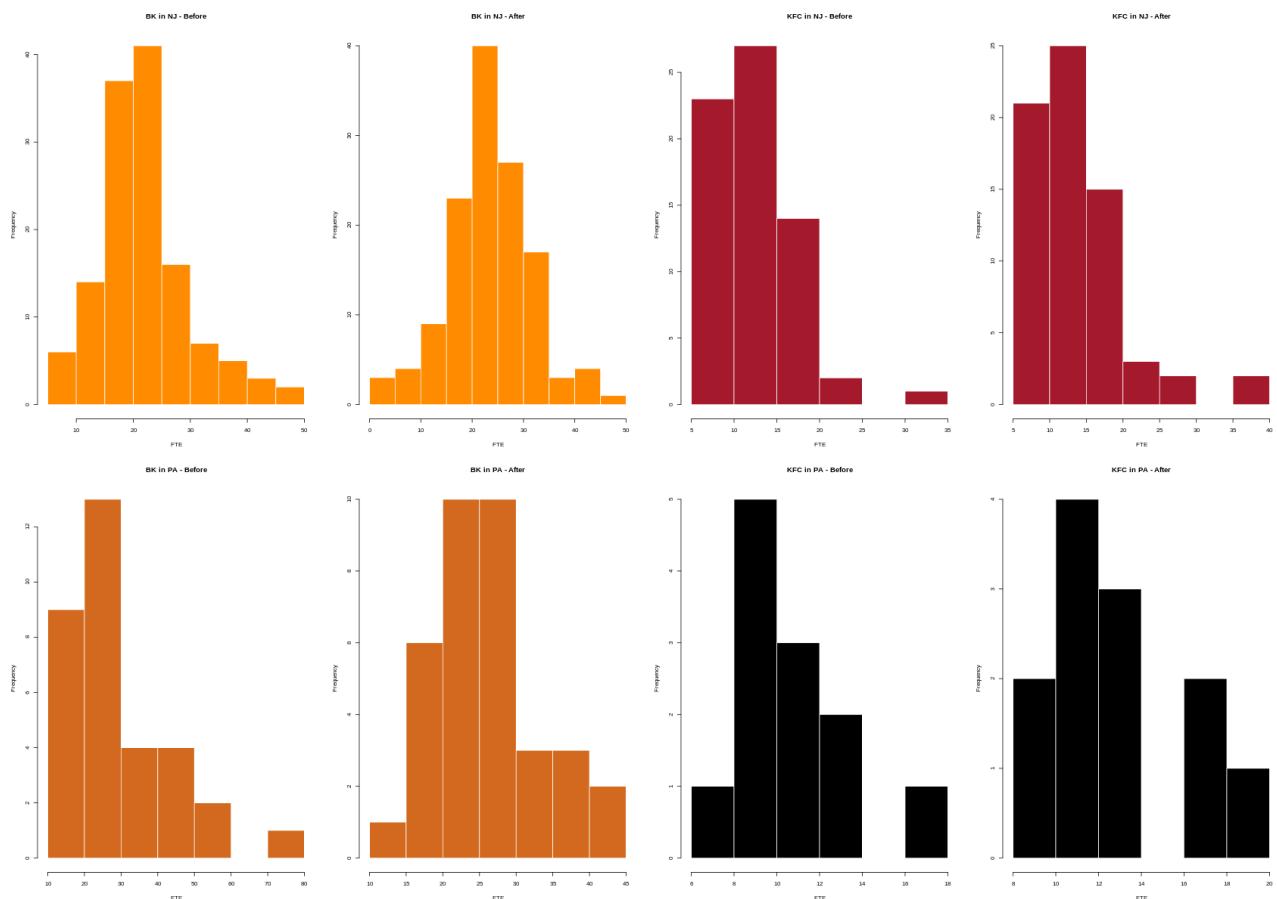


Figure 9 - Histograms for each chain, wave and state (BK and KFC). First row is NJ, second is PA.

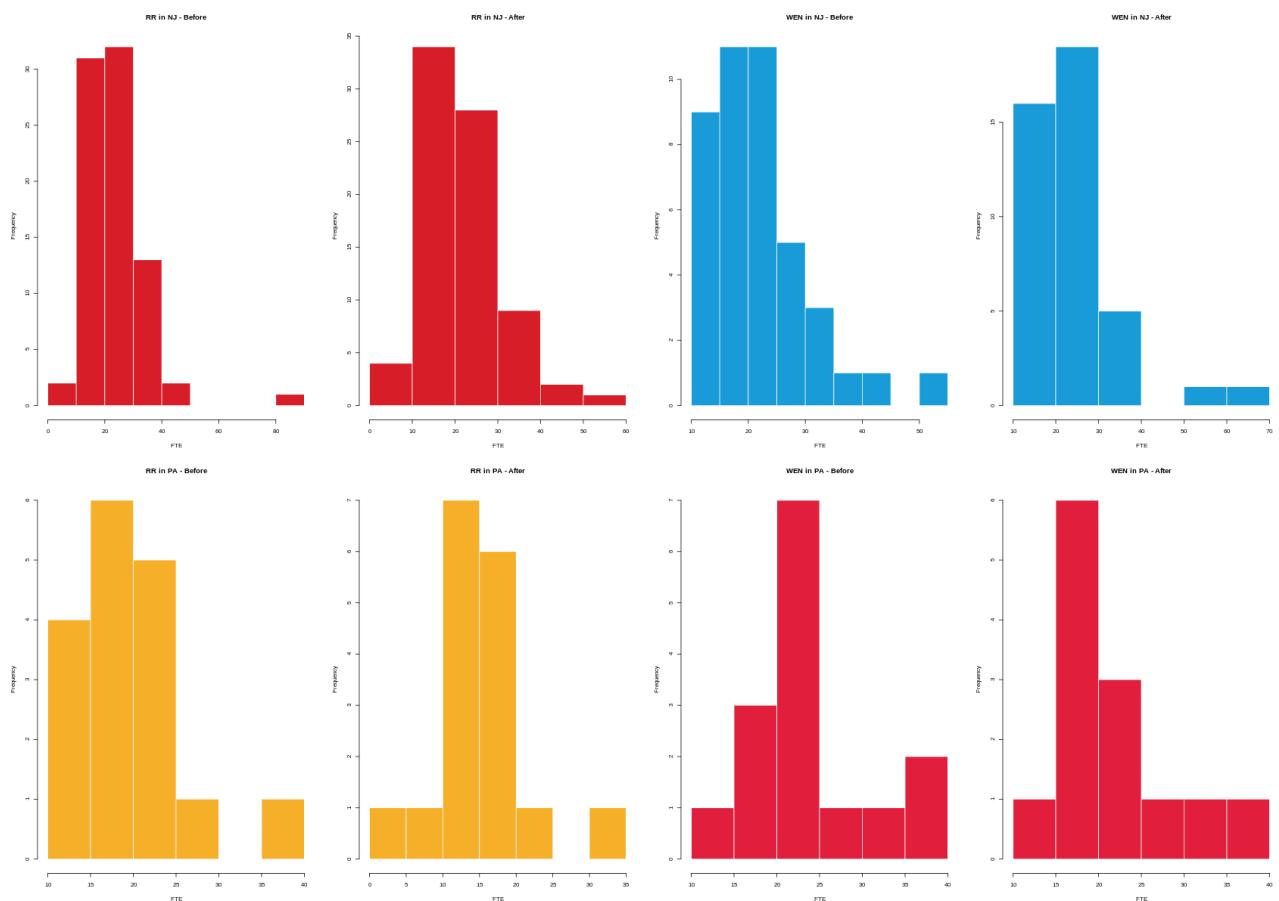


Figure 10 - Histograms for each chain, wave and state (Roy Roger's and Wendy's). The first row is NJ, the second is PA.

Thanks for your attention!

