

**Question 1.1:** How does the choice of research design, specifically a difference-in-differences approach, influence the validity and reliability of conclusions drawn from empirical studies examining the impact of policy changes, such as minimum wage increases, on economic outcomes like employment? Hint: Think about the parallel trend assumption.

The choice of a DiD approach definitely improves the reliability of the conclusions of studies as long as the parallel trend assumption is correct. DiD models are very good at isolating the causal effects policies by mitigating the effects of confounding variables. However, as mentioned, it heavily relies on the parallel trend assumption, i.e., in the absence of intervention, the treatment and control group trends would have been parallel. In this study, we assume that the trend in employment in fast food chains in New Jersey and Pennsylvania would have been the same had New Jersey not increased the minimum wage. Thus, a thorough examination of the trend in the period leading up to it is essential to support this assumption.



**Question 2.2:** What does each row in `dd_df` represent?

Our `DataFrame`, `dd_df`, contains data on different fast-food vendors in New Jersey and Pennsylvania in 1992. Each row represents the response from one of the 410 surveyed fast-food vendors. As all the vendors were surveyed twice – both before and after the minimum wage increase on April 1st 1992, there are two responses for each vendor, before and after the intervention marked with `Treatment`.



**Question 2.5:** What's the difference between the `Group` the `Treatment` columns?

The `Group` variable tells us whether the fast-food vendor is placed in New Jersey, `Group = 1`, or Pennsylvania, `Group = 0`. The `Treatment` variable, on the other hand, tells us if it is the vendor's response before `Treatment = 0` or after `Treatment = 1`, April 1st 1992, when the new minimum wage went into effect in New Jersey.



**Question 3.1:** Using the general diff-in-diff model below, specify the model we're about to estimate using L<sup>A</sup>T<sub>E</sub>X. Hint: Don't forget to add your controls.

(1.1)

$$Y = \beta_0 + \beta_1 \cdot \text{Group (our treatment)} + \beta_2 \cdot \text{Treatment (our post)} + \beta_3 \cdot \text{Group} \times \text{Treatment} \\ + \beta_4 \cdot \text{Hours.Opening} + \beta_5 \cdot \text{Fries} + \beta_6 \cdot \text{Soda} + e$$





**Question 3.4.2:** Describe in 1-2 sentences below what you did and how it might affect your later analysis. Also note how many observations you lost.

To remove the `nan` values from our dataset, I used the `df.dropna()` function, which reduced the number of observations from 820 to 757 (63 observations equivalent to an 8% reduction). This introduces bias in our results if there is a specific pattern in the fast-food vendors with `nan` values.

However, for the analysis in Q3.3./Q3.5, we could have reduced the number of observations dropped to 18 (keeping 802) by looking specifically at the relevant columns and not dropping rows with `nan` values even though we do not look at the columns where the `nan` values are. This could have been done with `df.dropna(subset=['Empl', 'Treatment', 'Post', 'Treatment_Post'])`.



**Question 3.6:** Using the Sign, Size, and Significance framework as described below, interpret your findings. Please format your markdown nicely (like the following cell) to aid readability.

### 0.0.1 Sign, Size, and Significance (SSS) framework for interpreting regression outputs

#### 1. Sign

- **Expected Sign:** What sign did you expect the estimated parameter(s) to have? Why?
- **Actual Sign:** Does your estimate(s) have this sign (i.e., are you surprised or reassured by your results)?

#### 2. Significance

- **Statistical Significance:** Is the estimate(s) statistically different from zero?
- **T-Statistic:** What is the t-statistic of this hypothesis?

#### 3. Size

- **Effect on Dependent Variable:** How do changes in this variable affect the dependent variable according to your estimation?
- **Economic Significance:** Is this an economically meaningful effect size?

This framework is borrowed from Berkeley's EEP C118 course. See more [here](#).

### 0.0.2 Sign, Size, and Significance (SSS) framework for interpreting regression outputs

#### 1. Sign

- **Expected Sign:**
  - *Treatment:* This captures any pre-existing differences in employment levels between the two groups before the policy change. As **Treatment** = 1 means we are in New Jersey, a positive sign would mean that New Jersey has a higher employment than Pennsylvania in general and vice versa if it is negative. Thus, I do not have any specific expectations for this parameter's sign.
  - *Post:* This term accounts for time trends affecting the treatment and control groups. **Post** is a binary indicator that equals 1 for the period after the policy change and 0 before. The coefficient thus captures general time effects on employment unrelated to the policy intervention. The US was coming out of the early 1990s recession, which could increase demand and thus employment, but at the same time, fast-food vendors might have improved efficiency, which could decrease employment. Thus, this sign could be positive or negative.

- *Treatment* $\times$ *Post*: This is the interaction term and key to our analysis. The **Treatment\_Post** variable is 1 for fast-food vendors in New Jersey after the policy intervention, i.e. after the increase in the minimum wage. Our hypothesis is that *An increase in the minimum wage is negatively correlated with employment*, and we expect this to be negative as employment should fall in New Jersey after the minimum wage increase.

- **Actual Sign:**

- *Treatment*: Negative. Hence, stores in New Jersey generally had fewer employees than their Pennsylvania counterparts.
- *Post*: Negative. Thus, there is a decrease in the average employment over time for all of the vendors.
- *Treatment* $\times$ *Post*: Positive. This is surprising as this suggests New Jersey stores are increasing their employment relative to Pennsylvania after adopting a higher minimum wage.

## 2. Significance

- **Statistical Significance:**

- All estimated coefficients are statistically significant at the 95% level.

- **T-Statistic:**

- *Treatment*:  $-2.745$
- *Post*:  $-2.015$
- *Treatment* $\times$ *Post*:  $2.397$

## 3. Size

- **Effect on Dependent Variable:**

- *Treatment*: If the vendor is in New Jersey, it, in general, has 2.847 employees less than if it had been in Pennsylvania.
- *Post*: The average number of employees decreased to 2.6943 employees between when the fast-food vendors were first surveyed and when they were last surveyed.
- *Treatment* $\times$ *Post*: The employment at fast-food vendors in New Jersey increased by 3.5708 compared to Pennsylvania after adopting the new minimum wage.

- **Economic Significance:**

- The results suggest that though New Jersey adopted a higher minimum wage, they increased the average number of employees by  $-2.6943 + 3.5708 = 0.8765$  (**Post+Treatment\_Post**). Further, we also see that the average employment in the two states is getting closer to each other as vendors in Pennsylvania decrease their average employment while New Jersey increases it. This could indicate that there might be some regression towards a mean – Pennsylvania might just be higher before and New Jersey lower. The net-effects post is just a regression towards an ideal employment level. Additionally, I see a very low  $R^2$  value, of just 1.1%, which indicates that our analysis only explains a small part of the variation.

**Question 3.8:** Controlling for opening hours, and prices of soda & fries - What is the diff-in-diff estimator for the impact on introducing a minimum wage in New Jersey? Remember to include units and give a brief interpretation of our findings following the SSS framework from above. Be sure to mention how your  $R^2$  changed, and it's practical implications.

The new coefficient for the `Treatment_Post` variable is 4.1275; thus, including our control variables for the number of hours open and if they serve fries and soda increased the estimated effect of adopting a higher minimum wage.

The  $R^2$  value increased from 1.1% to 8.8% when including the control variables; thus, the inclusion of control variables increases the explanatory power of our model though modestly. Our  $R^2$  still needs to be higher, indicating that several unobserved factors are not in the model that influence the average employment rates.

### 0.0.3 Sign, Size, and Significance (SSS) framework for interpreting regression outputs

#### 1. Sign

- **Expected Sign:**
  - *TreatmentPost*: As described previously, our hypothesis that *An increase in the minimum wage is negatively correlated with employment* would make us expect the coefficient to be negative.
- **Actual Sign:**
  - *TreatmentPost*: It is positive, which is surprising as this suggests New Jersey stores are increasing their employment relative to Pennsylvania after adopting a higher minimum wage.

#### 2. Significance

- **Statistical Significance:**
  - The `Treatment_Post` coefficient is statistically significant at the 95% level with a p-value of 0.004.
- **T-Statistic:**
  - *TreatmentPost*: 2.877

#### 3. Size

- **Effect on Dependent Variable:**
  - *TreatmentPost*: The employment at fast-food vendors in New Jersey increased by 4.1275 compared to Pennsylvania after adopting the new minimum wage.
- **Economic Significance:**

- The new results suggest that though New Jersey adopted a higher minimum wage, they increased the average number of employees by  $-1.4365 + 4.1275 = 2.6910$ . Additionally, I find an increased very low  $R^2$  value of just 8.8%, which indicates that our analysis still only explains a small part of the variation; however, it is much greater than in our initial analysis.

**Question 4.3:** Looking back to your response to question 1.1 and the plot from above, what is a central piece of evidence we're lacking from dataset that would strengthen the validity of our diff-in-diff analysis?

From the evidence seen here, I find it plausible that the parallel trend assumption is violated. Thus, we would need more data before the intervention to ensure this assumption is not violated. More data afterwards would be good to see if it is only short-term effects or if this effect is permanent.

