THE UNIVERSITY OF CHICAGO
HARRIS SCHOOL
OF PUBLIC POLICY

Program Evaluation Working Sample

Student: Jeremy Xu

University of Chicago Harris School of Public Policy

Background

Local air pollution is among the greatest threats to human health today. In recent years, China has embarked on a "war on pollution," using a variety of approaches to try to reduce pollution exposure. A new blue-ribbon commission, the Pollution Regulation Organization for Greater Regional Air Monitoring, Evaluation, Valuation, And Life (PROGRAMEVAL), has come to the Harris School to find a team of experts to help them understand the effectiveness of China's pollution regulations on air quality.

Theoretical Framework

The ideal experiment would be to conduct a randomized control trial (RCT), where we randomly assign some municipalities to impose air quality regulations, and others not impose air quality regulations, with 100% compliance.

To carry out this ideal experiment, we would need the dataset from every single municipalities regarding their baseline characteristics (GDP, geographic area, population, etc.), treatment status (being treated = 1; not being treated = 0) and observed outcome (PM 2.5).

We would like to calculate the *effect of provincial air quality regulations on local particulate matter (PM 2.5)* based on the potential outcomes framework:

$$\tau^{ATE} = E[Y_i(1)] - E[Y_i(0)]$$

(i here indicates every single municipality)

Here we would like to observe the difference between two potential PM 2.5 for the same individual municipality (i) imposing and not imposing air quality regulations simultaneously, so as to calculate the ATE. However, we cannot observe the PM 2.5 under both states of the world for the same municipality.

The good news is that, under RCT, the observed PM 2.5 of municipalities that impose air quality regulations is equal to the unobserved outcome of those that did not, and the observed outcome of those who did not impose air quality regulations is equal to the unobserved outcome of those that did. That is:

$$E[Y_i(D = 1)|D = 1] = E[Y_i(D = 1)|D = 0] = E[Y_i(1)]$$

$$E[Y_i(D = 0)|D = 0] = E[Y_i(D = 0)|D = 1] = E[Y_i(0)]$$

Therefore, we could recover the effect of air quality regulations by a simple difference in means:

$$\tau_i = \overline{Y_i}(D = 1) - \overline{Y_i}(D = 0)$$

And thus we could calculate the average effect of air quality regulations by observing the difference of PM 2.5 for municipalities with and without air quality regulations.

We would further apply the OLS regression model to estimate the treatment effect:

$$Y_i = \alpha + \tau D_i + \gamma X_i^{baseline} + \varepsilon_i$$

Here Y_i indicates outcomes for municipality i, α is a constant, D_i is a treatment dummy, $X_i^{baseline}$ is a set of baseline municipality controls, and ε_i is an error term.

Note that to get a good estimate of treatment effect τ, our regression model should satisfy the *zero conditional mean assumption*, in which $E(\varepsilon_i | D_i, X_i^{baseline}) = 0$.

Therefore, we could estimate the impact of provincial air quality regulations on local particulate matter (PM 2.5) by estimating the coefficient $\hat{\tau}$:

$$\hat{Y}_i = \hat{\alpha} + \hat{\tau} D_i + \hat{\gamma} X_i^{baseline}$$

If we simply compare the differences in air quality between municipalities with and without air quality regulations, we are actually using the naive estimator to indicate the observed outcomes so as to recover the treatment effect of air quality regulations:

$$\tau_i = \overline{Y_i}(D = 1) - \overline{Y_i}(D = 0)$$

This may cause selection bias in which municipalities with and without air quality regulations may systematically differ in air quality outcomes when isolating the effect of air quality regulations.

a. Selection on observables
Municipalities with and without air quality regulations differ along lines we can see.
Example 1: Municipalities with air quality regulations have fewer heavy industries than those without air quality regulations.
Example 2: Municipalities with air quality regulations have more educational institutions than those without air quality regulations.

b. Selection on unobservables
Municipalities with and without air quality regulations differ along lines we cannot see.
Example 3: Municipalities with air quality regulations tend to care more on population health and environment than those without air quality regulations.

If we observe municipalities at multiple points in time, we will be able to compare municipality i in t to i in *t-1* rather than comparing municipality i to j. That is, we can look at periods before and after air quality regulation begins for the same municipality. In this case, municipality i serves as a control for itself, which could largely reduce selection bias.

We would use a regression model to make time-series comparisons on municipalities themselves:

$$Y_{it} = \tau D_{it} + \beta X_i + \gamma U_i + \delta V_{it}$$

Here Y_{it} indicates air quality outcomes for municipality i in time t, D_{it} is a treatment dummy where $D_{it} = 0$ in $t = 0$ (before 2004) and $D_{it} = 1$ in $t = 1$ (after 2004), X_i indicates time-invariant observable characteristics, U_i indicates time-invariant unobserved characteristics, and V_{it} indicates a set of observed and unobserved time-varying characteristics.

By using this regression model, we are able to estimate the treatment effect τ of air quality regulations on particulate matter, with several control variables included.

To estimate the treatment effect, we have

$$\hat{\tau}^{TS} = Y_{i,t=1} - Y_{i,t=0} = \tau + \delta(V_{i,t=1} - V_{i,t=0})$$

We see that time-varying variables may create bias in $\hat{\tau}^{TS}$. In order for $\hat{\tau}^{TS}$ to equal τ, we need $\delta = 0$ or $V_{i,t=1} = V_{i,t=0}$. That is, to recover the causal effect of air quality regulations on particulate matter, we have to assume that the counterfactual trend is zero, but it is *untestable*.

Concern with this approach is that time-varying variables will create bias:
a. Time-varying observables
Example 1: An increasing number of residents in municipalities commuted by private cars instead of public transportation after 2004, compared to their commuting before 2004 on average. (We cannot separate $D_i t$ from the time-varying modes of transportation in this case.)

b. Time-varying unobservables
Example 2: Residents in municipalities tend to care more on health and well-being after 2004, compared to their lifestyle before 2004.
Example 3: Municipalities tend to focus more on effective governance on environmental friendly after 2004, compared to their governance before 2004.

By dividing multiple municipalities into two groups, we would be able to incorporate the difference-in-differences estimator, which combines the naive (cross-sectional) estimator and time-series estimator into a better estimate of treatment effect of air quality regulations.

The estimator that we would use with this dataset is the difference-in-differences estimator:

$$\hat{\tau}^{DD} = \hat{\tau}^{TS}_{D_i=1} - \hat{\tau}^{TS}_{D_i=0} = (\bar{Y}(treat, post) - \bar{Y}(treat, pre)) - (\bar{Y}(untreat, post) - \bar{Y}(untreat, pre))$$

Here the estimator compares treated to untreated units over time. That is, it compares the difference of *treatment effect* between municipalities that imposed air quality regulations in 2004 ($D_i = 1$) and municipalities that never imposed air quality regulations ($D_i = 0$).

The DD regression is:

$$Y_i = \alpha + \tau Treat \times Post_{it} + \beta Treat_i + \delta Post_t + \gamma X_{it} + \varepsilon_{it}$$

Here *Treat* is a dummy variable that indicates municipalities treatment status, *Post* is also a dummy variable that indicates status before or after the certain time points of treatment, and X indicates a set of observables as controls.

Our DD estimator based on this larger dataset would allow us to resolve the concerns on missing counterfactual trends in time-series estimators. Specifically, DD compares treated municipality i to itself over time to untreated municipality j to itself over time:

$$Y_{it} = \tau D_{it} + \beta X_i + \delta S_t$$

$$Y_{jt} = \beta X_j + \delta S_t$$

Here D_{it} indicates treatment status, X_i and X_j indicate time-invariant characteristics, and for both municipality groups we have time-varying S_t. Therefore, we can eliminate the concerns of time-varying variables with DD estimator:

$$\hat{\tau}^{DD} = (Y_{i,t=1} - Y_{i,t=0}) - (Y_{j,t=1} - Y_{j,t=0}) =$$

$$\tau(D_{i,t=1} - D_{i,t=0}) + \beta(X_i - X_i) + \delta(S_{t=1} - S_{t=0}) - \beta(X_j - X_j) - \delta(S_{t=1} - S_{t=0}) = \tau(D_{i,t=1} - D_{i,t=0}) = \tau$$

The identifying assumption of the DD is *parallel trends*, which is required for this approach to recover the causal effect of air quality regulations on particulate matter. It means that municipalities in both two groups should be on similar trajectories if not for treatment (air quality regulations).

The remaining concern is that unparallel trends will cause bias to our difference-in-differences estimator.
Example 1: Municipalities that imposed air quality regulations had higher increase rate of private car numbers prior to 2004 than municipalities that never imposed air quality regulations.
Example 2: Municipalities that imposed air quality regulations had higher speed in deforestation prior to 2004 than municipalities that never imposed air quality regulations.

Estimate the Effect of Air Quality Regulations

Since municipalities imposed air quality regulations across several different years, we could extend DD estimator to multiple treatment times:

$$Y_{it} = \tau D_{it} + \alpha_i + \delta_t + \beta X_{it} + \varepsilon_{it}$$

Here D_{it} can turn from 0 to 1 at different times (2003 to 2007) for different municipalities, α_i is a set of individual fixed effects which captures $Treat_i$, δ_t is a set of time fixed effects which captures $Post_t$. Note that we need $E[\varepsilon_{it}|\alpha_i, \delta_t, X_{it}] = 0$ for this model to work.

We could estimate the effect of air quality regulations on particulate matter by calculating τ, which gives us a weighted average of several comparisons above. We could further apply a more general model that allows differential effects over time, which "lines up" treatment at the same time for every municipality:

$$Y_{it} = \sum_{r=-S}^{R} \tau_r D_i \times 1[PeriodsPostTreatment = r]_{it} + \alpha_i + \delta_t + \beta X_{it} + \varepsilon_{it}$$

Here S indicates the number of pre-treatment periods, R indicates the number of post-treatment periods, and $1[PeriodsPostTreatment = r]_{it} = 1$ when we are r periods after implementing air quality regulations, and 0 otherwise.

```
## Simple comparison of average particulate matter between municipalities with and
## without air quality regulations.
# read data
data <- read.csv("ps4_data.csv")

# set group and time
data$treat <- ifelse(is.na(data$air_quality_regulation_year) == 1, 0, 1)
data$post <- ifelse(data$year >= data$air_quality_regulation_year, 1, 0)

# simple comparison
YT <- mean(data$particulate_matter[data$treat == 1])
YC <- mean(data$particulate_matter[data$treat == 0])

# average particulate matter for municipalities with air quality regulations
print(YT)
```

```
## [1] 41.83282
```

```r
# average particulate matter for municipalities without air quality regulations
print(YC)
```

```
## [1] 66.28139
```

```r
# difference between municipalities with and without air quality regulations
print(YT - YC)
```

```
## [1] -24.44856
```

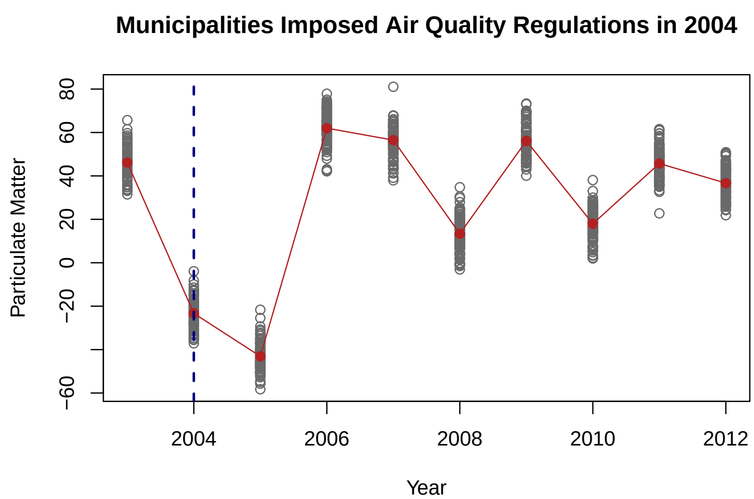
We find that the difference of average particulate matter between municipalities with and without air quality regulations is -24.44856. It indicates that municipalities with air quality regulations have 24.44856 lower PM2.5 levels than municipalities without air quality regulations on average.

```r
## Time-series analysis using only municipalities who introduced regulations in 2004.
# subset data
data_2004 <- subset(data, data$air_quality_regulation_year == 2004)

# time-series analysis
reg_time <- lm(particulate_matter ~ post, data_2004)
time_co <- coeftest(reg_time,
                    vcov = vcovHC(reg_time, type = "HC0", cluster = "group"))

# display regression results
stargazer(time_co,
          type = 'text',
          dep.var.labels = 'Particulate Matter',
          title = 'Time-series analysis')
```

```
##
## Time-series analysis
## ====================================
##              Dependent variable:
##          ---------------------------
##              Particulate Matter
## ------------------------------------
## post             -21.470***
##                    (1.374)
##
## Constant          46.132***
##                    (0.684)
##
## ====================================
## ====================================
## Note:    *p<0.1; **p<0.05; ***p<0.01
```

We find that the effect of air quality regulations is -21.470 on average for municipalities who introduced regulations in 2004 (statistically and economically significant), which has a lower size effect compared to what we estimated using the initial estimator (-24.44856). From this time-series analysis, we are looking at periods before and after air quality regulation imposed (2004) for the municipalities with air quality regulations in 2004, while the initial naive estimator estimates treatment effect by simply comparing two groups of municipalities with and without air quality regulations.

```
## Plot particulate matter against time for municipalities that imposed
## air quality regulations in 2004.
# grouped by year
data_2004_group <- data_2004 %>%
  group_by(year) %>%
  summarise(PM = mean(particulate_matter))

# plot graph
plot(data_2004$year, data_2004$particulate_matter,
     col = "dimgray",
     xlab = "Year",
     ylab = "Particulate Matter",
     main = "Municipalities Imposed Air Quality Regulations in 2004")
points(data_2004_group$year, data_2004_group$PM,
       type = "o",
       pch = 19,
       col = "firebrick")
abline(v = 2004, lwd=2, lty=2, col = "navy")
```

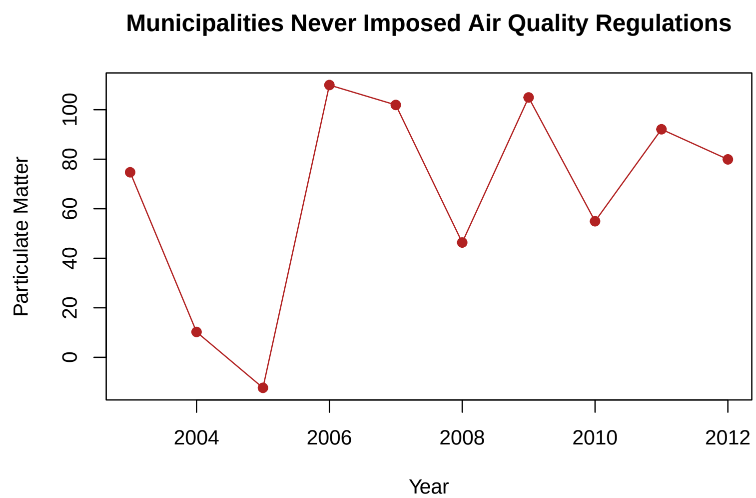


The graph shows that the average particulate matter decreases from 2003 to 2005, but increases and remains high between 2006 and 2012. It seems that the air quality restrictions didn't have salient effect on particulate matter on a long-term basis.

We also noticed that data from pre-treatment period is too short (only 2003), compared to the long post-treatment period data. This figure shows the dynamic trend of treatment effect, and it reveals the limitations of our dataset in time-series analysis (time-varying variables), which challenges the way we interpreted our estimates that are simply based on the difference of average outcome (PM2.5) before and after the treatment.

```
## Plot particulate matter against time for municipalities that never
## imposed air quality regulations.
# subset group
data_control <- subset(data, treat==0)
```

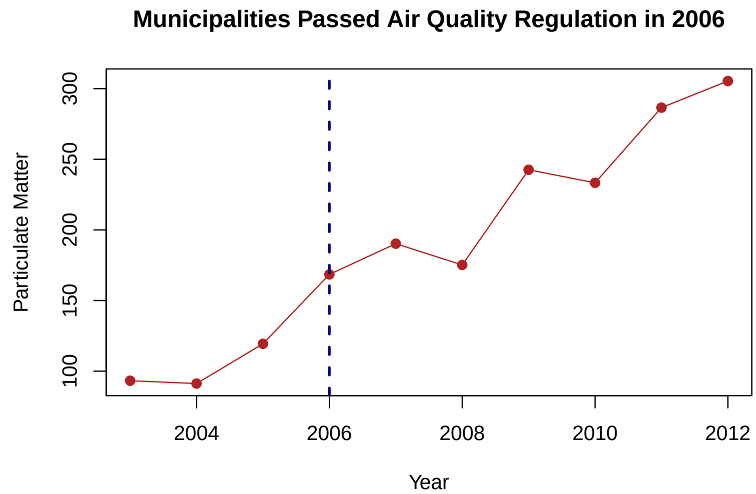
```r
# grouped by year
data_control_group <- data_control %>%
  group_by(year) %>%
  summarise(PM = mean(particulate_matter))

# plot graph
plot(data_control_group$year, data_control_group$PM,
     pch = 19,
     type = "o",
     col = "firebrick",
     xlab = "Year",
     ylab = "Particulate Matter",
     main = "Municipalities Never Imposed Air Quality Regulations")
```



Using these municipalities as a control group for the 2004 regulators will allow us to apply the DD estimator to estimate the effect of air quality regulations, which could mitigate the problem of time-varying variables in time-series analysis and produce a more reliable estimate. We find that parallel trends assumption is satisfied from the graphs (both decline from 2003 to 2004), and thus it is viable to use these municipalities as a control group for the 2004 regulators.

```r
## Plot particulate matter against time for municipalities who passed
## air quality regulation in 2006.
# subset data
data_2006 <- subset(data, data$air_quality_regulation_year == 2006)

# group by year
data_2006_group <- data_2006 %>%
  group_by(year) %>%
  summarise(PM = mean(particulate_matter))

# plot graph
plot(data_2006_group$year, data_2006_group$PM,
     pch = 19,
     type = "o",
     col = "firebrick",
```

```
      xlab = "Year",
      ylab = "Particulate Matter",
      main = "Municipalities Passed Air Quality Regulation in 2006")
abline(v = 2006, lwd=2, lty=2, col = "navy")
```



Using these municipalities as a control group for the 2006 regulators will also allow us to apply the DD estimator to estimate the effect of air quality regulations, which could mitigate the problem of time-varying variables in time-series analysis and produce a more reliable estimate. However, the pre-treatment trend for 2006 regulators is increasing, and the pre-treatment trend for non-regulating municipalities is decreasing. We find that parallel trends assumption is *not* satisfied from the graphs, and thus it is not viable to use non-regulating municipalities as a control group for the 2006 regulators.

```
## A simple difference in means.
# subset data
data_2006_control <- subset(data, data$air_quality_regulation_year == 2006 |
                              is.na(data$air_quality_regulation_year) == 1)
data_2006_control$post <- ifelse(data_2006_control$year >= 2006, 1, 0)

# difference in means
Y_treat_post <- mean(data_2006_control$particulate_matter
                     [data_2006_control$treat == 1 & data_2006_control$post ==1])
Y_treat_pre <- mean(data_2006_control$particulate_matter
                    [data_2006_control$treat == 1 & data_2006_control$post ==0])
Y_untreat_post <- mean(data_2006_control$particulate_matter
                       [data_2006_control$treat == 0 & data_2006_control$post ==1])
Y_untreat_pre <- mean(data_2006_control$particulate_matter
                      [data_2006_control$treat == 0 & data_2006_control$post ==0])
(Y_treat_post - Y_treat_pre) - (Y_untreat_post - Y_untreat_pre)
```

```
## [1] 67.46895
```

```
## A simple regression (no fixed effects).
# simple regression
reg_8_simple <- felm(particulate_matter ~ treat*post + treat + post | municipality_id,
                     cluster = 'municipality_id',
```

```r
                     data = data_2006_control)

# display regression results
stargazer(reg_8_simple,
          type = 'text',
          dep.var.labels = 'Particulate Matter',
          title = 'Simple Regression')
```

```
##
## Simple Regression
## ===============================================
##                         Dependent variable:
##                     ---------------------------
##                         Particulate Matter
## -----------------------------------------------
## treat
##                               (0.000)
##
## post                         60.093***
##                               (0.202)
##
## treat:post                   67.469***
##                               (0.545)
##
## -----------------------------------------------
## Observations                  11,990
## R2                             0.695
## Adjusted R2                    0.661
## Residual Std. Error     32.558 (df = 10789)
## ===============================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

```r
## Fixed effects regression.
# define treated variable (treat * post)
data_2006_control$TREATED <- data_2006_control$treat * data_2006_control$post

# fixed effects regression
reg_8_fixed <- plm(particulate_matter ~ TREATED +
                     as.factor(municipality_id) + as.factor(year),
                   data = data_2006_control,
                   model = "within",
                   effect = "twoway",
                   index = c("municipality_id", "year"))
fixed_co <- coeftest(reg_8_fixed,
                     vcov = vcovHC(reg_8_fixed, type = "HC0", cluster = "group"))

# display regression results
stargazer(fixed_co,
          type = 'text',
          dep.var.labels = 'Particulate Matter',
          title = 'Fixed Effects Regression')
```

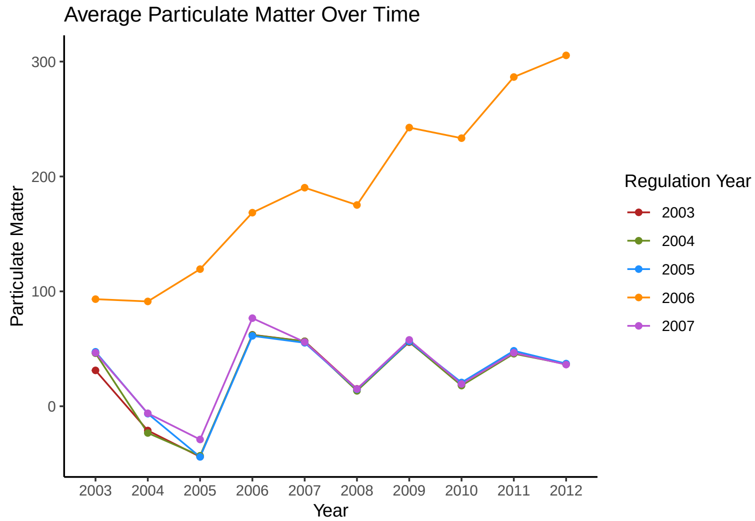
```
##
```

```
## Fixed Effects Regression
## ===================================
##             Dependent variable:
##         ---------------------------
##             Particulate Matter
## -----------------------------------
## TREATED          67.469***
##                   (0.544)
##
## ===================================
## ===================================
## Note:   *p<0.1; **p<0.05; ***p<0.01
```

We find that our estimated effect of air quality regulations on particulate matter (PM 2.5) is 67.469 by using the non-regulators and 2006 regulators. The results are the same among the models of *a simple difference in means, a simple regression (no fixed effects), and fixed effects regression.*

In this case, we find that imposing air quality regulation will increase particulate matter, which doesn't make sense. Compared to what we estimated the effect of air quality regulation in 2004 in (6) (naive estimator: -24.44856, time-series analysis: -21.470), our estimate effect of air quality regulation in 2006 turns to positive value and shows a larger size effect. This result also confirms our concern based on the plots in (7), in which violation of parallel trends assumption will lead to unreliable results.

```r
## Plot average particulate matter over time.
# grouped by regulation year and years
data_group <- data %>%
  filter(air_quality_regulation_year >= 2003 &
           air_quality_regulation_year <= 2007) %>%
  group_by(air_quality_regulation_year, year) %>%
  summarise(PM = mean(particulate_matter))

# plot average particulate matter over time
ggplot(data_group,
       aes(x = as.factor(year), y = PM,
           group = as.factor(air_quality_regulation_year),
           color = as.factor(air_quality_regulation_year))) +
  geom_path() +
  geom_point() +
  scale_colour_manual("Regulation Year",
                      values=c("firebrick", "olivedrab", "dodgerblue",
                               "darkorange", "mediumorchid")) +
  labs(x = "Year", y = "Particulate Matter",
       title = "Average Particulate Matter Over Time") +
  theme_classic()
```



Municipalities that regulated air quality in 2006 are different from the rest of the years. In general, the identifying assumption of the DD estimator is *parallel trends*, which means that municipalities should be on similar trajectories if not for treatment. It is obvious that the *pre-treatment trend* of municipalities that regulated air quality in 2006 is not parallel with the rest of the years, which violates the DD assumption and will cause bias to our difference-in-differences estimator.

```
## Using remaining municipalities to estimate a panel fixed effects regression.
# subset data
data_panel <- data %>%
  filter(air_quality_regulation_year >= 2003 &
           air_quality_regulation_year <= 2007 &
           air_quality_regulation_year != 2006)

# define variables
data_panel$post <- ifelse(data_panel$year >= data_panel$air_quality_regulation_year, 1, 0)
data_panel$TREATED <- data_panel$treat * data_panel$post

# fixed effects regression
reg_panel_fixed <- plm(particulate_matter ~ TREATED +
                         as.factor(municipality_id) + as.factor(year),
                   data = data_panel,
                   model = "within",
                   effect = "twoway",
                   index = c("municipality_id", "year"))
fixed_co <- coeftest(reg_panel_fixed,
                     vcov = vcovHC(reg_panel_fixed, type = "HC0", cluster = "group"))

# display regression results
stargazer(fixed_co,
          type = 'text',
          dep.var.labels = 'Particulate Matter',
          title = 'Fixed Effects Regression')
```

```
##
## Fixed Effects Regression
```

```
## ===================================
##             Dependent variable:
##         ---------------------------
##             Particulate Matter
## -----------------------------------
## TREATED         -15.167***
##                   (0.448)
##
## ===================================
## ===================================
## Note:   *p<0.1; **p<0.05; ***p<0.01
```

We find that our estimated effect of air quality regulations on particulate matter is -15.167 (statistically and economically significant) by using the panel fixed effects regression. Compared to what we estimated before (treatment effect in 2006: 67.469), our estimate effect of air quality regulation from the panel data with years *2003, 2004, 2005, 2007* turns to negative value and shows a lower size effect.

```r
## Use an event study regression to estimate how this treatment effect varies over time.
# periods to treatment (set -1 as the reference level)
data_panel$ptt <- data_panel$year - data_panel$air_quality_regulation_year
data_panel$ptt <- relevel(as.factor(data_panel$ptt), "-1")

# event study regression
reg_panel_event <- plm(particulate_matter ~ as.factor(ptt)*TREATED +
                         as.factor(municipality_id) + as.factor(year),
                       data = data_panel,
                       model = "within",
                       effect = "twoway",
                       index = c("municipality_id", "year"))
event_co <- coeftest(reg_panel_event,
                     vcov = vcovHC(reg_panel_event, type = "HC0", cluster = "group"))

# display regression results
stargazer(event_co,
          type = 'text',
          dep.var.labels = 'Particulate Matter',
          title = 'Event Effects Regression')
```

```
##
## Event Effects Regression
## ============================================
##                       Dependent variable:
##                   ---------------------------
##                       Particulate Matter
## --------------------------------------------
## as.factor(ptt)-4          -4.855***
##                            (1.046)
##
## as.factor(ptt)-3          -2.364**
##                            (1.025)
##
## as.factor(ptt)-2           -1.479*
```

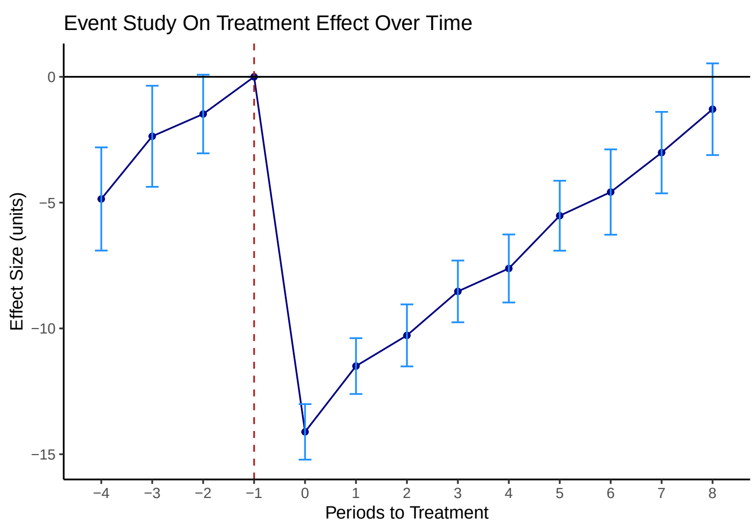
```
##                              (0.797)
##
## as.factor(ptt)0          -14.112***
##                              (0.563)
##
## as.factor(ptt)1          -11.496***
##                              (0.566)
##
## as.factor(ptt)2          -10.278***
##                              (0.629)
##
## as.factor(ptt)3           -8.529***
##                              (0.626)
##
## as.factor(ptt)4           -7.618***
##                              (0.689)
##
## as.factor(ptt)5           -5.521***
##                              (0.709)
##
## as.factor(ptt)6           -4.580***
##                              (0.865)
##
## as.factor(ptt)7           -3.013***
##                              (0.826)
##
## as.factor(ptt)8            -1.288
##                              (0.930)
##
## ============================================
## ============================================
## Note:            *p<0.1; **p<0.05; ***p<0.01
```

```
## Plot the resulting event study point estimates and 95 percent confidence intervals.
# create data frame
event_study <- data.frame(event_co[,1:2])
event_study$PTT <- rownames(event_study)
colnames(event_study) <- c("PM", "sd", "PTT")
event_study$PTT <- c(-4:-2, 0:8)
rownames(event_study) <- 1:nrow(event_study)

# set reference effect size at reference level
event_study[nrow(event_study)+1,] <- c(0, 0, -1)
print(event_study)
```

```
##            PM        sd PTT
## 1   -4.854524 1.0460833  -4
## 2   -2.364111 1.0248731  -3
## 3   -1.479081 0.7972085  -2
## 4  -14.111552 0.5631716   0
## 5  -11.496463 0.5662124   1
## 6  -10.277658 0.6287140   2
## 7   -8.529152 0.6261640   3
## 8   -7.617793 0.6894757   4
```

```
## 9   -5.521113 0.7090935   5
## 10  -4.580372 0.8654363   6
## 11  -3.012855 0.8257866   7
## 12  -1.288255 0.9297116   8
## 13   0.000000 0.0000000  -1
```

```
# plot event study point estimates
ggplot(event_study,
       aes(x = PTT,
           y = PM)) +
  geom_point(color = "navy") +
  geom_line(color = "navy") +
  geom_errorbar(aes(x = PTT,
                    ymin = PM - 1.96*sd,
                    ymax = PM + 1.96*sd),
                width = 0.25,
                color = "dodgerblue") +
  geom_vline(xintercept = -1, color = "firebrick", linetype = "dashed") +
  geom_hline(yintercept = 0) +
  scale_x_continuous(breaks = seq(-4, 8, by = 1)) +
  labs(x = "Periods to Treatment", y = "Effect Size (units)",
       title = "Event Study On Treatment Effect Over Time") +
  theme_classic()
```



The graph shows that imposing air quality regulations has a large effect of *decreasing* local particulate matter (PM 2.5) right after the treatment, but such effect will be gradually weakened over time. We want pre-treatment effect sizes to be centered on 0 and not trending, but the graph shows a trending (size effect decreasing) prior to the treatment, which is not ideal.

Conculsion

We find that the effect of air quality regulations on particulate matter is -15.167, which means that imposing air quality regulations has the effect of decreasing local particulate matter (PM 2.5). We regard this as a preferred estimate because it is based on the panel fixed effects regression that captures individual and time fixed effects, which mitigates the concerns of *time-varying variables and selection bias.* We also left out the data of air quality regulations in 2006 to meet the *parallel trends assumption* in our regression, which makes our results reliable.

We also separated out differential effects of air quality regulations over time, which indicates a dynamic trend of the impact of air quality regulations on PM 2.5 that aligns with our expectation. Therefore, the estimated results could be regarded as a preferred and credible estimate to answer our research question.

One potential shortcoming with these results is that we didn't include any baseline characteristics of municipalities as control variables in our estimate.

Recall that our fixed effects regression is:

$$Y_{it} = \tau D_{it} + \alpha_i + \delta_t + \beta X_{it} + \varepsilon_{it}$$

Here we need $E[\varepsilon_{it}|\alpha_i, \delta_t, X_{it}] = 0$ for this model to work.
Failure to include some observables as controls may cause omitted variable bias and make our estimate less accurate.

As mentioned earlier, the plot of event study shows that treatment effects have a trending and fail to be centered on 0 prior to the treatment, which challenges the identifying assumption and may cause bias to the results.

The estimated effect is -15.167 (statistically and economically significant), which suggests that the PROGRAMEVAL should promote air quality regulations. With that being said, considering the aforementioned shortcomings with the results, we may need a larger and more comprehensive dataset from municipalities at different years to check its external validity.