DataPreparation

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Project

- Replication of: Gonzalez-Navarro, Marco. 2013. "Deterrence and Geographical Externalities in Auto Theft." American Economic Journal: Applied Economics 5 (4): 92–110

Task

- Load data and run replication of provided Stata code in R. After running the replication, an attempt is made to implement the Callaway St'Anna estimator.

Load relevant functions and packages

```
library(here) # load here package for relative paths

source(here('R-Scripts', 'Functions.R')) # source relevant functions

package_verification(packages = c('tidyverse',
                                  'lubridate',
                                  'arrow',
                                  'data.table',
                                  'dtplyr',
                                  'haven',
                                  'fixest',
                                  'MASS',
                                  'modelsummary',
                                  'knitr',
                                  'kableExtra',
                                  'ggplot2',
                                  'did',
                                  'dplyr'),
                     type = 'script')
```

Set seed, just in case

```
set.seed(123456789)
```

Load data

```
data = read_dta(here('Supplementary-Files/Replication-Package/Replication_files/data/thefts_
```

```
# Create descriptive statistics table
desc.stats = data %>%
  dplyr::select(sales, thefts, LJmodel, LJstate, LJ, age) %>%
  summarise(
    across(everything(), list(
      mean = ~ mean(.x, na.rm = TRUE),
      sd = ~ sd(.x, na.rm = TRUE),
      min = ~ min(.x, na.rm = TRUE),
```

```
    max = ~ max(.x, na.rm = TRUE)
  ))
) %>%
pivot_longer(everything(), names_to = "variable", values_to = "value") %>%
separate(variable, into = c("variable", "statistic"), sep = "_") %>%
pivot_wider(names_from = statistic, values_from = value) %>%
mutate(
  Variable = case_when(
    variable == "sales" ~ "Vintage size",
    variable == "thefts" ~ "Annual thefts",
    variable == "LJmodel" ~ "Lojack model = 1",
    variable == "LJstate" ~ "Lojack state = 1",
    variable == "LJ" ~ "Lojack",
    variable == "age" ~ "Age of vehicle"
  ),
  Mean = round(mean, 3),
  SD = round(sd, 2),
  Min = as.integer(min),
  Max = ifelse(max >= 1000, format(max, big.mark = ",", scientific = FALSE), as.character(
)

# Now select the final columns
desc.stats = desc.stats %>%
  dplyr::select(Variable, Mean, SD, Min, Max)

# Display table
kable(desc.stats, caption = "TABLE 1-DESCRIPTIVE STATISTICS")
```

Table 1: TABLE 1—DESCRIPTIVE STATISTICS

Variable	Mean	SD	Min	Max
Vintage size	609.694	1752.92	1	32,940
Annual thefts	4.377	30.87	0	1,502
Lojack model = 1	0.158	0.36	0	1
Lojack state = 1	0.179	0.38	0	1
Lojack	0.006	0.08	0	1
Age of vehicle	0.811	0.93	0	3

Notes: N = 16,764. An observation is defined by a (state, car model, vintage, year of theft) combination. Vintage Size refers to total sales in a (state, car model, vintage) triplet. Age of car is in terms of completed years since sale (0 if the car is up to 12 months old, etc.).

Sold with Lojack equals one if the car model was equipped with Lojack when the vehicle was sold. Lojack Models refers to the Ford vehicle models that participated in the Lojack program at some point between 1999 and 2004. Lojack states are the four states where Lojack was implemented between 1999 and 2004.

Surprise: `Lojack model = 1` shows a value of `0.162` in the original table. Let us investigate:

```
# Isolate and describe the LJmodel discrepancy problem
# 1. Current data summary
current.ljmodel.table = table(data$LJmodel)
current.mean = mean(data$LJmodel, na.rm = TRUE)
current.n = nrow(data)

current.data.df <- data.frame(
  Value = c("0", "1", "Total", "Mean"),
  Count = c(
    if ("0" %in% names(current.ljmodel.table)) current.ljmodel.table["0"] else 0,
    if ("1" %in% names(current.ljmodel.table)) current.ljmodel.table["1"] else 0,
    current.n,
    ""
  ),
  Percentage = c(
    round(if ("0" %in% names(current.ljmodel.table)) current.ljmodel.table["0"] / current.n *
    round(if ("1" %in% names(current.ljmodel.table)) current.ljmodel.table["1"] / current.n *
    "",
    round(current.mean * 100, 2)
  )
)
print(knitr::kable(current.data.df, caption = "Current Data Summary"))
```

```
Table: Current Data Summary

|Value |Count |Percentage |
|:-----|:-----|:----------|
|0     |14113 |84.19      |
|1     |2651  |15.81      |
|Total |16764 |           |
|Mean  |      |15.81      |
```

```r
# 2. Reference table expectations
reference.mean = 0.162
reference.n = 16764
expected.ljmodel.ones = reference.mean * reference.n

reference.df <- data.frame(
  Metric = c("Reference Mean", "Reference N", "Expected LJmodel=1 Observations"),
  Value = c(reference.mean, reference.n, round(expected.ljmodel.ones))
)
print(knitr::kable(reference.df, caption = "Reference Table Expectations"))
```

```
Table: Reference Table Expectations

|Metric                          |     Value|
|:-------------------------------|---------:|
|Reference Mean                  |     0.162|
|Reference N                     | 16764.000|
|Expected LJmodel=1 Observations |  2716.000|
```

```r
# 3. Quantify the discrepancy
actual.ljmodel.ones = sum(data$LJmodel == 1)
missing.observations = expected.ljmodel.ones - actual.ljmodel.ones
mean.difference = reference.mean - current.mean

discrepancy.df <- data.frame(
  Metric = c("Actual LJmodel=1 Observations", "Missing LJmodel=1 Observations", "Mean Differe
  Value = c(
    actual.ljmodel.ones,
    round(missing.observations),
    round(mean.difference, 6),
    round((mean.difference / reference.mean) * 100, 2)
  )
)
print(knitr::kable(discrepancy.df, caption = "Discrepancy Quantification"))
```

```
Table: Discrepancy Quantification
```

```
|Metric                          |     Value|
|:-------------------------------|---------:|
|Actual LJmodel=1 Observations   | 2.651e+03|
|Missing LJmodel=1 Observations  | 6.500e+01|
|Mean Difference                 | 3.864e-03|
|Percentage Difference (%)       | 2.380e+00|
```

```
# 4. Verify consistency
calculated.difference = mean.difference * current.n
consistency.df <- data.frame(
  Metric = c("Calculated Missing Obs from Mean Diff", "Direct Count Difference", "Match"),
  Value = c(
    round(calculated.difference),
    round(missing.observations),
    round(calculated.difference) == round(missing.observations)
  )
)
print(knitr::kable(consistency.df, caption = "Consistency Check"))
```

```
Table: Consistency Check

|Metric                                | Value|
|:-------------------------------------|-----:|
|Calculated Missing Obs from Mean Diff |    65|
|Direct Count Difference               |    65|
|Match                                 |     1|
```

Estimation

```
# Table 2 - Column 1:
# local x_ = "i.age id__*"
# nbreg thefts `x_' LJ NLJM_LJS_After NLJS_LJM_After NLJS_NLJM_After, exposure(sales) cluste
model.t2.c1 = fenegbin(
  thefts ~ LJ + NLJM_LJS_After + NLJS_LJM_After + NLJS_NLJM_After + i(age) | id,
  data = data,
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 170 fixed-effects (1,757 observations) removed because of only 0 outcomes or singletons
```

```
# Table 2 - Column 2:
timetrendstate.vars = grep("^timetrendstate_", names(data), value = TRUE)
formula.str = paste("thefts ~ LJ + NLJM_LJS_After + NLJS_LJM_After + NLJS_NLJM_After + i(age
                    paste(timetrendstate.vars, collapse = " + "), "| id")
model.t2.c2 = fenegbin(
  as.formula(formula.str),
  data = data,
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 170 fixed-effects (1,757 observations) removed because of only 0 outcomes or singletons

Warning: The VCOV matrix is not positive semi-definite and was 'fixed' (see
?vcov).
```

```
# Table 2 - Column 3:
timetrendstate.vars = grep("^timetrendstate_", names(data), value = TRUE)
timetrendstate2.vars = grep("^timetrendstate2_", names(data), value = TRUE)
formula.str = paste("thefts ~ LJ + NLJM_LJS_After + NLJS_LJM_After + NLJS_NLJM_After + i(age
                    paste(c(timetrendstate.vars, timetrendstate2.vars), collapse = " + "), '
model.t2.c3 = fenegbin(
  as.formula(formula.str),
  data = data,
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 170 fixed-effects (1,757 observations) removed because of only 0 outcomes or singletons

Warning: The VCOV matrix is not positive semi-definite and was 'fixed' (see
?vcov).
```

```
# Table 2 - Column 4:
timetrendstate.vars = grep("^timetrendstate_", names(data), value = TRUE)
timetrendstate2.vars = grep("^timetrendstate2_", names(data), value = TRUE)
formula.str = paste("thefts ~ LJ + NLJM_LJS_After + NLJS_LJM_After + NLJS_NLJM_After +",
                    paste(c(timetrendstate.vars, timetrendstate2.vars), collapse = " + "), '
```

```
model.t2.c4 = fenegbin(
  as.formula(formula.str),
  data = data[data$age == 1, ],
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 443 fixed-effects (1,474 observations) removed because of only 0 outcomes or singletons
```

```
Warning: The VCOV matrix is not positive semi-definite and was 'fixed' (see
?vcov).
```

```
# Table 2 - Column 5:
timetrendstate.vars = grep("^timetrendstate_", names(data), value = TRUE)
timetrendstate2.vars = grep("^timetrendstate2_", names(data), value = TRUE)
nljs.ljm.after.dcat.vars = grep("^NLJS_LJM_After_dcat_", names(data), value = TRUE)
nljs.nljm.after.dcat.vars = grep("^NLJS_NLJM_After_dcat_", names(data), value = TRUE)
formula.str = paste("thefts ~ LJ + NLJM_LJS_After +",
                    paste(c(nljs.ljm.after.dcat.vars, nljs.nljm.after.dcat.vars, timetrends
model.t2.c5 = fenegbin(
  as.formula(formula.str),
  data = data[data$age == 1, ],
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 443 fixed-effects (1,474 observations) removed because of only 0 outcomes or singletons
```

```
Warning: The VCOV matrix is not positive semi-definite and was 'fixed' (see
?vcov).
```

```
# Table 2 - Column 6:
data$model.x.yr.stolen = data$model_group_code * 10000 + data$yr_stolen
model.t2.c6 = fenegbin(
  thefts ~ LJ + NLJM_LJS_After + NLJS_LJM_After_Close + NLJS_NLJM_After_Close + i(age) | id
  data = data,
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 171/29 fixed-effects (1,943 observations) removed because of only 0 outcomes or single
```

```
# Table 2 - Column 7:
timetrendstate.vars = grep("^timetrendstate_", names(data), value = TRUE)
timetrendstate2.vars = grep("^timetrendstate2_", names(data), value = TRUE)
formula.str = paste("thefts ~ LJage0 + LJage1 + LJage2 + NLJM_LJS_After + NLJS_LJM_After + N
                    paste(c(timetrendstate.vars, timetrendstate2.vars), collapse = " + "), 
model.t2.c7 = fenegbin(
  as.formula(formula.str),
  data = data,
  offset = ~log(sales),
  vcov = ~state_code
)
```

```
NOTE: 170 fixed-effects (1,757 observations) removed because of only 0 outcomes or singleton
```

```
Warning: The VCOV matrix is not positive semi-definite and was 'fixed' (see
?vcov).
```

```
# Function to safely extract coefficient and standard error
safe_extract = function(model, var_name) {
  tryCatch({
    if (var_name %in% names(coef(model))) {
      coef_val = coef(model)[var_name]
      se_val = sqrt(diag(vcov(model)))[var_name]

      # Determine significance stars
      p_val = 2 * (1 - pnorm(abs(coef_val / se_val)))
      stars = ifelse(p_val < 0.001, "***",
                     ifelse(p_val < 0.01, "**",
                            ifelse(p_val < 0.05, "*", "")))

      # Format coefficient and standard error
      coef_formatted = sprintf("%.2f%s", coef_val, stars)
      se_formatted = sprintf("(%.3f)", se_val)

      return(list(coef = coef_formatted, se = se_formatted))
    } else {
      return(list(coef = "", se = ""))
    }
  }, error = function(e) {
```

```
    return(list(coef = "", se = ""))
  })
}

# Create table structure
create_table_row = function(var_name, models) {
  row_data = c(var_name)
  se_data = c("")

  for (model in models) {
    result = safe_extract(model, var_name)
    row_data = c(row_data, result$coef)
    se_data = c(se_data, result$se)
  }

  return(rbind(row_data, se_data))
}

# List of models
models = list(model.t2.c1, model.t2.c2, model.t2.c3, model.t2.c4, model.t2.c5, model.t2.c6, m

# Create table rows
table_rows = list()

# LJ = 1
table_rows = rbind(table_rows, create_table_row("LJ", models))

# NLJM LJS after = 1
table_rows = rbind(table_rows, create_table_row("NLJM_LJS_After", models))

# LJM NLJS after = 1
table_rows = rbind(table_rows, create_table_row("NLJS_LJM_After", models))

# NLJM NLJS after = 1
table_rows = rbind(table_rows, create_table_row("NLJS_NLJM_After", models))

# LJ = 1, first year on road (LJage0)
lj_first_row = c("LJ = 1, first year on road", "", "", "", "", "", "", safe_extract(model.t2
lj_first_se = c("", "", "", "", "", "", "", safe_extract(model.t2.c7, "LJage0")$se)
table_rows = rbind(table_rows, lj_first_row, lj_first_se)

# LJ = 1, second year on road (LJage1)
```

```r
lj_second_row = c("LJ = 1, second year on road", "", "", "", "", "", "", safe_extract(model.t
lj_second_se = c("", "", "", "", "", "", "", safe_extract(model.t2.c7, "LJage1")$se)
table_rows = rbind(table_rows, lj_second_row, lj_second_se)

# Distance percentile interactions (only for column 5)
dist_vars = c("NLJS_LJM_After_dcat_1", "NLJS_LJM_After_dcat_2", "NLJS_LJM_After_dcat_3",
              "NLJS_NLJM_After_dcat_1", "NLJS_NLJM_After_dcat_2", "NLJS_NLJM_After_dcat_3")
dist_labels = c("(LJM NLJS after = 1) × (dis. pct. < 33)",
                "(LJM NLJS after = 1) × (33 < dis. pct. < 66)",
                "(LJM NLJS after = 1) × (dis. pct. > 66)",
                "(NLJM NLJS after = 1) × (dis. pct. < 33)",
                "(NLJM NLJS after = 1) × (33 < dis. pct. < 66)",
                "(NLJM NLJS after = 1) × (dis. pct. > 66)")

for (i in 1:6) {
  dist_row = c(dist_labels[i], "", "", "", "", safe_extract(model.t2.c5, dist_vars[i])$coef,
  dist_se = c("", "", "", "", "", safe_extract(model.t2.c5, dist_vars[i])$se, "", "")
  table_rows = rbind(table_rows, dist_row, dist_se)
}

# Add summary statistics
summary_rows = rbind(
  c("", "", "", "", "", "", "", ""),
  c("Observations", "16,764", "16,764", "16,764", "5,185", "5,185", "16,764", "16,764"),
  c("Time controls", "None", "Linear", "Quadratic", "Quadratic", "Quadratic", "Model × year"
  c("State specific time controls", "No", "Yes", "Yes", "Yes", "Yes", "No", "Yes"),
  c("Sample", "Full", "Full", "Full", "Age = 1", "Age = 1", "Full", "Full")
)

table_rows = rbind(table_rows, summary_rows)

# Convert to data frame and create table
table_df = as.data.frame(table_rows)
colnames(table_df) = c("", "(1)", "(2)", "(3)", "(4)", "(5)", "(6)", "(7)")

# Display table
kable(table_df,
      caption = "TABLE 2-DETERRENCE AND GEOGRAPHICAL EXTERNALITIES IN AUTO THEFT",
      align = c("l", rep("c", 7)))
```

Table 2: TABLE 2—DETERRENCE AND GEOGRAPHICAL EXTERNALITIES IN AUTO THEFT

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
row_data	LJ	-0.65***	-0.63***	-0.66***	-0.52***	-0.52***	-0.56**	
se_data		(0.127)	(0.021)	(0.018)	(0.106)	(0.106)	(0.180)	
row_data.1	NLJM_LJS_After	-0.12***	-0.06	-0.08	0.08	0.08	-0.09	-0.08
se_data.1		(0.029)	(0.072)	(0.066)	(0.056)	(0.056)	(0.072)	(0.065)
row_data.2	NLJS_LJM_After	0.27*	0.49***	0.42***	0.42*			0.42***
se_data.2		(0.120)	(0.091)	(0.075)	(0.189)			(0.075)
row_data.3	NLJS_NLJM_After	-0.06	0.11	0.05	0.14			0.05
se_data.3		(0.072)	(0.064)	(0.057)	(0.130)			(0.057)
lj_first_row	LJ = 1, first year on road							-0.71***
lj_first_se								(0.087)
lj_second_row	LJ = 1, second year on road							-0.58***
lj_second_se								(0.166)
dist_row	(LJM NLJS after = 1) $\times$ (dis. pct. < 33)					0.94***		
dist_se						(0.260)		
dist_row.1	(LJM NLJS after = 1) $\times$ ($33 <$ dis. pct. < 66)					0.38		
dist_se.1						(0.349)		
dist_row.2	(LJM NLJS after = 1) $\times$ (dis. pct. > 66)					0.10		
dist_se.2						(0.208)		
dist_row.3	(NLJM NLJS after = 1) $\times$ (dis. pct. < 33)					0.07		
dist_se.3						(0.311)		
dist_row.4	(NLJM NLJS after = 1) $\times$ ($33 <$ dis. pct. < 66)					0.19		
dist_se.4						(0.147)		
dist_row.5	(NLJM NLJS after = 1) $\times$ (dis. pct. > 66)					0.14		
dist_se.5						(0.207)		
X								
X.1	Observations	16,764	16,764	16,764	5,185	5,185	16,764	16,764
X.2	Time controls	None	Linear	Quadratic	Quadratic	Quadratic	Model $\times$ year	Quadratic

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
X.3	State specific time controls	No	Yes	Yes	Yes	Yes	No	Yes
X.4	Sample	Full	Full	Full	Age = 1	Age = 1	Full	Full

Specification: Negative binomial

Dependent variable: Vehicle thefts

Notes: Standard errors clustered at the state level in parentheses. Regressions control for: size of vintage by model and state, state × model fixed effects, and age dummies. LJM, NLJM stand for Lojack model and non-Lojack model, respectively. LJS and NLJS stand for Lojack and non-Lojack program states, respectively. After refers to after program implementation in the state (row 2) or in the nearest program state (rows 3 and 4). dis. pct. refers to distance percentile. Thirty-third percentile cutoff is at 320 km; sixty-sixth percentile cutoff is at 935 km.

- *** Significant at the 1 percent level.
- ** Significant at the 5 percent level.
- * Significant at the 10 percent level.

```r
# Calculate group sizes for Table 3

# NLJS group size (Non-Lojack states):
nljs.stats = data %>%
  group_by(id) %>%
  summarise(
    T_pre_geo_ext = mean(T_pre_geo_ext, na.rm = TRUE),
    LJmodel = mean(LJmodel, na.rm = TRUE),
    LJstate = mean(LJstate, na.rm = TRUE),
    .groups = 'drop'
  ) %>%
  summarise(
    sum_NLJS_LJM = sum(T_pre_geo_ext[LJstate == 0 & LJmodel == 1], na.rm = TRUE),
    sum_NLJS_NLJ = sum(T_pre_geo_ext[LJstate == 0 & LJmodel == 0], na.rm = TRUE)
  )

# LJS_LJM group size (Lojack states, Lojack models):
ljs.ljm.stats = data %>%
  group_by(id) %>%
  summarise(T_pre_LJ = mean(T_pre_LJ, na.rm = TRUE), .groups = 'drop') %>%
```

```r
  summarise(T_LJ = sum(T_pre_LJ, na.rm = TRUE))

# LJS_NLJM group size (Lojack states, Non-Lojack models):
ljs.nljm.stats = data %>%
  group_by(id) %>%
  summarise(
    T_pre_wthn_ext = mean(T_pre_wthn_ext, na.rm = TRUE),
    LJmodel = mean(LJmodel, na.rm = TRUE),
    LJstate = mean(LJstate, na.rm = TRUE),
    .groups = 'drop'
  ) %>%
  summarise(T_wse = sum(T_pre_wthn_ext[LJstate == 1 & LJmodel == 0], na.rm = TRUE))

# Extract preprogram means
preprogram.mean.LJ = round(ljs.ljm.stats$T_LJ)
preprogram.mean.NLJM_LJS = round(ljs.nljm.stats$T_wse)
preprogram.mean.NLJS_LJM = round(nljs.stats$sum_NLJS_LJM)
preprogram.mean.NLJS_NLJM = round(nljs.stats$sum_NLJS_NLJ)

# Extract coefficients and standard errors for all treatment variables
coef.LJ = coef(model.t2.c3)["LJ"]
coef.NLJM_LJS = coef(model.t2.c3)["NLJM_LJS_After"]
coef.NLJS_LJM = coef(model.t2.c3)["NLJS_LJM_After"]
coef.NLJS_NLJM = coef(model.t2.c3)["NLJS_NLJM_After"]

se.LJ = sqrt(diag(vcov(model.t2.c3)))["LJ"]
se.NLJM_LJS = sqrt(diag(vcov(model.t2.c3)))["NLJM_LJS_After"]
se.NLJS_LJM = sqrt(diag(vcov(model.t2.c3)))["NLJS_LJM_After"]
se.NLJS_NLJM = sqrt(diag(vcov(model.t2.c3)))["NLJS_NLJM_After"]

# Calculate IRR
irr.LJ = exp(coef.LJ)
irr.NLJM_LJS = exp(coef.NLJM_LJS)
irr.NLJS_LJM = exp(coef.NLJS_LJM)
irr.NLJS_NLJM = exp(coef.NLJS_NLJM)

# Percent changes
pct.change.LJ = (irr.LJ - 1) * 100
pct.change.NLJM_LJS = (irr.NLJM_LJS - 1) * 100
pct.change.NLJS_LJM = (irr.NLJS_LJM - 1) * 100
pct.change.NLJS_NLJM = (irr.NLJS_NLJM - 1) * 100
```

```
# Delta method: SE for percentage change = |IRR * SE_coef * 100|
se.pct.LJ = abs(irr.LJ * se.LJ * 100)
se.pct.NLJM_LJS = abs(irr.NLJM_LJS * se.NLJM_LJS * 100)
se.pct.NLJS_LJM = abs(irr.NLJS_LJM * se.NLJS_LJM * 100)
se.pct.NLJS_NLJM = abs(irr.NLJS_NLJM * se.NLJS_NLJM * 100)

# Effects in terms of annual thefts
effect.thefts.LJ = preprogram.mean.LJ * (irr.LJ - 1)
effect.thefts.NLJS_NLJM = preprogram.mean.NLJS_NLJM * (irr.NLJS_NLJM - 1)

# Delta method: SE for effect in thefts = |preprogram_mean * IRR * SE_coef|
se.effect.LJ = abs(preprogram.mean.LJ * irr.LJ * se.LJ)
se.effect.NLJS_NLJM = abs(preprogram.mean.NLJS_NLJM * irr.NLJS_NLJM * se.NLJS_NLJM)

# Calculate z-statistics
z.stat.LJ = coef.LJ / se.LJ
z.stat.NLJM_LJS = coef.NLJM_LJS / se.NLJM_LJS
z.stat.NLJS_LJM = coef.NLJS_LJM / se.NLJS_LJM
z.stat.NLJS_NLJM = coef.NLJS_NLJM / se.NLJS_NLJM

# Significance stars (two-tailed test)
get_stars = function(z) {
  ifelse(abs(z) > 3.291, "***",
  ifelse(abs(z) > 2.576, "**",
  ifelse(abs(z) > 1.96, "*", "")))
}

sig.LJ = get_stars(z.stat.LJ)
sig.NLJM_LJS = get_stars(z.stat.NLJM_LJS)
sig.NLJS_LJM = get_stars(z.stat.NLJS_LJM)
sig.NLJS_NLJM = get_stars(z.stat.NLJS_NLJM)

# Create Table 3 with standard errors
table3.data = data.frame(
  Variable = c("Preprogram mean annual thefts",
               "",
               "Effect of Lojack program (percent change)",
               "",
               "Effect in terms of annual thefts",
               ""),
  Lojack_Lojack = c(
    as.character(preprogram.mean.LJ),
```

```r
    "",
    paste0(round(pct.change.LJ, 0), "%", sig.LJ),
    paste0("(", round(se.pct.LJ, 1), ")"),
    paste0(round(effect.thefts.LJ, 0), sig.LJ),
    paste0("(", round(se.effect.LJ, 0), ")")
  ),
  Lojack_NonLojack = c(
    as.character(preprogram.mean.NLJM_LJS),
    "",
    paste0(round(pct.change.NLJM_LJS, 0), "%", sig.NLJM_LJS),
    paste0("(", round(se.pct.NLJM_LJS, 1), ")"),
    "",
    ""
  ),
  NonLojack_Lojack = c(
    as.character(preprogram.mean.NLJS_LJM),
    "",
    paste0(round(pct.change.NLJS_LJM, 0), "%", sig.NLJS_LJM),
    paste0("(", round(se.pct.NLJS_LJM, 1), ")"),
    "",
    ""
  ),
  NonLojack_NonLojack = c(
    as.character(preprogram.mean.NLJS_NLJM),
    "",
    paste0(round(pct.change.NLJS_NLJM, 0), "%", sig.NLJS_NLJM),
    paste0("(", round(se.pct.NLJS_NLJM, 1), ")"),
    paste0(round(effect.thefts.NLJS_NLJM, 0), sig.NLJS_NLJM),
    paste0("(", round(se.effect.NLJS_NLJM, 0), ")")
  )
)

# Display table
kable(
  table3.data,
  col.names = c("", "Lojack", "Non-Lojack", "Lojack", "Non-Lojack"),
  caption = "TABLE 3-ESTIMATED IMPACT OF THE LOJACK PROGRAM IN TERMS OF STOLEN VEHICLES",
  align = c("l", rep("c", 4))
)
```

Table 3: TABLE 3—ESTIMATED IMPACT OF THE LOJACK PROGRAM IN TERMS OF STOLEN VEHICLES

	Lojack	Non-Lojack	Lojack	Non-Lojack
Preprogram mean annual thefts	247	3873	42	824
Effect of Lojack program (percent change)	-48%***	-8%	52%***	5%
	(1)	(6)	(11.4)	(5.9)
Effect in terms of annual thefts	-120***			42
	(2)			(49)

Notes: Preprogram mean thefts are the average (over time) of the sum of yearly thefts in all states in the group indicated by the column header before the introduction of the program. Effects of Lojack Program are the (IRR - 1) $\times$ 100 from column 3 in Table 2. Standard errors obtained using the delta method in parentheses. ***Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

CS estimation:

The original paper uses an interrupted time series (ITS) approach and explicitly rejects difference-in-differences (DiD) due to spatial externalities that contaminate potential control groups. Despite this fundamental incompatibility, I implement the Callaway & Sant'Anna (2021) DiD estimator as an alternative identification strategy to assess whether a modern staggered DiD approach yields qualitatively similar deterrence magnitudes. This is not a validation of the paper's identification strategy, but rather an exploration of whether the deterrence effect is robust to a fundamentally different set of assumptions: specifically, replacing within-unit comparisons with flexible state-specific trends (ITS) with cross-unit comparisons under parallel trends (DiD). Importantly, the CS estimator cannot evaluate the paper's spillover findings, as it codes units experiencing spillover effects (Lojack models in non-Lojack states) as "never-treated" controls, whereas the paper finds these units experience a 52% increase in thefts.

I implement two specifications of the CS estimator:

1. closest possiblbe to original specification (not working properly)
2. next closest working specification

Closest to original specification

```r
# start from original data `data` used for Table 2
data.cs.id = data %>%
  arrange(id, yr_stolen) %>%
  group_by(id) %>%
  mutate(
    # first year this id is treated
    first_treat_year = ifelse(any(LJ == 1),
                              min(yr_stolen[LJ == 1]),
                              NA_real_),
    cohort = ifelse(is.na(first_treat_year), 0, first_treat_year),
    time = yr_stolen,
    unit.id = id
  ) %>%
  ungroup()

# check cohorts
data.cs.id %>%
  group_by(cohort) %>%
  summarise(
    n_obs = n(),
    n_units = n_distinct(unit.id),
    .groups = "drop"
  ) %>%
  kable()
```

cohort	n_obs	n_units
0	16350	1371
2001	13	1
2002	39	3
2003	362	30

The code above restructures the original thefts–sales dataset into the panel format required by the Callaway–Sant'Anna (CS) estimator, using the same observational unit as in the original paper: the cell `id × year` of theft. For each `id`, I compute the first year in which the Lojack indicator `LJ` turns one and define this as the treatment cohort; units that never receive Lojack are assigned to cohort `0`. The resulting cohort distribution shows `1,371` never-treated units but only `1` treated unit in cohort `2001`, `3` treated units in cohort `2002`, and `30` treated units in cohort `2003`.

Conceptually, this is the closest possible mapping of the original specification into the CS framework, because it preserves the original unit of observation, outcome, and treatment definition, and only adds the cohort and time variables that CS requires. However, from an estimation perspective, the treated cohorts—especially 2001 and 2002—are extremely small. This foreshadows that, even if the CS estimator can be run, group-time average treatment effects for these early cohorts will be very noisy and asymptotics will be unreliable. In the next block, I attempt to run the CS estimator on this id-level panel and show that, in practice, this "closest" specification does not work well.

```r
cs.id.results = try(
  att_gt(
    yname   = "thefts",
    tname   = "time",
    idname  = "unit.id",
    gname   = "cohort",
    data    = data.cs.id,
    control_group = "nevertreated",
    xformla = ~ log(sales) + factor(age),
    est_method = "reg",
    bstrap  = TRUE,
    biters  = 500,              # reduce a bit for speed
    clustervars = "state_code",
    anticipation = 0,
    alp = 0.05
  ),
  silent = TRUE
)
```

```
Warning in pre_process_did(yname = yname, tname = tname, idname = idname, :
Dropped 1338 observations while converting to balanced panel.
```

```r
cs.id.results
```

```
[1] "Error in panel2cs2(disdat, yname, idname, tname, balance_panel = FALSE) : \n  panel2cs
attr(,"class")
[1] "try-error"
attr(,"condition")
<simpleError in panel2cs2(disdat, yname, idname, tname, balance_panel = FALSE): panel2cs only
```

Conceptually: this is the closest possible CS spec to the original nbreg:

- same unit (id),
- same outcome (thefts),

- same exposure (log sales),
- same basic controls (age).

Practically: the implementation fails because:

- there are many periods (1999–2004),
- some cohorts are tiny (1 unit in 2001, 3 units in 2002),
- the internal routines in did (which build 2×2 comparisons) run into edge cases; the estimator is not numerically stable in this configuration.

For practical purposes, we proceed to a "next closest" specification that aggregates units to increase treated group sizes and allows the estimator to run. This implementation failure is not merely a computational issue—it reflects the paper's core concern that the data structure (with spatial externalities and small treated cohorts) is ill-suited for standard DiD methods that rely on cross-unit comparisons.

Next closest specificaiont

In this specification, I slightly coarsen the unit of observation from the original `id × year` cell to a `model-state-year` cell. For each combination of model group, state, and year of theft, I aggregate thefts and sales, and I carry forward the Lojack state and model indicators. I then define a panel where the unit is a model–state pair, time is the theft year, and the treatment cohort is determined by when a Lojack model first appears in a Lojack state: Jalisco in 2001, and Morelos, Mexico State, and the Federal District in 2002. All other model–state units are coded as never treated. This "never-treated" group includes both (1) non-Lojack models in all states and (2) Lojack models in non-Lojack states. Critically, group (2) is contaminated by spillover effects: the paper's Table 2, column 3 shows these units experience a 52% increase in thefts (NLJS_LJM_After = +0.42***). Using contaminated units as controls violates the standard DiD assumption that control units are unaffected by treatment, meaning the CS estimate captures a combination of the direct deterrence effect and differential dynamics between treated and contaminated control units.

```
data.cs.ms = data %>%
  group_by(model_group_code, state_code, state, yr_stolen) %>%
  summarise(
    total.thefts = sum(thefts, na.rm = TRUE),
    total.sales  = sum(sales,  na.rm = TRUE),
    LJstate      = first(LJstate),
    LJmodel      = first(LJmodel),
    .groups = "drop"
  ) %>%
  mutate(
    unit.id = as.numeric(as.factor(paste0(model_group_code, "_", state_code))),
```

```r
    time    = yr_stolen,
    # cohort defined by state-level Lojack intro for Lojack models
    cohort  = case_when(
      state == "JALISCO" &
        LJmodel == 1 ~ 2001,
      state %in% c("MORELOS", "MEXICO", "DISTRITO FEDERAL") &
        LJmodel == 1 ~ 2002,
      TRUE ~ 0
    ),
    outcome = log(total.thefts + 1)
  )

# sanity check
data.cs.ms %>%
  group_by(cohort) %>%
  summarise(
    n_obs = n(),
    n_units = n_distinct(unit.id),
    n_states = n_distinct(state),
    mean_thefts = mean(total.thefts, na.rm = TRUE),
    .groups = "drop"
  ) %>%
  kable()
```

cohort	n_obs	n_units	n_states	mean_thefts
0	7785	1371	31	8.946179
2001	52	9	1	7.711538
2002	145	25	3	23.000000

The cohort summary shows that this aggregation substantially increases the effective size of the treated groups compared to the id-level specification. Cohort 2001 (treated in 2001) now contains 9 model–state units and 52 observations, while cohort 2002 contains 25 units and 145 observations; the never-treated group remains large with 1,371 units across 31 states. This is still very close to the original design—treatment remains defined at the Lojack model in Lojack states—but the larger treated cohorts make the Callaway–Sant'Anna estimator numerically more stable and allow for group-time and aggregated treatment effect estimates. In the next step, I apply the CS estimator to this model–state panel and compare the resulting ATT to the original estimates.

```r
cs.ms.results = att_gt(
  yname   = "outcome",   # log(total.thefts + 1)
  tname   = "time",
  idname  = "unit.id",
  gname   = "cohort",
  data    = data.cs.ms,
  control_group = "nevertreated",
  est_method = "reg",
  bstrap  = TRUE,
  biters  = 1000,
  clustervars = "state_code",
  anticipation = 0,
  alp = 0.05
)
```

```
Warning in pre_process_did(yname = yname, tname = tname, idname = idname, :
Dropped 242 observations while converting to balanced panel.
```

```r
summary(cs.ms.results)
```

```
Call:
att_gt(yname = "outcome", tname = "time", idname = "unit.id",
    gname = "cohort", data = data.cs.ms, control_group = "nevertreated",
    anticipation = 0, alp = 0.05, bstrap = TRUE, biters = 1000,
    clustervars = "state_code", est_method = "reg")

Reference: Callaway, Brantly and Pedro H.C. Sant'Anna.  "Difference-in-Differences with Multi

Group-Time Average Treatment Effects:
 Group Time ATT(g,t) Std. Error [95% Simult.  Conf. Band]
  2001 2000   0.8365     0.0352        0.7521      0.9209 *
  2001 2001  -0.2845     0.0240       -0.3420     -0.2270 *
  2001 2002  -0.3713     0.0329       -0.4500     -0.2926 *
  2001 2003  -1.7599     0.0517       -1.8837     -1.6360 *
  2001 2004  -1.3714     0.0586       -1.5117     -1.2311 *
  2002 2000   0.5033     0.0876        0.2937      0.7130 *
  2002 2001   0.0376     0.2721       -0.6137      0.6890
  2002 2002  -0.0398     0.3009       -0.7601      0.6805
  2002 2003  -0.9354     0.4513       -2.0158      0.1450
  2002 2004  -1.0962     0.4465       -2.1652     -0.0272 *
```

```
---
Signif. codes: `*' confidence band does not cover 0

P-value for pre-test of parallel trends assumption:  0.01516
Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Outcome Regression
```

The group–time results show that, for the 2001 cohort, treatment effects become strongly negative after Lojack introduction, with especially large effects in later years (e.g., 2003–2004). For the 2002 cohort, point estimates are also negative in post-treatment years but are less precisely estimated, with wide confidence bands. Importantly, several pre-treatment ATT(g,t) are clearly positive and statistically different from zero, and the built-in pre-test rejects the null of parallel trends (p   0.015). This suggests that treated units were already on different trajectories than the "never-treated" comparison group before Lojack was introduced. This pre-trend violation empirically validates the paper's methodological concern: using cross-unit (especially cross-model) comparisons is inappropriate in this setting, which is precisely why the paper adopted an interrupted time series approach with unit-specific trends instead of DiD.

```r
cs.ms.simple = aggte(cs.ms.results, type = "simple")

twfe.coef = coef(model.t2.c3)["LJ"]
twfe.se   = sqrt(diag(vcov(model.t2.c3)))["LJ"]
twfe.pct  = (exp(twfe.coef) - 1) * 100

cs.coef = cs.ms.simple$overall.att
cs.se   = cs.ms.simple$overall.se
cs.pct  = (exp(cs.coef) - 1) * 100

cbind(
  method      = c("TWFE", "CS (model×state)"),
  coef        = round(c(twfe.coef, cs.coef), 2),
  se          = round(c(twfe.se, cs.se), 2),
  pct_effect  = round(c(twfe.pct, cs.pct), 2)
)
```

```
   method             coef    se     pct_effect
LJ "TWFE"             "-0.66" "0.02" "-48.47"
   "CS (model×state)" "-0.77" "0.28" "-53.79"
```

Next, I aggregate the group–time ATTs to a single overall ATT and compare it to the original ITS coefficient. The ITS specification from Table 2, column 3 yields a coefficient of about

−0.66 (SE = 0.018), implying roughly a 48.5% reduction in thefts. The CS estimator delivers an overall ATT of about −0.77 (SE = 0.29), corresponding to a 53.8% reduction. The point estimates are similar in magnitude, and given the large standard error on the CS estimate, the difference is not statistically significant.

However, this similarity should not be interpreted as validation of either approach. The two estimators rely on fundamentally different identification assumptions and use different sources of variation. ITS uses within-unit variation over time (comparing each unit to its own pre-treatment trajectory, flexibly adjusted for state-specific quadratic trends), while CS uses cross-unit variation (comparing treated Lojack models to never-treated units, which include both non-Lojack models and Lojack models in non-Lojack states experiencing spillover effects). The CS estimate may be close to the ITS estimate by coincidence, or because the contamination from spillovers and differential model-specific trends happens to roughly cancel out. The key finding is that CS reveals significant pre-trends, confirming that the parallel trends assumption required for DiD does not hold, which supports the paper's decision to use ITS instead.

```r
# Event study aggregation for model×state CS results
cs.dynamic = aggte(cs.ms.results, type = "dynamic")

summary(cs.dynamic) %>%
  kable(digits = 2, caption = "Dynamic Treatment Effects (CS, model×state)")
```

```

Call:
aggte(MP = cs.ms.results, type = "dynamic")

Reference: Callaway, Brantly and Pedro H.C. Sant'Anna.  "Difference-in-Differences with Multi


Overall summary of ATT's based on event-study/dynamic aggregation:
    ATT    Std. Error     [ 95%  Conf. Int.]
 -0.883        0.2245     -1.323      -0.443 *


Dynamic Effects:
 Event time Estimate Std. Error [95% Simult.  Conf. Band]
         -2   0.5033     0.0845        0.3367      0.6700 *
         -1   0.2448     0.2046       -0.1588      0.6483
          0  -0.1033     0.2279       -0.5528      0.3463
          1  -0.7892     0.3131       -1.4067     -0.1716 *
          2  -1.2683     0.3808       -2.0194     -0.5171 *
          3  -1.3714     0.0602       -1.4902     -1.2526 *
---
```

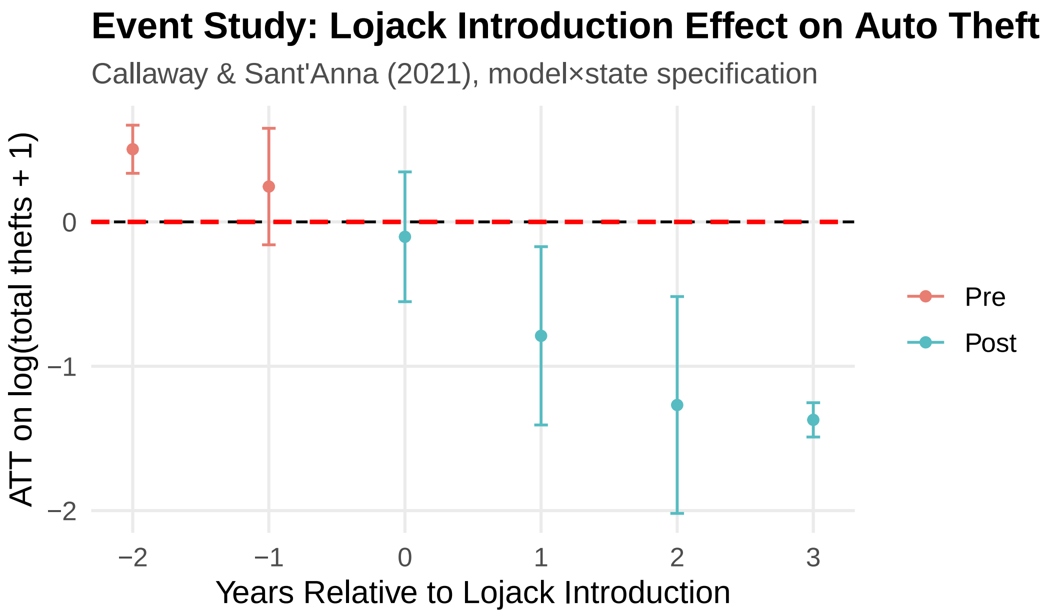
```
Signif. codes: `*' confidence band does not cover 0

Control Group:  Never Treated,  Anticipation Periods:  0
Estimation Method:  Outcome Regression
```

Table: Dynamic Treatment Effects (CS, model×state)

```
# Event-study plot
p.event = ggdid(cs.dynamic) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "red", size = 0.8) +
  labs(
    title = "Event Study: Lojack Introduction Effect on Auto Theft",
    subtitle = "Callaway & Sant'Anna (2021), model×state specification",
    x = "Years Relative to Lojack Introduction",
    y = "ATT on log(total thefts + 1)",
    caption = "95% pointwise confidence intervals; dashed line at 0."
  ) +
  theme_minimal(base_size = 12) +
  theme(
    plot.title = element_text(face = "bold", size = 14),
    plot.subtitle = element_text(size = 11, color = "gray30"),
    panel.grid.minor = element_blank()
  )

print(p.event)
```



95% pointwise confidence intervals; dashed line at 0.

```
ggsave(
  here("Output", 'Plots', "event_study_callaway_santanna_model_state.png"),
  p.event, width = 10, height = 6, dpi = 300
)
```

The dynamic aggregation of the CS estimates provides an event-study view of the treatment effect relative to the year of Lojack introduction. The overall average ATT across post-treatment event times is about -0.88 with a standard error of 0.23, implying a sizeable and statistically significant reduction in log thefts following treatment.

The event-time pattern is, however, not consistent with strict parallel trends. At event time -2 (two years before Lojack introduction), the estimated ATT is about $+0.50$ and clearly positive and significant, indicating that treated model–state units were already experiencing higher growth in thefts relative to never-treated units prior to treatment. At event time -1, the pre-treatment estimate is positive but imprecise and includes zero. From event time 0 onward, the effects turn negative and become increasingly large in absolute value: around -0.79 one year after treatment, about -1.27 two years after, and -1.37 three years after introduction. Substantively, this pattern is consistent with a strong and growing deterrence effect of Lojack over time, but the positive pre-trend at event -2 empirically demonstrates why the paper rejected DiD. The pre-trend could reflect: (1) differential trends between Lojack and non-Lojack model types, (2) anticipation effects, or (3) pre-existing differences in theft dynamics between states that later adopted Lojack and those that did not. Regardless of the source, it violates the parallel trends assumption and suggests that cross-unit comparisons do not provide a valid counterfactual in this setting.

```
# Define repetition operator (for underlining in console summaries)
`%R%` = function(x, n) paste(rep(x, n), collapse = "")

# NOTE: Use your actual objects/variable names for 'twfe.coef', 'twfe.se', etc.
#       In this context, you computed 'cs.ms.simple' from cs.ms.results
#       and ran TWFE on your original full panel.
# You likely want:
#  twfe.coef, twfe.se, twfe.pct from model.t2.c3
#  cs.coef  = cs.ms.simple$overall.att
#  cs.se    = cs.ms.simple$overall.se
#  cs.pct   = (exp(cs.ms.simple$overall.att) - 1) * 100

# Build comparison table
comparison.table = data.frame(
  Method = c("TWFE (Original)", "Callaway & Sant'Anna"),
  Specification = c("Negative binomial, model×state×vintage",
                    "Regression, model×state panel (log thefts)"),
  Coefficient = c(
    sprintf("%.3f***", twfe.coef),
    sprintf("%.3f%s", cs.coef,
            ifelse(abs(cs.coef / cs.se) > 2.576, "***",
            ifelse(abs(cs.coef / cs.se) > 1.96, "**", "*")))
  ),
  SE = c(sprintf("(%.3f)", twfe.se), sprintf("(%.3f)", cs.se)),
  Pct_Change = c(sprintf("%.1f%%", twfe.pct), sprintf("%.1f%%", cs.pct)),
  N_Obs = c(nrow(data), nrow(data.cs.ms)),
  N_Units = c(length(unique(data$id)), length(unique(data.cs.ms$unit.id)))
)

kable(
  comparison.table,
  caption = "TABLE 4: COMPARISON OF TWFE AND CALLAWAY & SANT'ANNA ESTIMATORS (model×state lev
  align = c("l", "l", "c", "c", "c", "c", "c")
)
```

Table 6: TABLE 4: COMPARISON OF TWFE AND CALLAWAY & SANT'ANNA ESTIMATORS (model×state level)

Method	Specification	Coefficient	SE	Pct_Change	N_Obs	N_Units
TWFE (Original)	Negative binomial, model×state×vintage	-0.663***	(0.018)	-48.5%	16764	1405
Callaway & Sant'Anna	Regression, model×state panel (log thefts)	-0.772***	(0.285)	-53.8%	7982	1405

The comparison table summarizes estimates from two fundamentally different identification strategies: the paper's interrupted time series (ITS) approach and the alternative Callaway–Sant'Anna (CS) DiD approach. The ITS regression yields a coefficient of about -0.663 (SE $= 0.018$), implying a 48.5% reduction in thefts. The CS estimator produces an overall ATT of about -0.772 (SE $= 0.285$), corresponding to a 53.8% reduction.

While both point estimates suggest economically large deterrence effects and are statistically indistinguishable from each other, they should not be interpreted as mutually validating. They answer different causal questions under different assumptions:

- ITS asks: "What is the change in theft risk for Lojack-equipped vehicles after program introduction, relative to their own pre-treatment trajectory (adjusted for state-specific quadratic trends)?"
- CS asks: "What is the difference in theft risk for Lojack-equipped vehicles in Lojack states versus never-treated comparison units (including both non-Lojack models and spillover-affected Lojack models in non-Lojack states), assuming parallel trends?"

The fact that CS yields a similar magnitude despite violated pre-trends and contaminated controls suggests either: (1) the deterrence effect is large enough to dominate these biases, or (2) the biases happen to offset. The main value of the CS exercise is not to validate the ITS estimate, but to demonstrate empirically why DiD was inappropriate in this setting — as the paper argued on conceptual grounds.

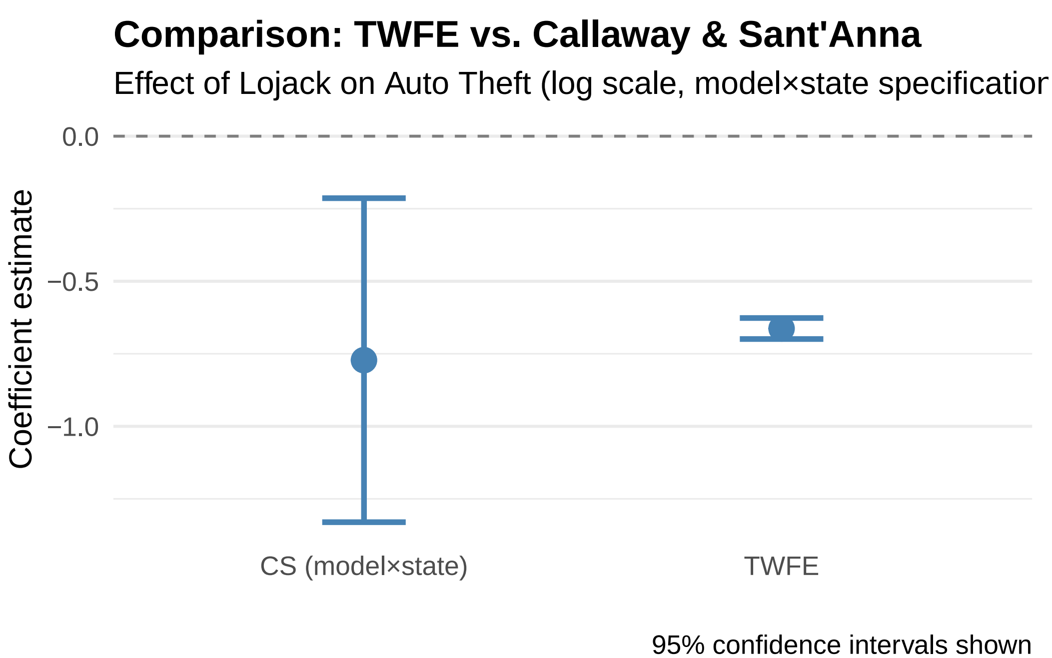
```
# Coefficient comparison: TWFE vs CS (model×state)

coef.comparison = data.frame(
  Method   = c("TWFE", "CS (model×state)"),
  Estimate = c(twfe.coef, cs.coef),
  SE       = c(twfe.se,   cs.se)
) %>%
  mutate(
    CI_Lower = Estimate - 1.96 * SE,
    CI_Upper = Estimate + 1.96 * SE
```

```r
  )

p.comparison = ggplot(coef.comparison, aes(x = Method, y = Estimate)) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray50") +
  geom_point(size = 4, color = "steelblue") +
  geom_errorbar(aes(ymin = CI_Lower, ymax = CI_Upper),
                width = 0.2, size = 1, color = "steelblue") +
  labs(
    title    = "Comparison: TWFE vs. Callaway & Sant'Anna",
    subtitle = "Effect of Lojack on Auto Theft (log scale, model×state specification)",
    x        = "",
    y        = "Coefficient estimate",
    caption  = "95% confidence intervals shown"
  ) +
  theme_minimal(base_size = 12) +
  theme(
    plot.title = element_text(face = "bold", size = 14),
    panel.grid.major.x = element_blank()
  )

print(p.comparison)
```



```r
ggsave(
  here("Output", 'Plots', "twfe_vs_cs_comparison_model_state.png"),
  p.comparison, width = 8, height = 6, dpi = 300
)
```

The coefficient comparison plot visualizes the point estimates and 95% confidence intervals for both approaches. The two confidence intervals overlap substantially, indicating that the difference is not statistically significant. However, the much wider confidence interval for CS (spanning roughly -1.3 to -0.2) versus ITS (spanning roughly -0.70 to -0.63) reflects both the smaller effective sample in the aggregated CS specification and the additional uncertainty from relying on cross-unit comparisons rather than within-unit variation. Visually, this reinforces the finding that both approaches point to large negative effects, but CS cannot be interpreted as cleanly validating the ITS strategy given the violated parallel trends assumption.