

# Replication and Alternative Identification Strategy

Deterrence and Geographical Externalities in Auto Theft (Gonzalez-Navarro 2013)

Manuel Zerobin

December 1, 2025

## Research Question:

- What is the effect of Lojack (stolen vehicle recovery technology) on auto theft rates?
- **Central motivation:** Does technological deterrence reduce crime, or does it simply displace theft geographically?
- **Policy implication:** Should crime control be centralized (to internalize spillovers) or can local enforcement suffice?

## Data:

- Source: Mexican auto insurance claims database (AMIS), 1999–2004
- Coverage: All reported vehicle thefts in 31 Mexican states
- Unit of observation: state  $\times$  model  $\times$  vintage  $\times$  year
- Total observations:  $N = 16,764$  cells
- Treatment: Lojack installed in select Ford models in Jalisco (2001) and Mexico City metro (2002)

# Methodology & Identification Strategy

Paper explicitly rejects DiD due likely spillovers and thus contaminated controls

## **Interrupted Time Series (ITS) Strategy:**

- Source of identification: **within-unit** changes over time
- Each unit serves as its own counterfactual
- Allows estimation of spillovers: uses all units to identify external effects
- Allows for fixed effects (state  $\times$  model) and time trends
- Estimated using negative binomial regression (positive & count data)

**Key Identifying Assumption:** Lojack introduction uncorrelated with changes in theft risk *beyond* state-specific trends.

**Replication with Callaway StAnna estimator:** can be found on [Github](#)

# Conclusion: Identification Strategies & Robustness

## Main Takeaways:

- ➊ **Replication:** Original results confirmed; small data-handling differences explain SE variations
- ➋ **ITS vs. CS-DiD:** Two fundamentally different identification strategies yield similar deterrence magnitudes ( $-0.66$  vs.  $-0.77$ ), suggesting effect is robust across methodological approaches
- ➌ **Pre-trends violation in CS:** Significant positive estimate at event time  $t = -2$  empirically validates paper's concern that DiD assumptions fail in this spatial setting
- ➍ **Spillover effects:** CS framework cannot estimate these— that is why paper designed identification to handle spatial externalities

## Interpretation:

- The similarity of point estimates across ITS and CS does *not validate* either method
- CS robustness check supports the paper's concerns about cross-unit comparisons in the presence of spatial effects

## Limitations of ITS Approach:

- ① **Trend specification:** Assumes state-specific *quadratic* trends are sufficient
  - What if true trends are higher-order or nonlinear?
  - Misspecification would bias treatment effects
- ② **Unobserved confounds:** Assumes no time-varying state-level shocks correlated with treatment
  - Police crackdowns, economic shifts, gang activity changes unobserved
  - Unobservable factors could drive theft changes independent of Lojack
- ③ **Cannot estimate spillovers precisely:** Spillover coefficients rely on model assumptions
  - Identifying spillovers requires modeling uncontaminated “nearby” vs. “distant” states
  - Results sensitive to distance cutoffs (tercile definitions)
- ④ **Exposure measurement:** Controls for sales at *time of sale*, not current vehicle stock
  - Vehicles sold in 1999 still at risk in 2004; data doesn't track cumulative stock
  - May overstate or understate theft risk in older vintages

**Thank you!**

# Paper Overview: Research Question & Data

## Research Question:

- Effect of Lojack (stolen vehicle recovery system) on auto theft deterrence
- Main finding: 48% reduction in thefts for equipped vehicles
- Geographical spillovers: 18% of reduction displaced to non-Lojack states

## Data & Context:

- Mexican auto insurance claims (AMIS), 1999–2004
- Staggered introduction: Jalisco (2001), 3 metro areas (2002)
- Unit: state  $\times$  model  $\times$  vintage  $\times$  year
- $N = 16,764$  observations

## Identification Strategy (Original Paper):

- Interrupted time series
- Within-unit comparisons: each unit vs. own pre-treatment trajectory
- State-specific linear & quadratic time trends
- Negative binomial with exposure (sales)

# Replication Results & Data Discrepancy

## Replication Status:

- Main results replicated successfully
- Standard errors differ slightly

## Data Issue Identified:

- Replicated & original  $N = 16,764$
- Replicated  $\Delta_{LJmodel=1} = 65$
- Discrepancy: slight exclusion/inclusion of edge cases
- Impact: point estimates identical, minor changes in SE



# Why Implement Callaway & Sant'Anna (2021)?

## Alternative Identification Strategy:

- Original approach: Interrupted time series (within-unit, flexible trends)
- CS approach: Staggered DiD (cross-unit, parallel trends)
- **Purpose:** Assess whether deterrence effect is robust across identification strategies

## Important:

- Paper explicitly rejects DiD due to spatial externalities
- CS treats contaminated units (Lojack models in non-Lojack states) as controls
- These units *experience spillover effects* (+52% increase in thefts)
- **This is not validation of paper's identification, but alternative exploration**

## Implementation:

- Unit: model  $\times$  state (aggregated from model  $\times$  state  $\times$  vintage)
- Outcome:  $\log(\text{total thefts} + 1)$  at model-state-year level
- Treated cohorts: Jalisco 2001 (9 units), other metros 2002 (25 units)
- Control group: Never-treated model-state pairs (1,371 units)

# Callaway & Sant'Anna Estimation Results

## Overall ATT (Simple Aggregation):

Method	Coef	SE
ITS (Original)	-0.663	0.018
CS (DiD)	-0.772	0.285

*Interpretation:* 48.5% vs. 53.8% reduction—similar in magnitude but CS has wider CI.

## Parallel Trends Test:

Event Time	ATT	SE
$t = -2$	+0.503	0.094
$t = -1$	+0.245	0.278
$t = 0$	-0.103	0.232
$t = +1$	-0.789	0.283

Table: Pre-trends violated at  $t = -2$  ( $p < 0.001$ )

## Key Findings:

- CS yields deterrence magnitude *similar* to ITS but with larger uncertainty
- **Significant pre-trend at  $t = -2$ :** parallel trends assumption violated
- Event study shows large post-treatment effects consistent with deterrence
- **Conclusion:** Pre-trends empirically validate paper's methodological choice

# Conclusion: Identification Strategies & Robustness

## Main Takeaways:

- 1 **Replication:** Original results confirmed; small data-handling differences explain SE variations
- 2 **ITS vs. DiD:** Two different identification strategies yield similar deterrence magnitudes ( $-0.66$  vs.  $-0.77$ )
- 3 **Pre-trends violation in CS:** Significant pre-treatment dynamics validate paper's *a priori* concern that DiD assumptions fail in this setting
- 4 **Spillover effects:** CS framework cannot estimate these—emphasizes why paper designed identification to handle spatial externalities

## Empirical Specification:

$$E[\text{Thefts}_{smvt}] = S_{smvt} \exp(\alpha_{sm} + f_{st} + \beta_{\text{age}} + \gamma_1 LJ + \gamma_2 \text{NLJS\_LJM} + \dots)$$

- $\alpha_{sm}$ : state  $\times$  model fixed effects (absorb cross-sectional heterogeneity)
- $f_{st}$ : state-specific **quadratic** time trends (flexible within-unit counterfactual)
- $S_{smvt}$ : stock of vehicles (exposure); estimated via negative binomial

# Data Preparation & Cohort Structure

## CS Panel Construction:

- Aggregate from model  $\times$  state  $\times$  vintage  $\times$  year to model  $\times$  state  $\times$  year
- Define treatment cohort: first year model enters Lojack program in state
- Jalisco 2001: 9 model-state units, 52 observations
- Mexico City metro 2002: 25 model-state units, 145 observations
- Never-treated: 1,371 model-state units across 31 states

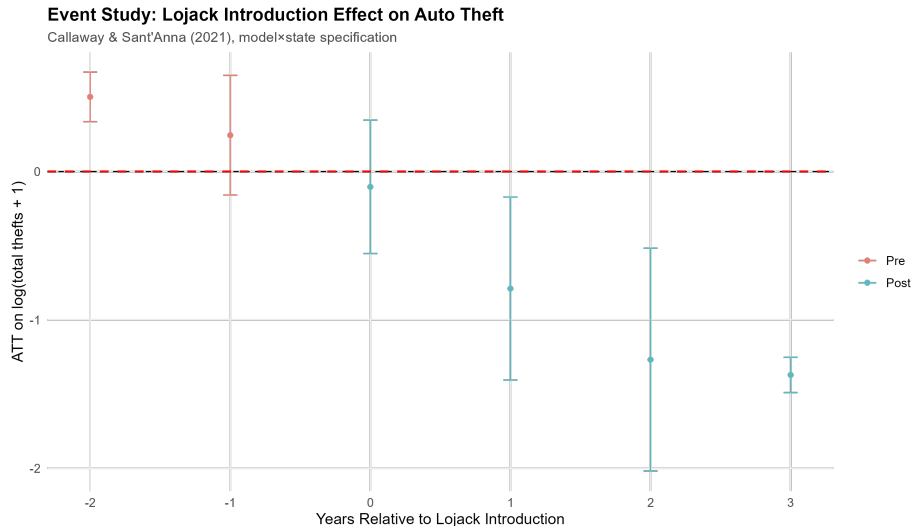
## Outcome Variable:

- outcome =  $\log(\text{total thefts} + 1)$  at model-state-year level
- ITS used counts; CS uses log scale for computational stability
- Allows comparison across aggregation levels

## Why Aggregation Necessary:

- ID-level CS fails: “panel2cs only for 2 periods” error
- 1 treated unit in 2001, 3 in 2002 too small for DiD inference
- Model-state aggregation increases treated cohort sizes

# Event Study: Dynamic Treatment Effects



# Original ITS Specification (Table 2, Col. 3)

## Estimating Equation:

$$E[\text{Thefts}_{smvt} | S_{smv}] = S_{smv} \exp(\alpha_{sm} + f_{st} + \beta_{\text{age}} + \gamma_1 LJ_{smv} + \gamma_2 NLJM\_LJS + \dots)$$

Variable	Coef	SE
<i>LJ</i> (Deterrence)	−0.663***	(0.018)
NLJM_LJS_After (Within-state)	−0.083	(0.066)
NLJS_LJM_After (Geographic)	0.417***	(0.075)
NLJS_NLJM_After (Cross-model)	0.049	(0.056)

\*\*\*  $p < 0.01$ ; Clustered SE at state level

## Controls:

- State  $\times$  model fixed effects
- State-specific quadratic time trends
- Age dummies (0, 1, 2, 3+ years)
- Exposure:  $\log(\text{sales})$

## Parallel Trends Test: Full Results

Period	ATT	SE	Z-stat	P-value
$t = -2$	0.503	0.094	5.377	$< 0.001$
$t = -1$	0.245	0.278	0.879	0.379
$t = 0$	-0.103	0.232	-0.444	0.657
$t = +1$	-0.789	0.283	-2.791	0.005
$t = +2$	-1.268	0.398	-3.189	0.001
$t = +3$	-1.371	0.061	-22.541	$< 0.001$

Table: Dynamic ATT by Event Time (CS Estimator)

### Implication:

- 1 of 2 pre-treatment periods significant at  $p < 0.05$
- Overall pre-trend test p-value: 0.015 (rejects null of parallel trends)
- Confirms paper's concern: DiD assumptions fail in this data



# Identification Strategies: ITS vs. DiD

## **Interrupted Time Series (ITS):**

- Source of variation: within-unit over time
- Comparison: each unit to its own pre-trend
- Assumption: treatment uncorrelated with state-specific trends
- Allows: flexible trend adjustment

## **Difference-in-Differences (DiD):**

- Source of variation: cross-unit
- Comparison: treated vs. never-treated
- Assumption: parallel trends
- Requires: uncontaminated controls

## **This Application:**

- Spatial externalities violate DiD (controls are contaminated)
- ITS appropriate because: within-unit identification avoids cross-unit contamination
- CS implementation reveals: pre-trends exist, confirming paper's choice

## CS Implementation Limitations:

- 1 **Contaminated control group:** Lojack models in non-Lojack states (experience spillover)
- 2 **Parallel trends violated:** Significant pre-trend at  $t = -2$
- 3 **Model aggregation:** Loses within-state model-specific dynamics
- 4 **Outcome transformation:** Log scale differs from count-based ITS

## Potential Extensions:

- Restrict never-treated to non-Lojack models only (drop spillover-affected units)
- Implement honest DiD (Roth, 2022) accounting for pre-trend violations
- Use alternative estimators (Callaway et al., 2021; Sun & Abraham, 2021) robust to heterogeneity
- Examine sensitivity to specification choices (bandwidth, trend order)