Replication and Alternative Identification Strategy

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

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Research Question & Data

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 St'Anna (2021) estimator: can be found on Github

Main Results

1. **Deterrence Effect on Lojack-Equipped Vehicles**
   - Lojack-equipped vehicles in Lojack states: ≈ -0.663 (SE ≈ 0.018) $\Rightarrow \approx 48\%$ **reduction** in theft risk

2. **Geographical Spillovers (Externalities)**
   - Lojack models in non-Lojack states (displacement): ≈ 0.417 (SE ≈ 0.075) $\Rightarrow \approx 52\%$ **increase** in thefts

3. **Net Crime Effect and Policy Implication**
   - Reduction in thefts in Lojack states exceeds increase in non-Lojack states
   - Conclusion: Lojack generates substantial deterrence with incomplete displacement
   - Policy implication: technologies can reduce overall crime, but spatial externalities justify centralized coordination

Conclusion: Identification Strategies & Robustness

Main Takeaways:

1. **Replication:** Original results confirmed; small data-handling differences explain SE variations
2. **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
3. **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
4. **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

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

Empirical Specification:

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

- α_{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

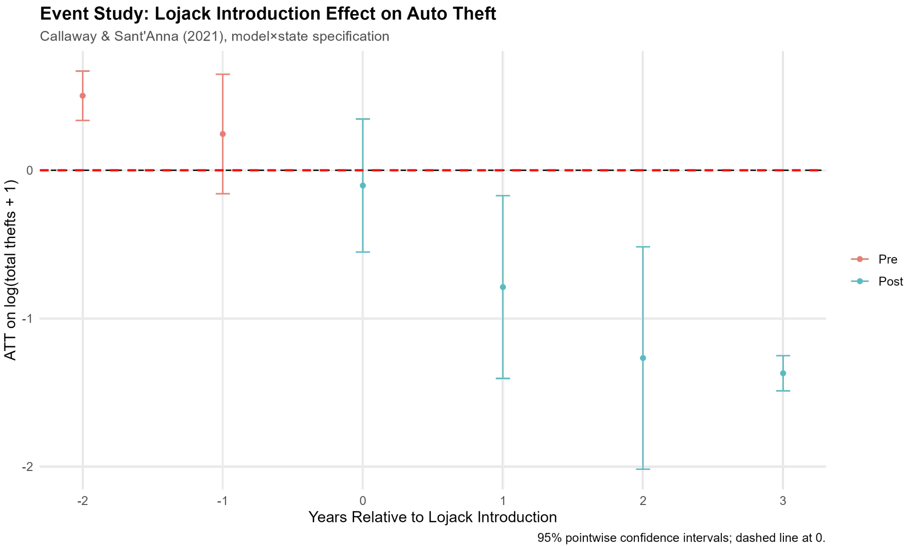
Outcome Variable:

- 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:

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

Variable	Coef	SE
LJ (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(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

Limitations & Extensions

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)