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Deterrence and Geographical Externalities in Auto Theft†

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Understanding the degree of geographical crime displacement is crucial for the design of crime prevention policies. This paper documents changes in automobile theft risk that were generated by the plausibly exogenous introduction of Lojack, a highly effective stolen vehicle recovery device, into a number of new Ford car models in some Mexican states, but not others. Lojack-equipped vehicles in Lojack-coverage states experienced a 48 percent reduction in theft risk due to deterrence effects. However, 18 percent of the reduction in thefts was displaced toward unprotected Lojack models in non-Lojack states, providing new evidence of geographical crime displacement in auto theft. (*JEL* H76, H77, K42, O17, O18, R23)

Crime has a deep negative impact on the well-being of individuals and societies (Sah 1991). In the United Sates alone, property crime amounts to $17 billion a year, and over half of it is a result of auto theft (FBI 2004). In the case of Mexico, a country with a similar auto theft victimization rate (Van Dijk, Van Kesteren, and Smit 2007), over 50 percent of vehicle thefts involve stealing at gunpoint, and hence more frequent murders (AMIS 2012).

Beyond its saliency as a crime for individuals, auto theft presents a challenge for policymakers because of its potential spatial displacement. An extensive theoretical literature explores the implications of crime displacement for law enforcement (cf. Clotfelter 1977, 1978; Shavell 1991; Clarke and Harris 1992; Hotte and van Ypersele 2008). However, empirical evidence demonstrating spatial crime displacement has remained elusive (Hesseling 1994).[1] This has led to a literature arguing that law enforcement should focus on high crime areas (cf. Sherman and Weisburd 1995). However, the targeting approach implicitly assumes that crime is

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[1] For recent evidence of displacement over time see Jacob, Lefgren, and Moretti (2007) and for displacement in import taxes see Yang (2008).

not highly mobile, otherwise, a crackdown in one location is simply replaced by crimes in other locations.

To shed light on the extent of auto theft displacement, I study the introduction in Mexico of one of the most ingenious technological innovations in crime reduction policies of recent decades—the Lojack stolen vehicle tracking technology. Lojack is a small device hidden in random places inside a vehicle that allows it to be tracked when a theft occurs. In Mexico, Lojack was introduced through an exclusivity agreement between Ford Motor and the Lojack company. The agreement consisted of installing Lojack *exclusively* in select Ford car models in participating states, free of charge. In the period of analysis, the program was introduced into four states containing Mexico's two largest metropolitan areas. The introduction of a car model into the Lojack program was accompanied by a sustained publicity campaign orchestrated by Ford distributors in the local media. Common knowledge of which car models were equipped with Lojack effectively made Lojack an observable theft deterrence device.

An observable theft deterrence system has the first-order effect of reducing risk for protected vehicles. The state-level implementation of the Lojack recovery system, and the fact that it was only installed in participating Ford models, means that the reduction in theft risk should be limited to what I call treated Lojack models in Lojack implementation states.

The second-order effect refers to external impacts Lojack imposes on owners of unprotected vehicles via theft risk reallocation. I focus on three groups of potentially affected vehicles: Lojack models in non-Lojack states, and non-Lojack models in either Lojack or non-Lojack states.

A diversion of theft risk toward non-Lojack car models in Lojack states occurs whenever demand from stolen vehicles is for general use, for example, vehicles for robbing banks or kidnappings, in which the specific brand of the vehicle is not a relevant consideration.

On the other hand, any theft risk displacement toward vehicles in non-Lojack states is a form of geographical externalities. Models of geographical externalities have been proposed by Freeman, Crogger, and Sonstelie (1996); Helsley and Strange (1999); Marceau (1997); and Lee and Pinto (2009). The main takeaway from this theoretical literature is that deterrence devices can create diversion from protected to unprotected areas but should have an aggregate crime reduction effect. I distinguish vehicles in non-Lojack states as Lojack models and non-Lojack models because effects on the former would be consistent with model-specific demand for stolen vehicles, which occurs when the stolen parts market drives vehicle theft.

In this paper, I use variation over time in theft risk, at the state and car model level, to identify both the impact of Lojack in deterring auto theft for Lojack-equipped vehicles and the displacements in theft risk that this generated on non-Lojack protected vehicles. The analysis uses a novel source of information—the database of all case-level reports of theft recorded by Mexican insurance companies before and after the introduction of the Lojack system. The use of such an extremely detailed source of crime data allows for an analysis of theft risk at the car model level within states, something that has not been done before.

The empirical analysis shows that Lojack was an extremely effective theft deterrence device, generating an estimated reduction in theft risk of 48 percent for

vehicles participating in the Ford Lojack program. I also find evidence of geographical displacement of theft risk toward Lojack models in non-Lojack coverage states.

In terms of stolen vehicles, the introduction of Lojack is estimated to have reduced on average 119 thefts annually for protected vehicles, whereas the increase in stolen vehicles in non-Lojack states as a result of the program is estimated at an average of 22 vehicles annually. Thus, about one-fifth of the reduction is displaced toward nonprotected states. I do not find clear evidence of theft risk displacement to non-Lojack car models, consistent with vehicle theft driven to a large degree by model-specific demand.

The results of this paper have implications for fiscal federalism. The literature on the distribution of responsibilities across government levels (cf. Tiebout 1961; and Donahue 1997) argues that government-provided services are not optimally supplied whenever provision exerts externalities on surrounding jurisdictions. The fact that most criminal law enforcement is performed by state and local governments implies that a limited amount of spatial spillovers in crime must be present for law enforcement to be provided at optimal levels (Newlon 2001). The results in this paper suggest that it may be welfare improving to delegate the responsibility for highly mobile crimes, such as auto theft, to higher levels of government, who can internalize the externality.

The empirical evidence presented here is also of interest because the externality imposed by the Lojack system in this case is negative, whereas it was shown to be positive in Ayres and Levitt (1998). In the US context, the Lojack recovery system was implemented in a way that thieves were unable to distinguish between protected and unprotected vehicles. Because all cars had a positive probability of being equipped with Lojack, auto theft risk was reduced for *all* vehicles in geographical areas with Lojack coverage, not only those actually protected. The unobservability of the technology was key in generating starkly different external effects. This points to the important role regulation can have on the aggregate effects of privately-provided theft deterrence devices.

The rest of the paper is structured as follows. Section I describes the recovery technology and how it was implemented in Mexico. Section II describes the data used in the paper. The estimation strategy is discussed in Section III, while Section IV presents the empirical results. Section V concludes.

I. Technology and Intervention

A. *Technology*

Lojack is an automobile recovery technology developed in the late 1980s in Massachusetts. After a successful expansion in its home country, Lojack had been introduced into over 30 countries by 2007.[2] Lojack uses radio technology to recover stolen vehicles. The system consists of two main components: a radio-frequency transceiver in the protected vehicles and a grid of locality-specific tracking antennas. Every geographic location that is covered requires a combination of tracking devices

[2] www.lojack.com

in fixed locations, vehicles, or aircraft in order to provide the recovery service. The specific combination depends on the topography, road system, and other relevant factors of the locality.

Lojack has an extremely high recovery rate, with 90 percent of vehicles being recovered within 24 hours of the report (Lojack 2013) and 95 percent eventually recovered (Romano 1991). This compares to a recovery rate of 48 percent in general in Mexico (AMIS 2006). Van Dijk (2008) also reports a 48 percent vehicle recovery rate throughout Latin America.

Its small size, similar to a deck of cards, allows it to be hidden in many possible places inside a car, making it hard to locate. The device has its own power source, meaning that it does not depend on the car's battery to operate. Cars equipped with the device do not signal its presence with decals of any sort.[3] Finally, it only emits the signal once it is activated remotely.

The Lojack radio transceiver remains dormant unless a theft occurs. If an owner realizes that the vehicle has been stolen, she calls Lojack and her specific device is remotely activated. Once the signal is active, any of the tracking devices can perceive it if the car is in close proximity. After a signal becomes visible for one of the trackers, mobile trackers can be sent to follow and find the stolen vehicle. The radio signal is perceptible to the tracking devices even if the vehicle is in a covered environment, like a warehouse, a building, or a container. Competing technologies based on GPS are mainly used for better logistics, not as recovery devices. GPS antennas are conspicuous, which makes them straightforward to deactivate by thieves.

B. *Intervention*

Installing a Lojack recovery system in a locality requires substantial fixed costs. These take the form of lengthy agreements with the local police, regulatory approvals, and the cost of installing the network of tracking equipment. The owners of the Lojack technology gave exclusive distribution rights to a Mexican company to introduce the system in Mexico. The patent holders supply the equipment and the Mexican company is in charge of the management of the system.

For a startup company, the large setup costs, together with uncertain demand for the product made the enterprise extremely risky. Hence, it made sense to offer a major car builder an exclusive agreement to have Lojack installed in its cars. The vehicle recovery company would instantly gain a large customer, improving the short-term viability of the company, and the large car manufacturer would be able to offer an exclusive benefit for its customers. Ford Motor Company of Mexico agreed to be the sole Lojack customer for a prearranged period, which I analyze here.

Ford Motor Company agreed to pay the Lojack company a fixed cost per unit installed. In exchange for the payment, the company provided the transceiver, installation costs, and one year of Lojack recovery services. After the first year, customers had the option of continuing the recovery service at an annual cost of around $100.

[3] The company argues that it sells recovery, not deterrence, services.

Figure 1. Lojack States and Non-Lojack States

Notes: Non-Lojack states grouped by terciles of distance from state capital to nearest Lojack state capital.

The system was first introduced into the Ford Windstar in 2001 in the state of Jalisco. In 2002, the Lojack tracking system was introduced into three more states in Mexico (Morelos, Estado de Mexico, and Distrito Federal) with Ford Windstar being the first car model to get the device. The four Lojack states are labeled in Figure 1, and contain Mexico's two largest metropolitan areas: Mexico City and Guadalajara. In total, nine different Ford models were sold with Lojack starting in 2003. Once a Ford model was introduced into the Ford-Lojack program, it maintained its Lojack status throughout the period being analyzed.

Like other automobile manufacturers in Mexico, Ford and its distributors have an agreement to sell new vehicles for the same price nationally. The Ford-Lojack program did not change this arrangement. Customers in Lojack states paid the same price for a vehicle as customers in non-Lojack states.

Lojack managers decided to operate the tracking system jointly with the local police forces. The high degree of control over the tracking system, as opposed to simply handing it over to the police, was arguably the best option in an environment where police forces were not deemed sufficiently trustworthy to operate the system up to its full capabilities. However, local police cooperation was always necessary given that repossessing stolen property is an exclusive attribute of police forces.

II. Data

The analysis uses a novel source of auto theft data—the stolen vehicle database compiled by the Mexican Association of Insurance Companies (AMIS).[4]

[4] www.amis.org.mx

This industry-funded organization continuously compiles case-level auto thefts reported to its member companies. The reports are automatically added to a database that is actually the police forces' main source of stolen vehicle license plates and VINs. The reports are also aggregated by AMIS to estimate national theft rates by make and model, which help member companies price insurance contracts.

The AMIS database has various advantages to analyze auto theft dynamics. First, the level of detail contained in the reports regarding the characteristics of stolen vehicles allows an analysis beyond aggregate theft statistics, which is the norm in the literature. Second, the consistency in data collection procedures over time and the lack of incentives to manipulate theft reports sets it apart from official statistics in terms of reliability (Van Dijk 2008; Mansfield, Gould, and Namenwirth 1974). I use countrywide theft cases reported to AMIS from January 1999 to December 2004. For each report, I use information on the model of the vehicle, the year the car was sold (vintage), and the date and state where the theft occurred.

Auto sales data were provided by the Mexican Association of the Automobile Industry (AMIA).[5] The data refer to annual dealership sales by model at the state level from 1999 to 2004. These sales data provide information on the size of each model vintage at the state level. AMIA sales data at the (state $\times$ model $\times$ vintage) level were matched to AMIS theft reports at the (state $\times$ model $\times$ vintage $\times$ year of theft) level.[6]

One caveat with the data is that it provides information about where the car was sold, but not where the car currently resides. However, the econometric strategy will account for this possibility. A second caveat is that I use thefts of insured vehicles instead of thefts of both insured and uninsured vehicles. This generates a bias in the estimated *level* of theft, but not in estimates of *changes in the level* of theft as long as treatment did not have any effect on the rate at which vehicles were being insured. Evidence of this is provided in Section IV.

III. Estimation Strategy

In the presence of spatial externalities, difference-in-differences estimation using observations from different geographical locations produces biased estimates of policy impact (cf. Miguel and Kremer 2004). The basic challenge is that whenever treatment in one geographical location also has effects in control locations, these are no longer valid counterfactual observations. Furthermore, difference-in-differences estimation precludes actual estimation of externalities unless there is a set of observations subject to externalities and a set of observations that is not, so that the latter can play the role of counterfactual.

For these reasons I do not use difference-in-differences estimation. Instead, I use an interrupted time series strategy in which the counterfactual is given by observations occurring before the intervention. The hypothesis being tested is whether the introduction of Lojack changed the time series theft risk for each of the potentially affected car groups. The specification accounts for a variety of possible time trends

[5] www.amia.com.mx

[6] Details about the construction of the database can be found in the online Appendix.

at the state level, as well as heterogeneity of theft risk over car models and space using model × state fixed effects. The identifying assumption is that the introduction of Lojack is not correlated with changes in theft risk beyond what is captured by the local time trends.

In the analysis, the dependent variable is the number of vehicles stolen in a state × model × vintage × year of theft observation, each dimension denoted by s, m, v, t, respectively. Because the dependent variable is nonnegative, integer-valued, and has a large mass at zero, I use negative binomial regression (see Cameron and Trivedi 1998).

There are four regressors of interest: Deterrence effects are captured with a dummy for whether the vehicle is equipped with Lojack (LJ_{smv}), it varies at the state, model, and vintage level. Within-state theft risk displacement effects across car models are captured with a dummy that equals one for non-Lojack models after Lojack has been introduced in the state ($LJS_NLJM_After_{smt}$). Cross state geographical externalities among Lojack car models are captured by a dummy that equals one after Lojack was introduced in the nearest Lojack state ($NLJS_LJM_After_{smt}$), it turns on starting in 2001 in the non-Lojack states surrounding Jalisco and turns on in 2002 in the non-Lojack states surrounding the Mexico City metropolitan area. Analogously, cross-state and cross-model externalities are captured with a similarly defined dummy variable $NLJS_NLJM_After_{smt}$, which equals one among non-Lojack car models in non-Lojack states after Lojack is introduced in the nearest Lojack state. The estimating equation is then

$$(1)\quad E[Thefts_{smvt}] = S_{smv} \cdot exp[\gamma_{sm} + f_s(t) + \delta_{age} + \beta_1 LJ_{smv} + \beta_2 LJS_NLJM_After_{smt} + \beta_3 NLJS_LJM_After_{smt} + \beta_4 NLJS_NLJM_After_{smt}],$$

where S_{smv} refers to the size of a state × model × vintage, and is a proxy for the stock of cars susceptible to being stolen. Because different models have radically different market shares, any analysis of auto theft that seeks to distinguish between car models in the same geographic location must control for the quantity of cars at risk of theft.[7] γ_{sm} is a state × model fixed effect, which accounts for the fact that theft risk varies by state and car model. A state-specific time trend $(f_s(t))$ absorbs local trends in auto theft due to time varying levels of investment in police forces, quality of police commanders, etc. Vehicle age dummies ($age = v - t$) reflect the fact that theft risk varies as the car ages. Standard errors are clustered at the state level as suggested in Bertrand, Duflo, and Mullainathan (2004).[8]

[7] In a negative binomial regression, this is referred to as "controlling for exposure." The exposure variable (S_{smv}) is usually incorporated with a coefficient constrained to unity. This introduces the assumption that thefts are a function of the stock of cars and that this relationship is the same across all car models. A doubling of the stock accompanied by a doubling of thefts is interpreted as keeping theft risk constant. The results are robust to a relaxation of the coefficient restriction on S_{smv}.

[8] Cameron, Gelbach, and Miller (2011) two-way clustered standard errors at the state and year level were also calculated, without changing the significance of the results.

Table 1—Descriptive Statistics

Variable	Mean	SD	Min	Max
Vintage size	609.7	1,752.9	1	32,940
Annual thefts	4.38	30.9	0	1,502
Lojack model = 1	0.162	0.36	0	1
Lojack state = 1	0.18	0.38	0	1
Lojack = 1	0.006	0.08	0	1
Age of vehicle	0.81	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.

The coefficient on *LJ* is expected to be negative if there was a deterrence effect of the Lojack program. If theft risk was reallocated within program states to non-Lojack car models, the coefficient on *LJS_NLJM_After* would be positive, reflecting a higher risk of theft. Evidence for geographical externalities in theft risk would take the form of positive coefficient estimates on either *NLJS_LJM_After* and/or *NLJS_NLJM_After*.

For the main results, I drop observations corresponding to preprogram Lojack vintages in Lojack states after Lojack is introduced, as this group could be potentially affected by the Lojack intervention positively or negatively. Summary statistics are presented in Table 1. The average vintage size is 610 vehicles, and on average 4.4 of those cars are stolen annually. This implies a mean annual theft rate of 7.2 cars per 1,000 vehicles. The vehicles are relatively new. They range from zero to three completed years on the road.[9]

IV. Results

Before presenting the estimation results, Figures 2 and 3 show the time variation in theft risk relative to the introduction of the Lojack program for the four car groups. The graphs plot coefficient estimates on a set of year dummies without any covariate adjustment (the omitted category is the first year of observation). Figure 2 focuses on Lojack models and shows that in Lojack states, vintages equipped with Lojack experienced a sharp fall in theft risk as soon as the program started (in year t). The same figure shows that the opposite occurred in non-Lojack states; there is a dramatic increase in theft risk coincidental with the Lojack program starting in the nearest Lojack state. Also, note that in the years before the program, the trends in theft risk were flat. Figure 3 shows that among non-Lojack models there was very little variation in aggregate theft risk, either in Lojack or non-Lojack states, and what little variation there was is not correlated with the introduction of the program.

[9] Age is set to 0 if the vehicle is less than 12 months old, 1 if it is between 12 and 24 months old, etc.

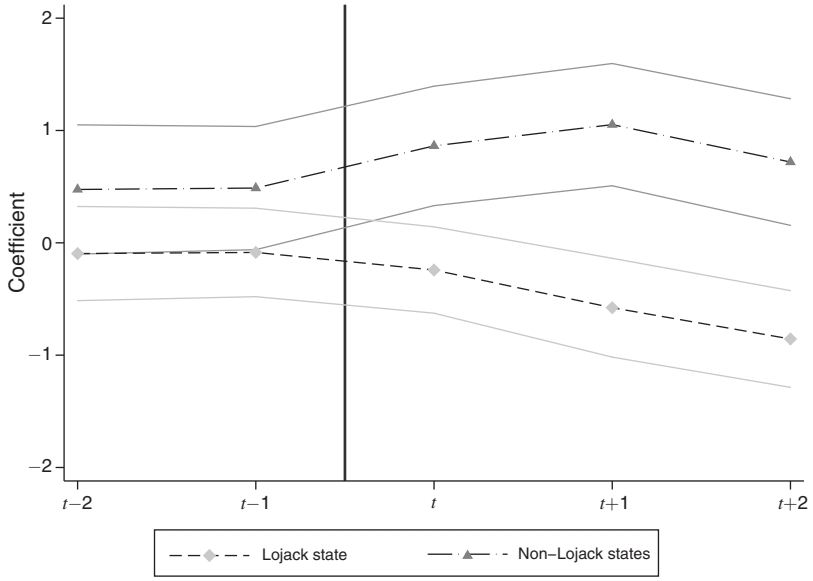

FIGURE 2. LOJACK MODELS

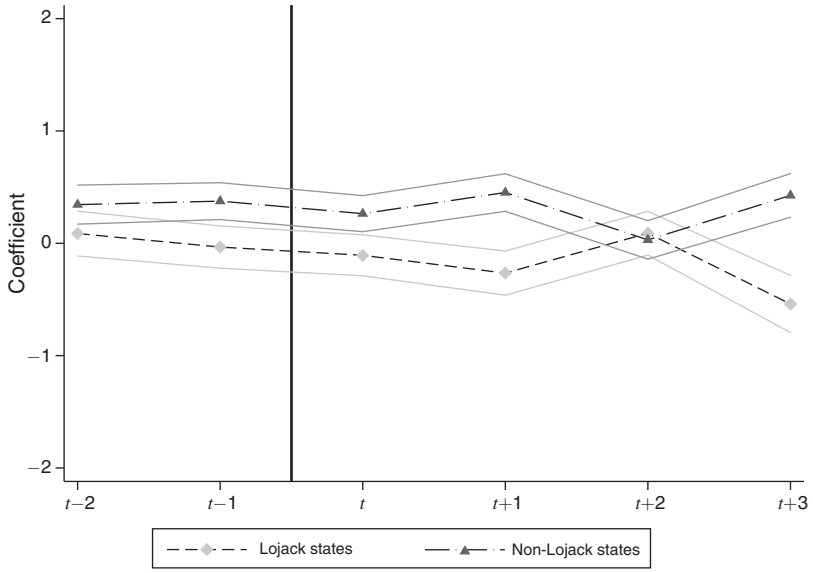

FIGURE 3. NON-LOJACK MODELS

Notes: Graphs show coefficient estimates and 90 percent confidence intervals from a negative binomial regression of thefts on year dummies relative to program introduction. For Lojack models in Lojack states, the dummies reflect vintage year relative to program introduction for the model in the state. For the other three groups, the dummies reflect year of introduction of the program in the state (*LJS_NLJM*) or in the nearest Lojack state (*NLJS_LJM* and *NLJS_NLJM*). The vertical line partitions the data into pre- and post-Lojack program.

Table 2—Deterrence and Geographical Externalities in Auto Theft

Specification: Negative binomial Dependent variable: Vehicle thefts	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LJ = 1	−0.65***	−0.63***	−0.66***	−0.52***	−0.52***	−0.56***	
	(0.127)	(0.021)	(0.018)	(0.104)	(0.104)	(0.178)	
NLJM LJS after = 1	−0.12***	−0.06	−0.08	0.08	0.08	−0.09	−0.08
	(0.028)	(0.072)	(0.066)	(0.056)	(0.056)	(0.071)	(0.065)
LJM NLJS after = 1	0.27**	0.49***	0.42***	0.42**		0.42***	0.42***
	(0.120)	(0.091)	(0.075)	(0.187)		(0.155)	(0.075)
NLJM NLJS after = 1	−0.06	0.11*	0.05	0.14		0.05	0.05
	(0.072)	(0.064)	(0.056)	(0.129)		(0.105)	(0.056)
LJ = 1, first year on road							−0.71***
							(0.086)
LJ = 1, second year on road							−0.58***
							(0.166)
(*LJM NLJS* after = 1) × (dis. pct. ≤ 33)					0.94***		
					(0.257)		
(*LJM NLJS* after = 1) × (33 ≤ dis. pct. ≤ 66)					0.38		
					(0.346)		
(*LJM NLJS* after = 1) × (dis. pct. > 66)					0.10		
					(0.206)		
(*NLJM NLJS* after = 1) × (dis. pct. ≤ 33)					0.07		
					(0.308)		
(*NLJM NLJS* after = 1) × (33 ≤ dis. pct. ≤ 66)					0.19		
					(0.146)		
(*NLJM NLJS* after = 1) × (dis. pct. > 66)					0.14		
					(0.205)		
Observations	16,764	16,764	16,764	5,185	5,185	16,764	16,764
Time controls	None	Linear	Quadratic	Quadratic	Quadratic	Model × year	Quadratic
State specific time controls	No	Yes	Yes	Yes	Yes	No	Yes
Sample	Full	Full	Full	Age = 1	Age = 1	Full	Full

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 933 km.

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

The main results are presented in Table 2. Columns 1–3 vary the type of state-specific time trend controls.[10] Column 1 has no time trends, column 2 considers state-specific linear time trends and column 3 allows for state-specific quadratic time trends. The results are remarkably similar regardless of the type of time trends being used.

In my preferred specification in column 3, the coefficient on Lojack equipped (LJ) is -0.66, implying a reduction in theft risk[11] of 48 percent for vintages

[10] Wolfers (2006) points out the benefits of using a broad range of time trend controls.

[11] The exponential form of the conditional expectation and the fact that the coefficients of interest are all associated to dummy variables make interpretation of coefficients intuitive. The ratio of expected thefts with and without the program is simply the estimated coefficient exponentiated. Hence, the percent change in theft is simply $e^{\hat{\beta}} - 1$.

Table 3—Estimated Impact of the Lojack Program in Terms of Stolen Vehicles

	Lojack states		Non-Lojack states	
	Lojack	Non-Lojack	Lojack	Non-Lojack
Preprogram mean annual thefts	247	3,873	42	824
Effect of Lojack program (percent change)	−48%***	−8%	52%***	5%
	(1)	(6)	(11)	(6)
Effect in terms of annual thefts	−119***	−298	22***	42
	(2)	(236)	(5)	(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.

equipped with Lojack. This magnitude is substantial. For comparison, Di Tella and Schargrodsky (2004) find that stationing a police officer full time in a street block in Buenos Aires reduces vehicle theft risk by 75 percent. The estimated reduction in theft risk can be interpreted as a deterrence effect because any actual theft of a vehicle, even if recovered by Lojack, would still be recorded in the dataset as a theft. Hence, the estimate reflects a pure reduction in attempted thefts.

For the non-Lojack models in Lojack states group (row 2), I do not find robust evidence of changes in theft risk coincidental with the introduction of Lojack in the state. Although all point estimates are negative in columns 1–3, the coefficient is only significant in the specification without time trend controls. This suggests limited displacement of theft risk toward non-Lojack protected vehicles in the same state. If anything, there seems to have been a slight reduction in theft risk with the introduction of the Lojack program.

In contrast, columns 1–3 are consistent with spatial externalities on Lojack models in non-Lojack states. The coefficient is significant in the three specifications and column 3 implies an increase in theft risk of 52 percent after the program is introduced in the Lojack states. This is evidence of the existence of a market for stolen vehicles that transcends state borders. This result together with the deterrence effect suggests that when Lojack made it more difficult to steal Lojack car models in Lojack protected states, the market for stolen vehicles simply began obtaining them in non-Lojack coverage states. Finally, the lack of clear evidence for cross-model external effects is consistent with stolen vehicle demand being driven by the stolen parts market, which generates model specific demand.

To help interpret the magnitudes in column 3 of Table 2, Table 3 presents the estimated impact in terms of number of vehicles stolen.[12] For Lojack models in Lojack

[12] This is simply the percent change in thefts attributable to the program multiplied by the preprogram average annual thefts in the group:

$$(e^{\hat{\beta}} - 1) \cdot \left(\sum_{sm \in \Lambda} E[Thefts_{smt} | \ PreLojackProgram] \right). \tag{2}$$

This expression is a function of the estimated coefficient and the size of the group of affected cars.

states, thefts are estimated to have gone from an average of 247 vehicles per year to 128 a year due to the Lojack program. In non-Lojack states, thefts of Lojack models are estimated to have gone up from 42 a year to 66 a year, implying a geographical displacement of 18 percent of the gross reduction in thefts. This kind of partial displacement is consistent with the predictions from the criminology literature (see for example Eck 1993).

Going back to Table 2, in column 4, only one observation per car model vintage at the state level is used for identification. This is to show that the age controls are not playing a decisive role in the analysis. As column 4 shows, the results are similar, although of smaller magnitude than under the main specification. The deterrence effect falls from -0.66 to -0.52 ($p < 0.01$), while the geographical externality effect is still estimated at 0.42 ($p < 0.05$).[13]

Column 5 explores the role of distance in the externality effects. In the set of states closest to those where Lojack was implemented,[14] theft risk of Lojack models increased by 156 percent ($p < 0.01$) with the introduction of Lojack. For the more distant states (second and third terciles), the magnitudes are positive but not statistically significant. Non-Lojack models, on the other hand, were not significantly affected at any distance.

In column 6 of the table, I present results from a different identification strategy. In this specification, I assume that far away states (in the furthest tercile of distance from Lojack states) are unaffected by the program and use them as controls.[15] This allows the use of model $\times$ year dummies to flexibly account for national model-specific time trends. Under this alternative identification strategy, the deterrence effect is slightly smaller, while the geographical externality effect is the same as in the baseline specification.

Taken together, the evidence suggests that Lojack was highly effective in reducing thefts of Lojack protected vehicles through a deterrence effect. Nevertheless, the reduction in thefts of Lojack-protected models generated a negative spatial externality in Lojack models located in non-Lojack states. The estimations did not produce evidence of displacement across car models within or across state lines.[16]

In column 7 of Table 2, I subdivide the Lojack dummy into two regressors, *Lojack equipped first year on the road*, and *Lojack equipped second year on the road*, to inquire if the deterrence effect is decreasing over time. This is of interest because after the first year on the road, continuation of the recovery service was conditional on a payment of around $100. Only 60 percent of Lojack equipped vehicles actually renewed their service after the first year. Because it is impossible to know from the exterior if the vehicle purchased the recovery service after the first year, Lojack

[13] I thank an anonymous referee for suggesting this restricted sample as a robustness check.

[14] The tercile of closest states is referred to as the nearby states in Figure 1, the distance cutoff for this group is 320 kilometers. The second tercile of states is referred to as mid-distance states in the figure, with a 930 km cutoff. The last group of states has a distance in excess of 930 kilometers.

[15] This means setting the Lojack externality regressors to zero for the far away states.

[16] In the online Appendix, I also estimate a regression that splits non-Lojack models in Lojack states into two groups: vehicle categories in which a Lojack model is present (minivan, SUV, sedan, luxury sedan, and compact car), and those in which there is no Lojack model (sports car, subcompact, and pickup truck). I do not find that vehicles similar to Lojack models experienced higher thefts post-Lojack introduction. The coefficient on the interaction is in fact negative.

Table 4—Displacement to Other Crimes

Specification: OLS Dependent variable:	Kidnapping rate	Drug offense rate	Theft rate
Lojack in state = 1	−0.005	0.039	0.076
	(0.009)	(0.048)	(0.036)
Observations	27	28	28
R^2	0.74	0.79	0.96
Mean of dependent variable	0.016	0.14	0.80

Notes: Rates defined as convicted criminals/1,000 adults. Clustered standard errors at the state level. Additional controls: state fixed effect, state specific time trend.

in effect gradually becomes an unobservable theft deterrence device within the set of participating vintages. The first year on the road, the deterrence effect corresponds to a 51 percent reduction in theft risk; while in the second year, the effect is a 44 percent reduction. The similarity of these magnitudes suggests that the deterrence effect of Lojack is relatively unaffected even if the proportion of vehicles actually having the recovery service falls from 100 percent to 60 percent. While it may be possible that auto thieves were not aware of the voluntary continuation of the service, another explanation is that the marginal impact of Lojack on theft deterrence is very high with a small proportion of vehicles protected, and decreases rapidly as the proportion of vehicles protected increases. Indeed, Ayres and Levitt's (1998) study also finds evidence of a rapidly decreasing marginal impact of Lojack as the proportion of protected vehicles increases. In their estimation, a 2 percent coverage rate generates a 60 percent reduction in theft. If the results of both studies were strictly comparable, the evidence presented here would suggest that the impact of Lojack is not much increased by Lojack coverage rates beyond the low single digits.

A. *Other Crime Categories*

Up to this point the analysis has focused on auto theft. However, there is the possibility that Lojack diverted criminals toward other types of crime. In order to address this point, I use state-level data from the Mexican National Statistical Agency (INEGI) with information on the number of criminals convicted for different offenses. The data has two major shortcomings. One is the small number of observations, one per year, per state. The second is the low level of disaggregation of crime categories. I analyze the number of criminals convicted (per 1,000 adults) for kidnapping, drug trafficking, and general theft offenses to determine if Lojack diverted criminals toward other types of crime.[17] Table 4 presents results from OLS regressions of conviction rates on Lojack presence in the state. First note that kidnapping and drug related offenses in Lojack states did not change following the Lojack program introduction. This suggests either that crime was not diverted toward these two crime categories, or under no displacement, that Lojack states did not seem to be experiencing general reductions in crime across multiple crime categories. In any

[17] Under the assumption that the perceived probability of arrest did not change for other crimes, this is a valid strategy. Lochner shows that a higher perceived probability of arrest reduces criminal activity.

Table 5—Lojack, Market Share, and Insurance Coverage

Specification: OLS Dependent variable:	Market share (1)	Market share in category (2)	Share insured nationally (3)	Share insured nationally (4)
$LJ = 1$	−0.003***	−0.03***	0.023	0.036
	(0.0001)	(0.003)	(0.250)	(0.225)
NLJS after = 1	−0.003***	−0.06***		
	(0.0005)	(0.007)		
Mean of dep. var.	0.023	0.197	0.48	0.20
Car model × state dummies	Yes	Yes	No	No
Car model dummies	No	No	Yes	No
Age dummies	No	No	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Sample	Full	Full	$t \geq 2003$	Full
Observations	7,960	7,960	354	1,510

Notes: Column 2 are AMIA vehicle categories: Compact, subcompact, sedan, luxury sedan, sports car, minivan, SUV, pickup. Average market share (column 1) is 2 percent and average share in category (column 2) is 20 percent. Robust standard errors in parentheses clustered at the state level for columns 1 and 2. Columns 3 and 4 are proportion of cars in a model group × vintage combination that are insured nationally in a given year divided by the national size of the vintage. The regression in column 3 uses data for 2003 and 2004 providing a cross sectional identification. The regression in column 4 includes model-specific fixed effects and uses 1999–2004 observations. Robust standard errors in parentheses for columns 3 and 4.

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

case, one cannot reject the null hypothesis that kidnapping and drug related offenses in Lojack states did not change following Lojack program introduction.

The second noticeable aspect in the table is that theft convictions in Lojack states were close to statistical significance ($p = 0.13$), and show that theft convictions went up by around 10 percent (0.08 per thousand adults) following Lojack introduction. This could be reflecting increased convictions by auto thieves related to Lojack program introduction. However, it could also reflect diversion of crime from auto theft to other forms of theft. The lack of finer disaggregation of theft reports in Mexico precludes a stronger conclusion regarding this point.

B. *Discussion*

The Ford Lojack program in Mexico was halted in 2006. Under severe cost cutting pressures, the automaker decided to cancel the program. Ford executives had established the program with the objective of increasing sales of its vehicles. I provide evidence in Table 5 that market shares did not increase for Lojack models, justifying the shutting down of the program.

After the Ford deal collapsed, the Lojack-selling company started offering Lojack to anyone interested in having the recovery service, effectively ending the strategy of marketing to an exclusive set of cars. The company launched an aggressive publicity campaign and expanded their service to many other states, and now offer coverage in all states. This way of selling Lojack should result in generalized declines

Table 6—Changes in Preprogram Theft Risk and Lojack Program Participation

Specification: OLS Dependent variable:	Preprogram change in theft risk	Preprogram change in thefts
Future Lojack participation = 1	−0.0003	−0.945
	(0.0018)	(1.52)
Observations	1,171	1,171
Control for vintage size	No	Yes
Mean dep. var.	0.0018	0.454

Notes: Theft risk in column 1 defined as thefts/vintage size. Observations refer to changes in theft risk over the [1999–2000] period. Regressions include state dummy controls. Standard errors clustered at the state level.

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

in theft rates, with large positive externalities and a positive net social benefit from the technology, as Ayres and Levitt (1998) have argued.

The results presented in this paper imply that selling Lojack to a discernible set of cars severely limits its potential positive spillovers. This finding should be useful in future scenarios to better inform policymakers about how to regulate and adopt new technology so as to maximize society's welfare. In the United States, the requirement of unobservability led to positive spillovers, but too few Lojacks sold to the public. Whereas the observable implementation of Lojack in Mexico led to more Lojacks sold to the public, but with negative externalities.

Finally, these results may be relevant for the industrial organization literature because they suggest that goods with negative spatial externalities may be optimally deployed in a sequential expanding manner: introduction of the good in one geographical area increases the demand for it in the contiguous jurisdictions.

C. *Robustness Checks*

Identification.—For identification it is important to verify that the future introduction of the Lojack program is not associated with an increase in pre-Lojack-introduction vehicle theft. To do this, Table 6 presents regressions of changes in model-specific theft rates (column 1) and changes in thefts (column 2) during the pre-Lojack era on a dummy for subsequent inclusion in the Lojack program. The estimated coefficients are far from significant in both columns. This shows that car models that would participate in the Lojack program in the future did not experience differential changes in theft risk or number of thefts compared to nonprogram vehicles, as required by the identification assumption. Furthermore, the table corroborates the graphical evidence in Figure 2, which showed flat theft risk before the program, as well as what was conveyed to me by Ford executives, who argued that their objective with the Lojack program was to increase sales, not reduce auto theft, suggesting the two should be uncorrelated.

Selection.—An extensive literature has focused on the difficulty in measuring program effects when participation is voluntary (Heckman 1979). This problem is

minimal in Ford's Lojack program. Ford's vehicles were sold for the same price nationally, regardless of whether the state was participating in the Lojack program. This yields two benefits for the analysis. First, conditional on buying a Lojack model, participation in the program was not voluntary. Ford engaged in this program under the rationale that it would be able to sell more cars, albeit with a lower profit margin. Any effect of Lojack on sales is controlled for in the empirical analysis through the vintage size exposure control. Second, the single national price, together with the locality-specific recovery service, means that there was practically no incentive for customers to buy their cars in a different state from where they lived. With equal prices, a customer in a Lojack state had no incentive to buy a car in a non-Lojack state. Similarly, a customer in a non-Lojack state had scant incentive to buy a Lojack-equipped car and drive it to a state that did not have the Lojack recovery service available. In fact, the evidence in Table 5 showing that Lojack did not increase sales also reduces concerns about the Lojack program changing the theft risk profile of Ford drivers.

Measurement Error.—The specification used in the analysis is robust to multiplicative error in the exposure variable. However, an identification problem arises if there is temporal variation in the probability that the vehicle is insured that is correlated with the introduction of the Lojack program.[18] Hence, Table 5 presents evidence that: Lojack-equipped vehicles were just as likely to be insured as non-Lojack-equipped vehicles in the years after Lojack was introduced; and insurance likelihood of Lojack models evolved in an identical manner to non-Lojack models once Lojack was introduced. This provides evidence that Lojack introduction was uncorrelated with insurance coverage probability, as required by the econometric model.

I use the AMIS time series of the number of cars insured by year nationally for every car model. Since Lojack states command 40 percent of nationwide sales, a change in the insurance coverage of Lojack models would emerge in the national insurance coverage rate for those models. I use national sales for the years 1999–2005, and the number of national insurance contracts, to construct a database that partitions the data into combinations of triplets (model group, vintage, year). I then generate the variable *proportion insured,* which is defined as the number of vehicles insured divided by the stock of cars sold for every cell. I first use data for the years after the introduction of Lojack to regress the proportion insured on a dummy indicating whether the vehicle was sold with Lojack ($Lojack_{mv}$), calendar year dummies to capture time trends in national insurance coverage, and a set of age-of-car dummies that capture average changes in the insurance probability as the car ages. The estimated equation in column 3 of Table 5 is

$$Proportion\ Insured_{mvt} = \beta_0 + \beta_{Lojack} \cdot Lojack_{mv} + \delta_{age} + \beta_t + u_{mvt},$$

where m refers to the model group, v to the year the vintage was sold, and t refers to the year of the observation. The coefficient of interest is β_{Lojack}. In the table, the

[18] See the online Appendix for details on this as well as for specification robustness checks.

estimated coefficient on the Lojack dummy is insignificant and small (2 percent increase in insurance likelihood), meaning that after Lojack was implemented, Lojack models were just as likely to be insured as non-Lojack models.

The fourth column addresses whether there were differential *changes* over time in insurance coverage for Lojack models with respect to non-Lojack models. The equation estimated in the second column of the table is

$$Proportion\ Insured_{mvt} = \beta_m + \beta_{Lojack} \cdot Lojack_{mvt} + \delta_{age} + \beta_t + u_{mvt},$$

which differs from the previous regression in that it includes a model-specific intercept and uses data from all pre- and post-Lojack years. The table shows that Lojack models experienced changes in insurance coverage likelihood that were not significantly different from non-Lojack models. In addition, the estimated coefficient is only 3.6 percent, ruling this out as a threat to estimation.

V. Conclusion

Knowledge of the extent of crime displacement is extremely important in the design of effective crime prevention strategies. In spite of a firm theoretical grounding in the economics of crime literature, crime displacement has proved difficult to document in previous empirical work. This paper used the introduction of the Lojack vehicle recovery technology to a discernible group of cars in Mexico to measure the extent of theft displacement from vehicles protected by an observable theft deterrence device to unprotected vehicles.

Basic predictions from the economics of crime (Freeman, Grogger, and Sonstelie 1996; Helsley and Strange 1999; Marceau 1997; and Lee and Pinto 2009) suggested that an observable theft deterrent device should reduce theft risk for protected vehicles, but could displace theft risk to unprotected vehicles.

The empirical analysis shows that Lojack was an extremely effective theft deterrence device, generating an estimated reduction in theft risk of 48 percent for vehicles participating in the Ford-Lojack program. I also find evidence of geographical displacement of theft risk toward Lojack models in non-Lojack coverage states. In terms of stolen vehicles, the introduction of Lojack is estimated to have reduced, on average, 119 thefts annually for protected vehicles, whereas the increase in stolen vehicles in non-Lojack states as a result of the program is estimated at an average of 22 vehicles annually. Thus, about one-fifth of the reduction is displaced toward non-protected states. I do not find clear evidence of theft risk displacement to non-Lojack car models, suggesting that in this context vehicle theft seems to be model-specific (for parts) instead of general (for vehicle use).

The fact that actions to reduce auto theft in one state generated negative externalities in contiguous states has important implications for crime prevention policies. An influential view advocated by Sherman, Gartin, and Buerger (1989) is that law enforcement officials should focus their efforts on "crime hot spots" defined as high crime locations and times. Whenever there is relatively little displacement of crime, the recommendation of targeted interventions is adequate. However, this paper suggests that whenever crime is mobile, a more comprehensive approach is warranted.

The evidence presented here shows that auto theft is a high-mobility crime which may not be adequately combatted in a spatially targeted manner. For high-mobility crimes, interjurisdictional coordination in crime prevention policies, or a shift in the level of government in charge of this function may be a more desirable course of action for achieving reductions in crime than having independent and local criminal law enforcement efforts.

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