Deterrence and Displacement in Auto Theft

by

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CEPS Working Paper No. 177
October 2008

Acknowledgments: I would like to thank Angus Deaton, Adriana Lleras-Muney, Sam Schulhofer-Wohl, Anne Case, Chris Paxson, Climent Quintana, Rodrigo Barros, and David Atkin for their help and advice in this research project. The data used here would not have been available without the help of Enrique Olmedo Salazar and Laura Espinoza from AMIS, Juan Moreno from Lojack, and Carlos Sánchez and Susana Pineda from Ford. I would also like to thank the participants of the development lunch seminar and the Public Finance Working Group at Princeton University for their useful comments. Financial aid from the Woodrow Wilson Scholars and Princeton University's Center for Economic Policy Studies is gratefully acknowledged. Any errors contained in the paper are my own.

Deterrence and Displacement in Auto Theft*

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October 15 2008

Abstract

Lojack is a stolen vehicle tracking technology that achieves extremely high recovery rates. Ayres and Levitt (1998) show that introduction of the system produced large reductions in vehicle thefts in areas where it was implemented in the United States. The reduced theft risk was shared by all vehicle owners, not only those who bought Lojack. This paper, in contrast, uses the introduction of Lojack to a publicly known set of Ford car models in some Mexican states to show that Lojack generates negative externalities if thieves can distinguish between Lojack and non-Lojack-equipped cars. The empirical analysis suggests that, although Lojack-equipped vehicles experienced a reduction in theft risk of 55%, most of the averted thefts were replaced by thefts of non-Lojack-equipped automobiles in neighboring states. The increase in thefts in non Lojack-serviced states was especially strong for the same car models that in Lojack-serviced states were sold equipped with Lojack.

JEL: K420, H230

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1 Introduction

Auto theft is an extremely salient property crime: the value of the stolen goods is substantial and violence is often involved. Auto theft can be seen as a conflict between vehicle owners, manufacturers, and authorities on one side - - whose objective is to minimize thefts - - and thieves and the black market in general on the other side, who gain from the theft of automobiles. In this game, technological improvements arrive continuously and can upset the equilibrium number of vehicles being stolen. In terms of of technological innovations that make auto theft more difficult, Lojack is one of the most ingenious in recent decades. Lojack is a tracking technology that allows stolen vehicles to be located, and that produces extremely high recovery rates.

While it has proven to be an extremely effective recovery device for those who own it, there also has been much interest in the externalities that the introduction of Lojack may have generated. Ayres and Levitt (1998) showed that, in the United States, introduction of the Lojack system resulted in large reductions in auto theft - - on the order of 10%-50% - - where the service became available. While only a small proportion of vehicle owners actually purchased the recovery system for their cars, the deterrence effect of Lojack was shared by all cars in the same geographic location because thieves had no way of knowing which vehicles had Lojack and which did not. In other words, those who purchased the system generated large positive externalities for other vehicle owners.

In contrast, this paper shows that the existence of positive externalities depends crucially on thieves not being able to distinguish Lojack-equipped vehicles from non-Lojack-equipped ones. Selling Lojack to a discernible group of cars in fact generates a negative externality in terms of displaced thefts from owners of Lojack-equipped vehicles to those without the tracking system.

I analyze the impact of the introduction of Lojack in Mexico, where it was publicly and *exclusively* installed in new cars sold by Ford within a specific subset of vehicle models. The Lojack recovery device was installed, free of charge, and the recovery service was paid for during one year in new Ford cars included in the program from participating states. The program was rolled out gradually, both on the intensive margin - - with new Ford models entering the program at different moments in time - - and the extensive one, with an expansion over time in the number of states where the program was implemented. I use variation over time in theft risk, at the state and car model level, to measure 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 vehicles.

In Mexico, I find Lojack generated increased thefts of vehicles in states close to those where Lojack was implemented, with especially strong impacts on the same models that were sold with Lojack in the Lojack states. In states distant to those where Lojack was introduced, I find no significant impact on theft rates. Within Lojack serviced states, I find no statistically significant change in thefts among non-Lojack-equipped vehicles. Regarding Lojack-equipped vehicles, I find reductions in theft risk of around 55%. Further, among Lojack-equipped cars, although Lojack coverage over time went from 100% when the cars were new to 40% when they were three years old, the effect on thefts was roughly constant. This suggests that the deterrence effect of Lojack is similar for Lojack coverage rates varying from 40% to 100%. Another way of saying this is that the maximal deterrence effect of Lojack may well be attained with Lojack coverage rates below 40%, and closer to the 1.5% to 2% that Ayres and Levitt (1998) analyzed.

The importance of this paper is twofold. First, it shows that Lojack was effective in reducing auto theft of vehicles equipped with it in Mexico. The problem of reducing auto theft in developing countries has been especially difficult to tackle because of corrupt and/or incompetent police forces. Lojack may be an effective tool in reducing auto theft in such contexts. Second, the paper is important because it measures the spillovers that Lojack generated on vehicles not equipped with the device when it was sold to a distinguishable - - from the thieves' point of view - - set of cars. As stressed by Clarke and Harris (1992), or Karmen (1981), some anti-theft devices simply generate a displacement of theft to unprotected vehicles. In the case of Lojack, the same device can generate either positive or negative externalities depending on how it is offered to the public; this suggests that regulation of similar technologies in terms of how the product is offered to the public, can have important consequences for societal welfare.

The rest of the paper is structured as follows: Section 2 describes the recovery technology and how it was implemented and offered to the public in Mexico. Section 3 provides a theoretical framework for thinking about Lojack and the implications of selling it to an anonymous, rather than a distinguishable, set of cars. Section 4 describes the data used in the paper. The estimation strategy is discussed in Section 5, while Section 6 presents the empirical results. Section 7 concludes.

2 Technology and Intervention

2.1 Technology

Lojack is an automobile recovery technology developed in the late 1980s in Massachusetts (United States). After a successful expansion in its home country, Lojack had been introduced into over 30 countries by 2007.[1] 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 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% of vehicles being recovered within 24 hours of the report (LoJack (2006)) and 95% eventually recovered (Romano (1991)).[2] 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. The company sells recovery – not deterrence – services, and announcing the presence of Lojack in the vehicle may compromise the likelihood of recovery. Finally, it only emits the signal once it is activated remotely. The combination of these factors make it impossible to know from a visual exterior inspection if a car is equipped with Lojack.

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. In fact, GPS antennas are conspicuous and are severely compromised if the vehicle is under a roof.

[1] www.lojack.com

[2] The information on Lojack is based on discussions with company executives in Mexico and on information from their web page.

2.2 Intervention

Installing a Lojack recovery system in a locality requires large 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 would supply the equipment and the Mexican company would be 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. The Mexican company decided 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 offer an exclusive benefit for its customers. Ford Motor Company of Mexico agreed to be the sole Lojack customer for a prearranged period.

Ford Motors 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.

The system was first tested at the end of 1999 in a single Mexican state with a single Ford model. In 2002, after the trial period, the Lojack tracking system was introduced into four states in Mexico. Once the recovery system had been implemented, Ford distributors in the covered states engaged in large publicity campaigns to inform the population which of their models were equipped with Lojack. Lojack gradually was introduced into different models beginning in 2002, and continuing until 2005. In total, 13 different Ford models came equipped with Lojack in the period I study. A list of the Lojack models, the states, and dates of introduction into the program can be found in Table 1. Once a Ford model in a state came equipped with Lojack, it maintained its Lojack status throughout the period being analyzed. That is, once a car became part of the Lojack program, all newer version of the cars were sold with the device.

Like other major 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.

The company administrating Lojack was in charge of obtaining the permits and necessary regulatory approvals. 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 or reliable to operate the system up to its full capabilities. However, local police cooperation was always necessary given that, in Mexico, taking possession of stolen property is an exclusive attribute of police forces.

3 Theoretical Framework

The following simple framework aims to clarify why different effects on auto thefts can be expected according to the way Lojack is offered to the public. Assume that when making the decision to steal, the thief takes into account the costs and benefits of his action. Let B_{ij} represent the monetary payoff to the thief of stealing a car, model i in state j, and delivering it to the local chop shop. The probability of failure is $P^{thief}(Lojack_{ij})$. The thief does not obtain payment if he is caught by the police or if the car is recovered by Lojack before he gets to the shop. The probability of failure depends explicitly on whether the car that is stolen is equipped with Lojack.

During the time that the thief is in possession of the stolen vehicle, the police or Lojack may recover it and, in the process, apprehend the perpetrator. Assume that if the car is recovered before the thief delivers it, the thief is sent to jail. This generates a utility loss for the thief of $-J < 0$.

Let Q_{ij} denote the total number of cars of model i stolen in state j during a year. The (marginal) cost to the thief of stealing a car can be described by $C(Q_{ij}, S_{ij}, \mathbf{X}_i)$, where S_{ij} is the stock of cars in the state and $\mathbf{X}_i$ represents vehicle characteristics like the difficulty in picking the lock and starting the vehicle. For a given stock of cars on the road, the more stolen, the higher is the cost of finding and stealing the car, i.e. $\partial C/\partial Q_{ij} > 0$. It is reasonable to assume that cars that are targeted first are those that are easy to steal: those located close to the chop shop, or those that are parked on the street, as opposed to inside a garage, for example. This would make the (marginal) cost of stealing the cars increase with the number stolen, after controlling for vehicle characteristics ($\mathbf{X}_i$) and the amount subject to being stolen (S_{ij}). The cost of stealing is incurred independent of the success of the theft attempt. It consists of time and the equipment cost of the theft. The thief will decide to steal a car whenever

$$B_{ij} \cdot (1 - P^{thief}(Lojack_{ij})) - J \cdot P^{thief}(Lojack_{ij}) \geq C(Q_{ij}, S_{ij}, \mathbf{X}_i)$$

the left-hand side represents the expected benefit of the theft attempt, which is compared to the marginal cost of doing so on the right-hand side of the equation.

When a chop shop buys a stolen car, it benefits from the purchase through possibly various channels. First, it can reintroduce the car into the legitimate market with false documents and a fake vehicle identification number (VIN). Second, it can export the car to another country, where it can be sold as a legally imported vehicle. Third, it can chop up the car and sell the stolen parts. Fourth, it can sell the car as "an input" to other crimes. These input cars are usually abandoned a few minutes after a major crime, like kidnapping, or a bank robbery, has been committed. The income for the chop shop from the combination of these activities can be subsumed into an increasing and concave function of the number of cars processed by the shop. Let $\omega(q_{ij}^k)$ represent gross income for shop k in state j from processing q stolen cars of model i. In deciding how many cars to process, the chop shop is assumed to maximize expected utility. The cost of buying an additional car is B_{ij}, the cash that is paid to the thief for delivering a vehicle to the shop. For each additional car processed, the shop obtains $\omega'(q_{ij}^k)$ if its operation is not discovered by the police. For every car processed by the shop, there is an independent probability $P^{shop}(Lojack_{ij})$ of the operation being discovered and shut down. The shop has the following objective function:

$$\max_{q_{ij}^k} \left(\omega(q_{ij}^k) - B_{ij} \cdot q_{ij}^k\right) \left(1 - P^{shop}(Lojack_{ij})\right)^{q_{ij}^k}$$

The more cars processed by the shop, the larger the cumulative probability that the operation is discovered. The first order condition for an optimum is

$$F \equiv \left(\omega'(q_{ij}^k) - B_{ij}\right) \left(1 - P^{shop}(Lojack_{ij})\right)^{q_{ij}^k} - \left(\omega(q_{ij}^k) - B_{ij} \cdot q_{ij}^k\right) \frac{\partial (1 - P^{shop}(Lojack_{ij}))^{q_{ij}^k}}{\partial q_{ij}^k} = 0$$

The first term of the condition is the usual marginal benefit $(\omega'(q_{ij}^k))$ equals marginal cost (B_{ij}), while the second term in F is the incurred cost of processing an additional car in terms of the increase in the probability of the shop being discovered. Considering that the income one shop generates is affected by what other shops do, the benefit function should be thought of as depending on other factors beyond the quantity processed by shop k. Specifically, it is taken to be a function of

$$\omega(q_{ij}^k, \sum_{l \neq k} q_{ij}^l, S_{ij}, \mathbf{X}_i, B_{-ij}, B_{i-j}) \tag{1}$$

The second component in (1), representing the number of cars of the same model processed by other shops, is introduced because competition means that if the number of cars processed by other shops ($\sum_{l \neq k} q_{ij}^l$) increases, this will depress the benefits obtained by shop k. B_{-ij} is expected to generate a positive effect because of substitutability across car models for many of the components that drive ω. For example, the demand for stolen cars as an input to other crimes should exhibit a large amount of substitutability across car models. In terms of ω, the higher the price for car models different from those processed by shop k, the higher the benefits. Similarly, the higher the price of cars processed by shop k in other states (B_{i-j}), the higher the benefits. This occurs because of spatial spillovers: if the price of stolen parts of a certain car increase in one state, then consumers of stolen parts in neighboring states will increase demand for parts in the state with lower prices.

In equilibrium, $B_{ij} = \frac{C(Q_{ij}, S_{ij}, \mathbf{X}_i) + J \cdot P^{thief}(Lojack_{ij})}{(1 - P^{thief}(Lojack_{ij}))}$. It is straightforward to check that

$$\frac{\partial F}{\partial P^{thief}} < 0 \;, \qquad \frac{\partial F}{\partial P^{shop}} < 0 \;, \text{and} \qquad \frac{\partial F}{\partial q_{ij}^k} < 0.$$

Because Lojack increases the probability of being caught, both for the thief and the shop, the equilibrium quantity stolen falls if the car is equipped with Lojack: $\frac{\partial q_{ij}^{k*}}{\partial \, Lojack} < 0$, where q_{ij}^{k*} solves $F = 0$.

I now can compare two distinct ways of making the device available to the public. In the United States, wherever Lojack recovery services were available, the device was offered to anyone who wished to purchase it. Because cars bore no visible indication of having Lojack - - such as decals - - thieves had a hard time determining if the car they intended to steal had Lojack. In such a framework, it is as if there are n cars in state j, and a proportion γ of them randomly get Lojack. Because thieves have difficulty determining whether a car has Lojack, a rational thief will assign probability γ to any car being equipped with the device. (More specifically, he would assign the same probability of having Lojack to all cars of similar visible characteristics.) In the model's equilibrium, thefts decrease for both Lojack and non-Lojack equipped vehicles: the theft deterrence provided by Lojack is shared equally among all cars. Given that non-Lojack car owners took no action but benefitted from lower theft probability, Lojack can be said to be providing positive externalities. Ayres and Levitt (1998) investigate the effects of making Lojack available to the public in this way in the United States. Consistent with the model, they document a strong reduction in theft rates for all cars in localities where Lojack was introduced. In fact, the total externality - - in monetary terms - - is estimated to be around ten times as large as the private benefit to the Lojack car owner. However, as with most goods with positive externalities, there is underprovision relative to the socially optimal level.

The way Lojack was offered in localities where it was introduced in Mexico can be described as selling Lojack only to a discernible group of cars: Ford models participating in the Lojack program. This allowed thieves to identify and differentiate between those cars with Lojack and those without. Thieves could avoid cars that had a high probability of having Lojack. The model predicts a fall in the thefts of Lojack equipped cars. Additionally, given that different models are substitutes, the reduction in thefts of Lojack-equipped cars can be displaced towards non-Lojack-equipped ones ($\frac{\partial F}{\partial B_{-ij}} > 0$). If this prediction of the model is correct, then car owners of non-Lojack vehicles might be saddled with increased theft rates, even though they took no action. In other words, Lojack equipped car owners may have generated a negative externality for other vehicle owners. What should be clear from the model is that the same theft prevention technology can have either positive or negative externalities depending on how it is offered to the public.

On the other hand, there is the possibility that Lojack promoted a reduction in chop shops in a locality, or increased the incarceration rates of auto thieves. In that case, Lojack may have had a positive effect on the theft rates of non-Lojack-equipped vehicles. This would happen if for some reason chop shops dealt with both Lojack and non-Lojack vehicles. With Lojack increasing the probability of detection of the shop's operation, it would reduce the equilibrium number of cars processed, both Lojack and Non-Lojack cars.

The theoretical prediction of differing externality consequences according to the degree of discernibility for thieves of Lojack equipped vehicles begs the question of why the Lojack company decided not to explicitly signal that a car was protected with Lojack with a decal. The main reason is that Lojack's business is to provide a reliable recovery service in the event of theft. Advertising that a car has Lojack may compromise recovery rates because thieves may take actions to make the recovery less likely. Lojack provides important deterrence effects, which are the focus of this study, although that is not the main concern of the auto recovery system managers.

The negative externality produced by Lojack can be subdivided into two categories: within a Lojack state and in non-Lojack states. The former are referred to as Within-State Externalities while the latter are referred to as Geographical Externalities. The framework presented here focuses exclusively on thefts of vehicles. However, the intervention could be analyzed from the more comprehensive framework of crime in general (Becker, 1968). This is not attempted in this paper because of lack of state-level crime data in Mexico. However, the possible displacement of auto theft with the introduction of Lojack towards other kinds of property crime was investigated by Ayres and Levitt (1998). They used available crime data for the United States, but found no displacement effects.

4 Data

The data used in this research consist of detailed auto sales and theft reports at the Mexican state level. Because there is no country-wide auto theft database compiled by a government agency in Mexico, no longitudinal crime studies using Mexican data have been performed up to now. This paper is the first to use detailed auto theft data on Mexico from a a novel source, the internal reports generated by the Mexican Association of Insurance Companies (AMIS).[3]

AMIS is a non-profit organization funded by insurance companies that compiles industry-wide theft and accident rates. These statistics are then used by members of the association to price insurance contracts. AMIS associated companies have a market share of over 80% of the automobile insurance market. The AMIS auto theft dataset is not publicly available, but its use was authorized for this study. The database is generated continuously in this automatic manner: when an insured vehicle is stolen, the owner calls his insurance company to file a report; as soon as the employee of the insurance company fills out the electronic report for the company's use, a copy of it is automatically sent to the compiling system at AMIS. Note that, under this system, if a stolen

[3] www.amis.org.mx

vehicle is recovered, the report of the robbery is still preserved.

In this study I use AMIS data on all countrywide theft cases reported from January 1999 to August 2005. Each entry in the dataset is a theft report, which includes the brand and model of the car, the date and state where the robbery occurred, and the year the car was sold. Unlike the case of uninsured vehicles, thefts of insured vehicles are very likely to be recorded for financial reasons.

The auto sales data were provided by the Mexican Association of the Automobile Industry (AMIA).[4] AMIA is a non-profit organization formed by the principal vehicle distributors and manufacturers in the country, which compiles detailed data on automobile sales. The series used here are annual dealership sales at the state level from 1999 to 2005. The data were available aggregated into various categories of brand and car type. For each brand, the vehicles were classified into categories: subcompacts, compacts, luxury cars, sports cars, SUVs, minivans, and trucks. The AMIS theft data was aggregated to match the AMIA sales data (annual state sales for each model group) and both datasets were then merged. The resulting groups of cars are shown in Table 1. Some of the groups consist of single models, while others contain various models. Throughout the paper, the terms model and model-group are used interchangeably to refer to the groupings of vehicles in Table 1.

The econometric analysis uses variation in theft risk over time to identify the effect of Lojack. For that reason, the unit of observation should be car models whose theft risk can be followed throughout the analysis period. All thefts cases of cars sold up to 1998 but stolen between 1999 and 2005 were not used as units of observation because of lack of data on the stock susceptible to being stolen: state level sales of any car model marketed before 1999.

The second type of discarded observations was car models introduced into the national market after Lojack was implemented. For these vehicles, it is impossible to analyze theft risk *before* Lojack was introduced. Therefore, car models introduced after 2001 were not used in this study. Similarly, some models were discontinued before the Lojack intervention. For these models, there is no post-treatment data available to analyze theft behavior, so they are left out. After these deletions, I have data on car models for which information on theft risk is available *before* and *after* Lojack was implemented. In total there are 69 model-groups (some brands have more than one car model per

[4] www.amia.com.mx

category and are grouped in the data) for which I have up to 28 observations in each of 32 Mexican states: 7 annual theft observations per state for cars sold in 1999, 6 annual theft observations per state for cars sold in 2000, and so on, with only one theft observation for cars sold in 2005. However, the data do not consist of these 59,892 possible cases mainly because some car models have no distribution channels in low population states. Further, some car models - - especially sports cars and luxury cars - - are not sold in some of the poorer states. The final dataset has a total of 36,406 observations available for analyzing the impact of Lojack on auto theft dynamics. As I mentioned before, 13 of the 69 car groups are Ford models that obtained Lojack. This Lojack intervention occurred in four states during the period of analysis. The summary statistics of auto theft behavior are presented in Table 2.

In panel A of the table, a summary of the variables used in the statistical analysis are presented. The unit of observation is a quadruple (model group, state, year sold, year stolen) combination with available data. The average unit of observation has 619 vehicles, and 3.5 thefts. This results in a mean annual theft rate of 6 cars per 1000 vehicles. The maximum number of thefts in any of the observation units was 1,502. The cars being studied are relatively new: they range from zero to six completed years on the road.[5] The average car age is 1.95 years. The mean age is not three because, by construction, the data has fewer observations of older cars: all cars are observed when they are new, but the only observations available for six year old cars are those that were made in 1999. Lojack is a dummy variable equal to one if the car is equipped with Lojack. Out of all the observation units, 0.64% had Lojack installed when they were new.

Panel D in the table focuses on vehicles that were Lojack equipped when they were sold. Lojack equipped vehicles are newer than those in the entire sample, with a mean age of 0.72 years, because the Lojack program was introduced in the latter part of the analysis period. Lojack equipped observations have a mean of 2.97 thefts and a mean stock of 558 vehicles. Panels B and E of the table divide the observations into two groups, Lojack and non-Lojack models. In the table, as throughout the paper, a Lojack model is one of the 13 Ford models that participated in the Lojack program. In panel B, all observations pertaining to Lojack models are included, even those for years before the program was implemented and for states where Lojack was never implemented. Lojack models had an average stock of cars susceptible to being stolen of 225 units, while non-Lojack

[5] 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.

models had an average stock of 721 units. Mean theft cases for Lojack models are correspondingly smaller than those for non-Lojack models: 1.08 and 4.15, respectively. Dividing mean thefts by the mean stock of cars on the road reveals that theft rates were smaller for Lojack models: 4 per 1000 versus 5 per 1000 (this rate is an underestimate of the theft rate because the numerator only includes thefts of insured vehicles.) Finally, panels C and D of the table divide the observations into two groups: Lojack States and non-Lojack States. This partition highlights the fact that average sales in Lojack states are larger than in non-Lojack states. The mean stock of cars in the observation units in the former is 1,703, while in non-Lojack states it is 381. Furthermore, Lojack states on average are high crime states: dividing mean thefts by the mean stock of cars yields an estimate of nine thefts per 1000 in Lojack states and only two per 1000 in non-Lojack states. Finally, the table indicates that 3.5% of Lojack state observations correspond to vehicles that were equipped with Lojack when they were sold.

A first caveat with this data is that it provides information about where the car was sold, but not where the car currently resides. Although the latter is preferred, if the probability that a car of a given model and year migrates from state j to state i is equal to the probability that a car of the same model and year migrates from state i to j, then the first variable is a noisy but unbiased measure of the number of cars in a state. However, one can imagine that some states are net exporters of cars to other states. This would induce a systematic error in the measure of cars exposed to theft, and receives attention in the section on robustness checks.

A second and more important caveat is that the data available here are not total number of thefts, but rather total number thefts of insured vehicles. The Robustness Checks section provides evidence that Lojack introduction did not have any effect on the rate at which Lojack models were being insured; this is important in identifying the effect of Lojack on theft risk for different vehicles.

5 Estimation Strategy

This paper focuses on the evolution of theft risk and its relationship to the introduction of Lojack. The theft variable used is the number of vehicles stolen; it is non-negative and integer-valued. A histogram of the theft variable is presented in Figure 1. As the figure makes clear, over 60% of the observations are zero. When the dependent variable is this type, OLS is problematic because the conditional mean function takes on negative values. I therefore use the canonical model for count data in my estimations: the Poisson regression model. The estimated equation is:

$$E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = (S_{ijy}) \cdot exp\left(\gamma_{ij} + \beta_j \cdot t + \beta_{Lojack} \cdot Lojack_{ijyt} + \sum_{a=0}^{6} \beta_a \cdot I[Age = a]\right) \quad (2)$$

where the dependent variable ($Thefts_{ijyt}$) is the number of vehicles stolen in any given state, model group, year made, and year stolen combination. S_{ijy} refers to the state-specific annual sales of each car model, which is a proxy for the stock of cars susceptible to being stolen in every state, model-group, and production year combination. The estimated equation also includes a fixed effect (γ_{ij}) for every combination of state and car model in the data. This incorporates the fact that theft risk varies according to location (state) and type (model group). A time trend, specific to all vehicles in a state ($\beta_j \cdot t$) is also included. The purpose of this regressor is to allow for state-specific dynamics in theft risk. All vehicles in the same state are subject to the same police and judiciary institutions, which may have different dynamics over time in every state.

In the regressions, the coefficient of interest is some variant of a dummy variable indicating that Lojack had been implemented. For expositional purposes, the regressor of interest is simply denoted $Lojack_{ijyt}$ in the remainder of this section. However, in the Results section, the specific definition of the regressor is presented and the data used are clearly defined for each of the estimated regressions.

Finally, all of the regressions include a full set of vehicle-age dummies ($I[Age = t - y]$). These regressors, in a completely flexible way, capture the mean theft schedule according to the age of the car. This is relevant because theft risk varies by how old the car is. Typically, newer cars are subject to higher theft risk because they provide a higher payoff in the black market. All regression standard errors are clustered at the state level (Bertrand, Duflo, and Mullainathan (2004)).[6]

S_{ijy} allows for a meaningful comparison of theft even if the quantity of cars subject to risk varies by model. That is, given that different models have radically different market shares, any analysis of auto theft that distinguishes among models in the same geographic location must control for the quantity of cars subject to theft. In a Poisson regression, this is referred to as "controlling for

[6]Cameron, Gelbach, and Miller (2006) two-way clustered standard errors at the state and year level were also calculated, without changing the significance of the main results.

exposure". The exposure variable (S_{ijy}), 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.[7]

The descriptive statistics showed that there is much heterogeneity in theft risk depending on the model and/or the state in question. In such situations, one major worry is that estimated effects may simply be capturing cross-sectional differences in theft risk, particularly in cases such as this one in which the treatment was not randomly assigned. This concern is addressed by including a fixed effect (γ_{ij}) for every (state, car model) in the data. In other words, average differences in theft behavior across car models or states are not the source of identification of the coefficient of interest.

The fact that various observations are available for the years before Lojack was introduced means that I do not rely on the assumption that time trends in theft dynamics were identical in treated and non-treated states. The specification that I use directly estimates a linear time trend of theft risk that is common to all car models in a particular state ($\beta_j \cdot t$). So, all states are allowed to have differential trends in theft, guaranteeing that the results are not driven by differential theft dynamics at the state level. I obtain identification of β_{Lojack} from an upward or downward shift in the theft rate in the years *after* Lojack was implemented from what was predicted by the linear trend estimated from the years *before* the introduction of Lojack. This specification makes the traditional concerns about the selection of the control group in a difference-in-difference context much less relevant (see Miguel and Kremer (2004) for more on this). Many studies rely on an assumption of equality of trends in the pre-treatment periods; in this case, the identification of the coefficient of interest does not come from control and treatment group differences, but rather from deviations from a linear time trend estimated using pre-treatment data.

The exponential form of the conditional expectation, and the fact that the coefficient of interest, β_{Lojack}, is associated with a dummy variable, makes interpretation of the coefficient highly intuitive. The ratio of expected thefts conditional on having Lojack to expected thefts conditional on not

[7]The results are robust to a relaxation of the coefficient restriction on S_{ijy}. See the Robustness Checks section.

having Lojack is:

$$\frac{E[Thefts_{ijyt}|\mathbf{x}_{ijyt}, Lojack_{ijyt}=1]}{E[Thefts_{ijyt}|\mathbf{x}_{ijyt}, Lojack_{ijyt}=0]} = e^{\beta_{Lojack}}$$

Note that the effect is independent of the values of the other regressors in $\mathbf{x}_{ijyt}$. For this reason, I report exponentiated coefficients, also known as incidence rate ratios (IRR), in addition to the Poisson regression coefficients for each regression in the results tables.

Poisson regressions have this advantage: it is straightforward to obtain an estimate of the magnitude of the effect in terms of the number of cars stolen. So, the third column in each of the regressions in the tables, labeled *Count*, reports a transformation of the Poisson coefficient into an estimate of the number of cars stolen as a consequence of the introduction of Lojack. The calculation is:

$$\sum_{ij\in\Lambda} \left(E[Thefts_{ijyt}|\mathbf{x}_{ijyt},\ Lojack_{ijyt}=1] - E[Thefts_{ijyt}|\mathbf{x}_{ijyt},\ Lojack_{ijyt}=0]\right)$$

Because of the conditional expectation's form, this simple sum can be rewritten as the percent change in thefts attributable to Lojack multiplied by the pre-Lojack average annual thefts in the group:

$$(IRR-1)\cdot\left(\sum_{ij\in\Lambda} E[Thefts_{ijt}|\ Lojack_{ijyt}=0]\right) \tag{3}$$

This is simply a function of the Poisson coefficient and the size of the group of affected cars. The standard errors are obtained with the delta method, using those reported in the coefficient column.

The theoretical framework suggests that β_{Lojack} should clearly be negative for vehicles equipped with Lojack. It also suggests that the reduction in thefts from Lojack vehicles should have generated higher thefts in vehicles not equipped with Lojack, because of substitution effects. Evidence of negative externalities would take the form of a positive Lojack coefficient in the specifications using data from vehicles not equipped with Lojack. Furthermore, I expect the spillover effect to be present in states close to those where Lojack was introduced, but decreasing with distance from the closest treated state.

An extensive literature has focused on the difficulty in measuring program effects when participation is voluntary. This problem is not present in Ford's Lojack program though. The Ford's were sold for the same price nationally, regardless of whether the state was participating in the Lojack program. This yields two benefits. 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 margin. Any effect of Lojack on sales is controlled for in the empirical analysis through the stock-of-cars 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.

The use of fixed effects in the estimation generates a stronger requirement for the error term than in a cross section. Specifically,

$$Thefts_{ijyt}|\gamma_{ij}, S_{ij1}, ..., S_{ijY}, Lojack_{ij11}, ..., Lojack_{ijYT} \sim Poisson(\mu_{ijyt}) \quad t = 1, ..., T \; y = 1, ..., Y$$

where μ_{ijyt} is given by (1). Conversations with Ford executives suggest that the decision of which cars to equip with Lojack were not based on recent theft behavior of Ford vehicles; that provides some assurance that the exogeneity assumption is valid.

Finally, remember that the Poisson regression model assumes conditional equidispersion of the dependent variable. This is a consequence of the fact that the expectation of the random variable is equal to its variance in the Poisson distribution. Conditional overdispersion invalidates inference because estimated standard errors are too small. Whenever the data present a large degree of overdispersion, the alternative is to allow the conditional variance to be a function of the conditional mean: this model is known as Negative Binomial. However, unlike the Poisson model, the Negative Binomial model is not robust to distributional misspecification. That is, if the data is not Negative-Binomial distributed, then the estimated coefficients are inconsistent. On the other hand, the Poisson model is robust to mispecification, in the sense that estimation is consistent even if the dependent variable is not Poisson distributed (Cameron and Trivedi, 1998). Its only requirement for consistency is that the conditional mean be correctly specified, which is identical to the condition of the classical OLS model.

For this reason, unless there are high levels of overdispersion, the Poisson model is preferred.

The strategy I adopt is to estimate the degree of conditional overdispersion present in the data, and to show that it very limited. Second, in the Robustness Checks section I present the estimates from the Negative Binomial regression and show that the standard errors are virtually unchanged from one estimation method or the other. Given that the trouble with overdispersion is having standard errors that are too small, the results allow me to focus on the Poisson estimation results.

I use the test suggested in Cameron and Trivedi (1998) to measure the presence and extent of dispersion in the data. Let

$$H_0: \ E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = V[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = \mu_{ij}$$

and

$$H_a: \ E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = \mu_{ij} \quad \& \quad V[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = \mu_{ij}(1+\alpha\mu_{ij})$$

The second condition implies that $E[(Thefts_{ijyt} - \mu_{ij})^2 - Thefts_{ijyt}|\mathbf{x}_{ijyt}] = \alpha\mu_{ij}^2$. However, under H_0, $\alpha = 0$. This suggests the following dispersion test: let the fitted values of the Poisson regression be $\hat{\mu}_{ij} = e^{\mathbf{x}'_{ijyt}\hat{\beta}}$. If the following model is estimated,

$$\frac{(Thefts_{ijyt} - \hat{\mu}_{ij})^2 - Thefts_{ijyt}}{\hat{\mu}_{ij}} = \alpha\hat{\mu}_{ij} + u_{ijyt}$$

one obtains an estimate for the value of α. Under equidispersion, $\alpha = 0$. If $\alpha < 1$, overdispersion is modest and the Poisson and Negative Binomial yield similar results because the Poisson model is the special case of the Negative Binomial with no overdispersion. In the reported tables, an estimate of α obtained in this fashion is presented in the last row.

6 Results

A preliminary analysis of the data can be obtained by reporting theft rates (defined as $Thefts/Stock\ of\ Cars$), as is done in Table 3. To generate a simple comparison between groups, I report theft rates before and after Lojack introduction. In the table, I split the observations into three groups: Lojack states, nearby non-Lojack States and distant non-Lojack states. Each of these is then subdivided into Lojack and non-Lojack model columns. The first two rows distinguish between observations that occurred before and after the Lojack program was implemented.[8]

In the table, the first thing to notice is that Lojack models in Lojack states, as a group, experienced a strong decrease in theft rates once Lojack was introduced. This is preliminary evidence that Lojack had a strong impact on thefts of Lojack cars, generating a reduction on the order of 45%, according to the simple comparisons in the table. None of the other groups seem to have experienced higher theft rates in the years after Lojack was introduced in Lojack states. The approach used in the table, with a rate as the dependent variable, has the problem that cells with small denominators can change the results because they can easily generate extremely large theft rates. Indeed, the results presented in the table do not include observations in which fewer than five cars were susceptible to being stolen. This is one important reason for using a methodology like the Poisson regression, which does not suffer from observations with small denominators driving the results.

I first determine whether there is any evidence that Lojack generated negative externalities in states that were not part of the Lojack program - - i.e. Geographical Externalities. I do this by using data from non-Lojack states and looking for unexpected increases in theft once Lojack is introduced in the nearest Lojack state. Figure 2 diagramatically explains the identification strategy. I use data from non-Lojack states, estimate a state specific time trend of thefts, and introduce a dummy regressor called $After\ Lojack$ which is equal to 1 if Lojack has been introduced into the nearest Lojack state. The estimated equation is:

$$E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = (S_{ijy})\cdot exp\left(\gamma_{ij} + \beta_j \cdot t + \beta_{After\ Lojack} \cdot After\ Lojack_{ijyt} + \sum_{a=0}^{6} \beta_a \cdot I[Age = a]\right)$$

There are two things to notice here: Only non-Lojack state data is used, but each state is allowed its own time trend, so the $After\ Lojack$ coefficient identifies mean changes in thefts that are coincidental with the introduction of Lojack into the nearest Lojack state. As explained before, I expect negative externalities to be less important the more distant a state is to where Lojack was implemented. For this reason, I subdivided the non-Lojack state observations into three groups,

[8]Since Lojack was not implemented at the same time in all intervention states, each model in each state has a different cutoff date that defines its *before* and *after*. This is useful for the econometric analysis, but not so for the purposes of the table, that uses a unique cutoff point. Table 3 takes the approach of using 2003 as the cutoff date, when most of the vehicles were treated. It excludes Lojack models that were treated in 2004 and 2005. A different approach is taken in Table 7, which does not exclude models treated in 2004 and 2005. Both tables present the same behavior.

as shown in Figure 3: states contiguous to Lojack states, states adjacent to the contiguous states, and the rest of states.

For each distance category, I estimate a regression, and the results are presented in Table 4. For each distance category (top, middle, and bottom panels), I report the results of the three regressions: effects on all cars, on Lojack cars only, and on non-Lojack cars only.

As explained in the Estimation Strategy section, for each regression presented in the tables, the first column reports the Poisson coefficient associated with the *After Lojack* regressor. The second column reports Incidence Rate Ratios, which are exponentiated coefficients obtained from the Poisson regression. They are interpreted as the ratio of expected thefts with Lojack to expected thefts without the Lojack intervention. An incidence rate ratio of 1 means there is no difference in expected thefts from one situation to the other. The third column, labeled *Count*, reports the estimated impact of Lojack in terms of additional cars stolen (if positive) or decreased cases of theft (if negative).

The results of the top panel indicate that, coincident with the introduction of Lojack in contiguous states, there was a statistically significant increase in thefts of all cars. Moreover, the effect was particularly strong for Lojack models. The increase is on the order of 120% for Lojack models and 25% for non-Lojack ones. The count columns in the top panel suggest that an annual increase of 90 auto thefts occurred in contiguous states with the introduction of Lojack. Of these, the other two regressions suggest that approximately 21 corresponded to Lojack models and 80 to Non Lojack models.

In the middle panel of the table, the same regression is fitted using observations of states in the second ring around Lojack states. The same qualitative results hold: an increase in thefts beyond what a state-specific linear time trend would have predicted in those states.

Finally, the last panel of the table shows that there is no statistically significant effect of Lojack in states far from those where Lojack was implemented. When estimated separately, no significant effects were found for either Lojack or non-Lojack models. In conclusion, the evidence in Table 4 suggests that the introduction of Lojack was accompanied by increases in thefts in neighboring states; and among Lojack cars, thefts nearly doubled, while other car models saw an increase of 25% in their theft risk. For states far from those where Lojack was introduced, there was no statistically significant effect on theft risk associated with Lojack introduction.

The second group of vehicles that could have been affected by the introduction of Lojack are those in Lojack states that were not Lojack models. To analyze the theft risk of this group, I use observations of non-Lojack models in Lojack states and non-Lojack models in the third distance category states. The geographical externality regressions suggested that states distant from Lojack ones were unaffected by Lojack and thus can serve as control observations. However, it should be clear that the impact of the choice of the control group on the estimations is very limited, because the Lojack coefficient is estimated from a break in theft trends in the Lojack state data[9] The coefficient of interest is captured by the *After Lojack* dummy variable, which is equal to one if the car model does not have Lojack but another car model in the state does. The theoretical framework section predicted a displacement effect towards this group of cars. However, as also was mentioned there, this group may have experienced a decrease in thefts because of a reduction in chop-shops, or higher incarceration of auto thieves. The estimated regression model is:

$$E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = (S_{ijy}) \cdot exp\left(\gamma_{ij} + \beta_j \cdot t + \beta_{After\ Lojack} \cdot After\ Lojack_{ijyt} + \sum_{a=0}^{6} \beta_a \cdot I[Age = a]\right)$$

Note that the *After Lojack* variable is different from the one written above: this one refers to Within-State Externalities, while the previous regression captured Geographical Externalities. In the first column of Table 5 there is an insignificant impact of Lojack on this group. Although there may have been some displacement to non-Lojack models, the effect may be too small relative to the number of non-Lojack cars sold and stolen in the group to capture an effect precisely. In Lojack states, Lojack models represented 6.5% of average annual sales. Even if I assumed a displacement effect towards other cars that fully offset the decrease in thefts of Lojack equipped cars, the impact on the non-Lojack cars in Lojack states would be so small (in percentage terms) that it would be hard to identify in the data. On the other hand, that is not the case in surrounding (smaller sales) states, where displaced thefts could have large relative effects that could more easily be captured by the regressions.

I also can focus more specifically on an interesting subgroup of the one above: Lojack models produced before Lojack was introduced. The expected direction of the spillover on this group is not obvious. If a model looks very similar in the years just before and just after it got Lojack, it

[9] In the Robustness Checks section, the equation is estimated using only Lojack state data, with very similar results to those of the main specification.

may have been difficult for thieves to distinguish between those equipped with Lojack from those that were not. Furthermore, even if they were distinguishable but the thieves were unsure about when the program started, then one would expect some positive spillover effect of having Lojack installed in future versions of the model. However, if there is little confusion for thieves about which models had Lojack, and the cars are close substitutes, then one could find negative spillovers along this dimension, too. In other words, if auto thieves realize that Ford Windstars sold after 2000 have Lojack, do they increase or decrease the theft of close substitutes, like a Ford Windstar sold in 1999?

To capture this effect, I use the $Old\ Lojack\ Model$ dummy regressor, which is one for Lojack models built before the model came equipped with Lojack, in years after Lojack was introduced in its newer versions. The data used in the regression are observations of old Lojack models in Lojack states and of old Lojack models in distant states. The results shown in Table 5 suggest that this type of spillover was non-existent; i.e. there was no net displacement towards older versions of Lojack models.

The results on the impact of Lojack on Lojack-equipped vehicles are presented in Table 6. The estimated regression model is:

$$E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = (S_{ijy})\cdot exp\left(\gamma_{ij} + \beta_j \cdot t + \beta_{Lojack} \cdot Lojack\ Equipped_{ijyt} + \sum_{a=0}^{6} \beta_a \cdot I[Age = a]\right)$$

Where Lojack equipped is a dummy variable equal to one if the car came equipped with Lojack when it was first sold. The data used in the regression are for Lojack models in Lojack states and Lojack models in distant states, where no geographical externalities were found. The estimated coefficient indicates that Lojack generated a reduction in the theft rate of Lojack equipped vehicles of 55%. In terms of thefts averted, the regression estimates that 152 vehicles were prevented from being stolen annually due to the deterrence effects of Lojack.

Although the previous regression captures the *average* effect of Lojack on the theft rate of Lojack equipped vehicles, it is also of interest to see how the effect changed as the cars got older. All cars in the Ford Lojack program had one year of recovery service; afterwards the renewal of the service was voluntary. Lojack executives calculate that roughly 60% of Lojack equipped vehicles re-enrolled at the end of the first year, but the proportion was 40% at the end of the second year.

The data allow me to estimate the impact of Lojack as the proportion of cars that effectively had it was declining. Within this group of cars, it would be impossible for thieves to distinguish which had continued the service and which had not. Such high uncertainty about which cars had Lojack resembles the way that Lojack was sold in the United States, albeit at much higher Lojack coverage rates in Mexico. Ayres and Levitt (1998) were only able to observe Lojack coverage rates in the range of 0-2%, and found large but rapidly decreasing marginal effects.

I subdivide the Lojack dummy into three categories: a dummy for Lojack equipped and age up to one year, Lojack equipped and age between one and two years, and Lojack equipped and age between two and three years. The data are on Lojack models in Lojack states and in distant states. The last three columns in Table 6 report the results of my estimation. At every age the coefficients are very similar to the average effect shown in the first three columns of the table. This suggests that the deterrence effect of Lojack was very similar in magnitude regardless of how old the vehicles were. One interesting aspect of this result is that as the cars grew older, their likelihood of having the Lojack recovery service fell from 100% to 40%. Given that I am controlling for age, this suggests that the reduction in thefts obtained as a deterrence effect by installing Lojack in *all* of the vehicles of a certain model could have been obtained by a random - - from the point of view of thieves - - installation of a proportion much smaller than one. Ayres and Levitt (1998) estimated an effect of Lojack of around -50% in thefts if the proportion of cars equipped with Lojack was around 1.5%. They also noted that the marginal effect would have to decrease rapidly after the level of coverage. If the effects estimated here lie on the same function as the one in their paper, then it could be reasonable to conclude that the additional deterrence effect from having Lojack penetration rates above 1.5%-2.0% is extremely small.

The regression results point to an almost total displacement of thefts averted from Lojack-equipped models into vehicles in neighboring states. Indeed, using the *Count* columns in the tables, it is possible to add the number of statistically significant *reductions* and *increases* in auto theft generated by the introduction of Lojack. This sum is around zero, suggesting that all of the thefts averted in the Lojack-equipped group were displaced towards non-Lojack-equipped vehicles in nearby states. As a corollary, from a social point of view, the program generated a net social loss for society, given that the costs of implementing Lojack served only to displace thefts across car owners. Notwithstanding, this conclusion may not be entirely correct from a longer term perspective, as is argued next.

The Ford Lojack program in Mexico was halted in 2006. Under severe cost cutting pressures, the automaker decided to drop the program. In spite of this, over these years the company providing the Lojack recovery service had acquired experience and installed capacity to continue providing the service at a reasonable cost. After the Ford deal collapsed, the company started offering Lojack to anyone interested in having the recovery service, 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 - - similar to the way it was sold in the United States - - should result in generalized declines in theft rates, with large positive externalities and a positive net social benefit from the technology, as Ayres and Levitt (1998) have argued.

From this long term perspective, the temporary exclusivity agreement - - over the period analyzed here - - with no net positive social benefits, may have been a necessary initial phase that allowed for a generalized decrease in thefts in the future. Nevertheless, the results presented in this paper imply that selling Lojack to a discernible set of cars severely limits its potential positive spillovers. This finding may be useful in crafting future scenarios in which policymakers are better informed about how to regulate and adopt new technology so as to maximize society's welfare.

6.1 Robustness Checks

6.1.1 Data Limitations

This section reviews the implications for the analysis of using insured vehicle theft data together with total stock of cars, instead of only the insured vehicle stock of cars. The intuition of the problem this presents is relatively simple: the interpretation of the results is invalid if Lojack generated changes in the likelihood of a Lojack-equipped vehicle being insured. If buying a car with Lojack made owners less likely to buy insurance, then this would reduce the number of cars exposed to theft that are captured in the data, potentially influencing some of the results.

The problem can be seen in terms of the estimated model. The data available, in which total stock of cars instead of the insured vehicle stock is used as the exposure variable, can be understood as a situation in which the true exposure variable is overblown by a factor larger than one. Assume that π_{ij} is the probability that a vehicle model i in state j is insured. Then the true stock of cars is $S_{ijy}^{True} = \pi_{ij} \cdot S_{ijy}^{Obs}$, where S^{Obs} refers to the stock of vehicles observable to the econometrician, while S^{True} refers to the actual stock of insured cars on the road. Then, if the true model is

$$E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = (S_{ijy}^{true}) \cdot exp\left(\gamma_{ij} + \beta_j \cdot t + \beta_{Lojack} \cdot Lojack_{ijyt} + \sum_{a=0}^{6} \beta_a \cdot I[Age = a]\right)$$

Substituting $S_{ijy}^{True} = \pi_{ij} \cdot S_{ijy}^{Obs}$ in the equation above yields

$$E[Thefts_{ijyt}|\mathbf{x}_{ijyt}] = (S_{ijy}^{Obs}) \cdot exp\left(ln(\pi_{ij}) + \gamma_{ij} + \beta_j \cdot t + \beta_{Lojack} \cdot Lojack_{ijyt} + \sum_{a=0}^{6} \beta_a \cdot I[Age = a]\right)$$

$ln(\pi_{ij}) + \gamma_{ij}$ is then absorbed by the model and state-specific fixed effect and the error in the exposure variable does not bias the results. In conclusion, the specification used is robust to error in the exposure variable. However, if π_{ij} falls when Lojack is introduced, then the coefficient of interest (β_{Lojack}) is not identified. For this reason, I now present evidence that: 1) Lojack-equipped vehicles were just as likely to be insured as non-Lojack-equipped vehicles; and 2) insurance likelihood of Lojack models evolved in an identical manner to non Lojack models once Lojack was introduced. This allows me to conclude that Lojack introduction was uncorrelated with insurance coverage (π_{ij}) probability, as required by the econometric model.

First, note that the scope for this behavioral response would be muted by the fact that in the years after Lojack was introduced, around 70% of new vehicles were bought with financing loans, which require insurance coverage during the life of the loan. Cars bought through a loan are required to be insured because the financing company otherwise can lose the collateral that can be repossessed in case of an accident or theft. The insurance requirement for cars bought on credit was not relaxed because the car had Lojack.

The data I use to measure the possible impact of Lojack introduction on insurance probability is the AMIS time series of the number of cars insured by year in the whole country for every car model. Since Lojack states command 40% of nationwide sales, a reduction in the insurance coverage of Lojack models would show up 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, year sold, year insured). 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 (model group, year sold, year insured) 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 ($Lojack_{ij}$), calendar year dummies ($I[t = 1999], ..., I[t = 2005]$) to capture time trends in national insurance coverage, and a set of age-of-car dummies ($I[Age = 1], ..., I[Age = 6]$) that flexibly capture average changes in the insurance probability as the car ages. The estimated equation in the first column of Table 8 is

$$Proportion\ Insured_{iyt} = \beta_0 + \beta_{Lojack} \cdot Lojack_{iyt} + \beta_{age=t-y} \cdot I[Age = t-y] + \beta_{year=t} I[Year = t] + u_{iyt}$$

where i refers to the model group, y to the year the cars were sold, and t refers to the year of the observation. The coefficient of interest is β_{Lojack}. In the table, the Lojack coefficient is insignificant; this suggests that after Lojack was implemented, Lojack models were just as likely to be insured as non-Lojack models. Thus buying a car equipped with Lojack did not reduce the probability of the car being insured as long as Lojack models were as likely to be insured as their counterparts *before* Lojack was introduced. The second regression addresses this issue by looking for differential *changes* over time in insurance coverage for Lojack models.

The equation estimated in the second column of the table is

$$Proportion\ Insured_{iyt} = \beta_i + \beta_{Lojack} \cdot Lojack_{iyt} + \beta_{age=t-y} \cdot I[Age = t-y] + \beta_{year=t} I[Year = t] + u_{iyt}$$

which differs from the previous regression in that it includes a model-specific intercept and uses data from all observations available: for the years 1999-2005. The insignificance of the coefficient in the table again suggests that Lojack models neither observed a decrease nor an increase in insurance likelihood, compared to other car models, once Lojack was introduced.

The regressions lead me to conclude that Lojack did not induce a reduction in the probability of insuring vehicles for customers who bought Lojack-equipped cars. There may have been various reasons for this. People who bought the car with credit had no option of opting out of insuring their vehicle even if they wanted to. Another reason is that people value the services of insurance companies aside from theft coverage: insuring vehicle damage in case of accidents, medical expense insurance for vehicle occupants, and civil responsibility.

Aside from the concern about Lojack altering the likelihood of insuring a car, a second data caveat that should be raised here is the extent to which the results are exclusive to the set of insured vehicles in Mexico. At best, if theft risk is not correlated with the insurance status of the car - - conditional on all observable characteristics like model group, age, and state - - then the results should generalize to all vehicles, as if the data resulted from a traditional random sampling scheme, where the sample was insured vehicles. Conditional on vehicle characteristics, there are arguments for why insurance status does not affect theft risk. The first is that, conditional on characteristics, thieves cannot distinguish vehicles that are insured from those that are not. The second is that the insurance status of the car does not affect the payoff to the thief.

In the worst case scenario, theft risk has different dynamics according to the insurance status of the vehicle, even after conditioning on available characteristics. For example, insurance status may be correlated with the geographic location (or risk environment) of where the vehicle is driven. It may be the case, for example, that in rural areas, where theft is almost nonexistent, car owners are much less likely to insure their vehicles. If this is the case, – and I have no way of knowing which of these two scenarios is closer to reality – the results presented here only will pertain to insured vehicles. But even if this is the case, the results are important, because the majority of vehicles in Mexico are insured.

6.1.2 Specification Robustness Checks

I now report the results from variants of the main regressions in order to verify their robustness. Tables 9, 10, and 11 report results from the main specification in the first line, together with the results of the different robustness checks described below.

The first robustness check, presented in the row labeled Negative Binomial in Tables 9, 10, and 11, replicates the main regressions using a Negative Binomial estimation procedure. Cameron and Trivedi (1998) warn that fitting a Poisson when there is overdispersion in the data generates standard errors that are too small. As an approximation, with an overdispersion parameter of α, the standard errors should be α^2 larger than estimated by a Poisson regression. A Negative Binomial regression does not suffer from this fact, but is sensitive to misspecification of the data generating process, unlike the Poisson regression.

Comparing the standard errors of both estimated models shows that those of the Negative Binomial are very similar, and in some cases even smaller than those in the Poisson regression. The extremely small α's found in the Poisson specification suggested that the standard errors in the Poisson and the Negative Binomial regression would not be very different. The size of the standard errors in the Negative Binomial estimation confirm this intuition. The estimated coefficients in the Binomial model are extremely close and of the same sign as those in the Poisson model. Given the robustness of the Poisson model to misspecification, and the small degree of overdispersion in the data, I take it as the preferred model.

The second specification robustness check is suggested by Cameron and Trivedi (1998). It consists of ignoring the Poisson model and working under the assumption that the conditional mean is correctly specified as $E[Thefts|\mathbf{x}] = e^{\mathbf{x}'\beta}$. The rows labeled Non-Linear Least Squares report the estimations of $Thefts$ on $e^{\mathbf{x}'\beta}$, where all the covariates are the same as those of the baseline specification. The qualitative results are the same as in the baseline Poisson model, except that the geographical externalities and impact coefficients are larger than those of the Poisson regression.

The third specification test uses another approach to the problem of having only insured vehicle theft data. I inflate theft cases by the corresponding reciprocal of the *national* insurance rate for each (model group, year made, year stolen), so that if only half of the vehicles are insured, the observed theft cases are multiplied by two. This new dependent variable would adequately correct for the lack of information on insured vehicle stocks at the state level if national insurance rates were the same as state rates, and if theft risk were uncorrelated with insurance status. This is a crude correction, but in exchange it directly scales the dependent variable proportional to any national changes in insurance likelihood. With inflated thefts, the table shows that negative geographical externalities persist only for Lojack cars. The impact on Lojack vehicles in Lojack states (Table 11) shows a larger drop in theft with this measure than with the uncorrected theft measure. In contrast to the main specification, however, the regression that uses inflated thefts displays negative externalities to non-Lojack vehicles in Lojack states. Also in contrast to the main specification, the use of inflated thefts suggests that old Lojack car models in Lojack states benefitted from lower theft rates after the introduction of Lojack.

The fourth specification test is shown in Tables 10 and 11. It consists of eliminating the control observations used in the main specification. In particular, observations from distant Lojack states are not used. As was explained in the Estimation Strategy section, and is shown in the tables, the results are virtually unchanged from the main specification results.

The last robustness check deals with an alternative explanation for the results. The theft-risk function used in the analysis assumes that there is a linear relationship between the stock of vehicles and the number of thefts, by constraining the coefficient on the stock of vehicles to enter lineally in the regression. However, this might not be a good model of how theft actually works. For example, it may be that the demand for stolen vehicles is simply a target number of stolen cars, independent of the stock available (See Camerer, Babcock, Loewenstein, and Thaler (1997)). If this were the case, and Lojack generated an increase in sales of Lojack-equipped models, then my assumed specification would show a *fall* in theft risk, even though Lojack only generated an increase in sales. Any feature in a car that increased sales – like lower prices or more add-ons – would have the same effect as Lojack. This would make my interpretation about the effects of Lojack completely misleading.

The main specification can be altered to accommodate this alternative hypothesis. This is done by eliminating the restriction that the stock variable have a coefficient equal to one. If the targeting hypothesis is true, then the stock coefficient would be smaller than one and the coefficient on Lojack would be sharply reduced (in absolute value). The rows labeled Unconstrained Exposure in Tables 9, 10, and 11 report the coefficients from this alternative specification, together with the coefficient on the exposure variable. The results are virtually unchanged from the main specification. Furthermore, the coefficient on the exposure variable does not seem to be consistently below or above one. In conclusion, the targeting hypothesis does not seem be supported in the data.

To expand that hypothesis, the stock of cars can be assumed to have a differential impact on theft according to the type of car. For example, sports cars or luxury cars might behave more like the targeting hypothesis above, while compact cars might track sales closely. I modified the regression above to allow for a differential impact of the stock of cars according to the vehicle categories of Table 1. I achieved this by allowing the stock coefficient to be different for each of the seven vehicle categories. The results, available in the web appendix to this paper, again are unchanged. These two tests suggest that an increase in sales is accompanied by a proportional increase in thefts, regardless of the kind of vehicle that is being considered.

Another exercise (only reported in the web appendix for space reasons) is to run the baseline regression sequentially deleting all of the observations for one of the car models. This would confirm that it is not one model that is driving the results. The coefficients are extremely similar to those of the baseline results.

7 Conclusion

This paper has analyzed the impact on auto theft of the introduction of the Lojack vehicle recovery system to a discernible group of beneficiary cars. The theoretical auto theft model predicted that this would result in Lojack deterrence benefits being confined to Lojack equipped cars. It also predicted a displacement of thefts to non-Lojack equipped vehicles.

The econometric analysis of the theft data pointed to a reduction in thefts of Lojack-equipped vehicles on the order of 55%. The reduction in thefts is a product of thieves attempting fewer appropriations of Lojack-equipped vehicles, that is a deterrence effect. Nevertheless, this effect was accompanied by an increase in thefts of vehicles in states surrounding those where Lojack was implemented. That increase in thefts was around 120% for Lojack models and 25% for non-Lojack models. Thefts were not found to be affected in states far from those where Lojack was introduced.

Displacement of thefts to non-Lojack-equipped vehicles in Lojack coverage states did not appear to be statistically significant. This may be because the pool of non-Lojack-equipped vehicles was so large in Lojack states relative to Lojack-equipped ones that the effect was too small to be detected in the data.

Lojack models built before the introduction of Lojack experienced no significantly different theft risk than would have been expected without the introduction of Lojack. The signs of the coefficient suggested a slight reduction in thefts, but not at statistically significant levels.

Finally, the analysis showed that the effect of Lojack as Lojack-equipped cars aged - - and as the proportion of vehicles with Lojack coverage went from 100% to 40% - - were very similar in magnitude. As the proportion covered by Lojack fell, the coefficients of impact did not decrease. Given that the estimation included controls for age, and together with results from Ayres and Levitt (1998), this points to a very small additional deterrence effect of Lojack when the proportion of cars with the device goes beyond 1.5% or 2%.

Adding up the estimated impacts of Lojack on all car groups suggests that the deterrence effect, generating lower thefts for Lojack-equipped vehicles, was almost completely mirrored by increased thefts of non-Lojack-equipped cars. Given the large real cost of providing the recovery service, the fact that it only generated displacement effects means that the Ford Lojack program in Mexico resulted in a net loss for society. Nevertheless, the intervention as implemented in the analysis period may have served as a platform upon which Lojack recovery services were later made available to all vehicle owners (after 2006). This change in the way that Lojack was offered to the public provides an avenue for future work, in which theft reductions generated by Lojack in the entire car fleet are quantified. Another avenue for future work is determining whether insurance companies reduced insurance prices for Lojack-equipped vehicles. This would measure the degree of responsiveness in the insurance industry to changes in theft rates. A decrease in the price of insuring such vehicles would be evidence of competitiveness in the sector.

Comparing both strategies for selling Lojack revealed that offering Lojack to all car owners presents the problem of underprovision because of the substantial positive externalities that the device generates. On the other hand, selling Lojack only to a distinguishable set of cars simply generates a redistribution of theft risk across car owners. One possible solution may be for governments to randomly provide the device to a proportion of vehicle owners, in such a way that the marginal social benefits are equated with the marginal social costs. This policy would be socially preferred to mandating the installation of a recovery device on all vehicles, as was being attempted by Mexico City officials in 2008.

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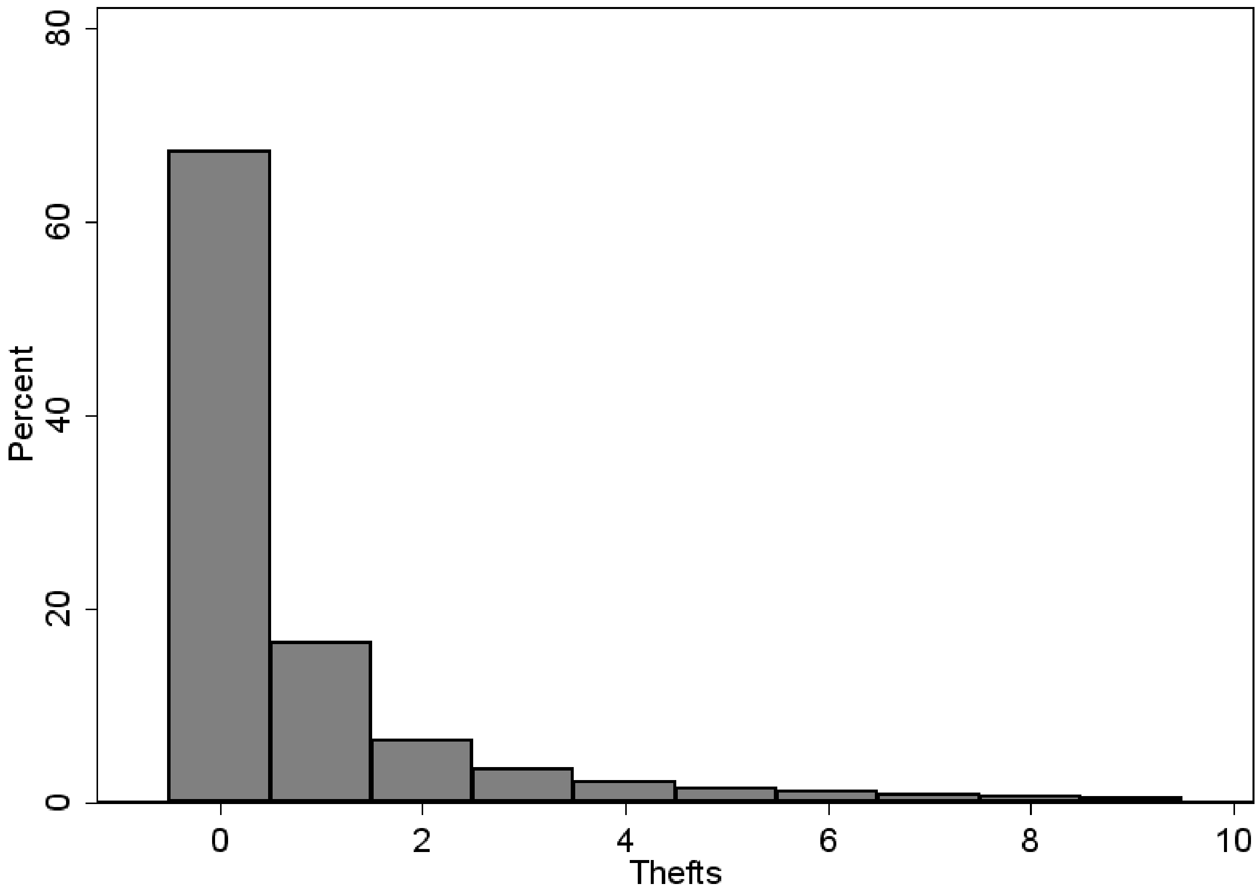
8 Figures and Tables

Figure 1: Histogram of Thefts



The unit of observation is the number of thefts in each model group, state, year made, and year stolen combination.
Note: Graph truncated at 10 thefts for visibility purposes. The full distribution follows the same pattern.

Figure 2: Geographical Externalities Identification Strategy

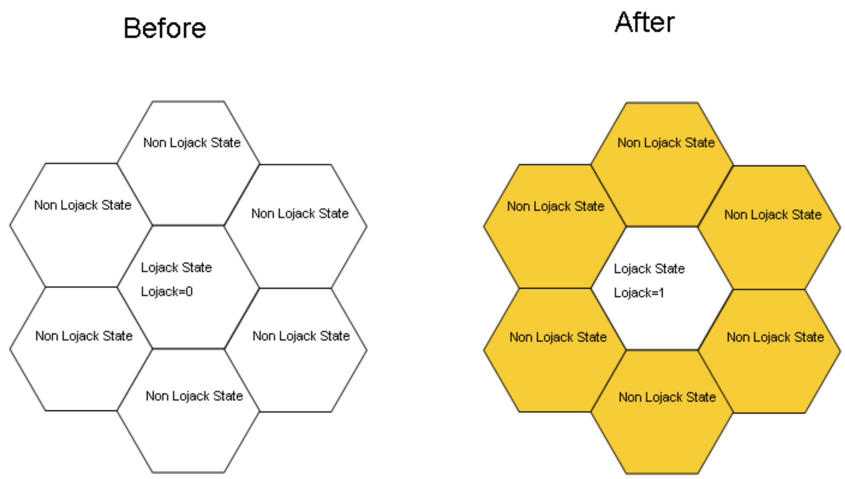


Figure 3: Geographical Externalities Identification Strategy: Distance Categories

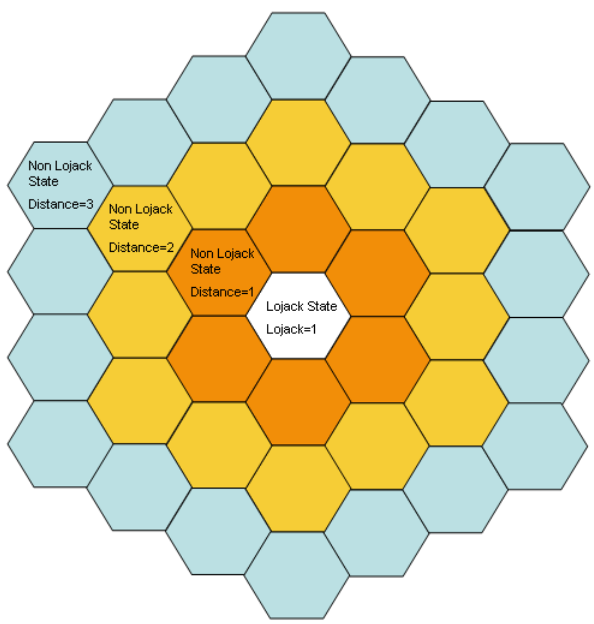


Table 1: States, Dates and Models where Lojack was Introduced

Model Group	Category	Lojack Introduction Dates by State			
Treatment Group		Jalisco	Estado de Mexico	DF	Morelos
Windstar	Minivan	Sep 2000	Mar 2002	Mar 2002	Mar 2002
Explorer	SUV	Jun 2002	Jun 2002	Jun 2002	Jun 2002
Escape	SUV	Sep 2002	Sep 2002	Sep 2002	Sep 2002
Mondeo	Sedan	Dec 2002	Dec 2002	Dec 2002	Dec 2002
Expedition	SUV	Sep 2002	Sep 2002	Sep 2002	Sep 2002
Focus	Compact	Mar 2003	Mar 2003	Mar 2003	Mar 2003
Excursion	SUV	Sep 2002	Sep 2002	Sep 2002	Sep 2002
Grand Marquis	Luxury sedan	Sep 2002	Sep 2002	Sep 2002	Sep 2002
Sable	Sedan	Sep 2002	Sep 2002	Sep 2002	Sep 2002
Mustang	Sports car	Sep 2004	Sep 2004	Sep 2004	Sep 2004
Lobo	Truck	Sep 2004	Sep 2004	Sep 2004	Sep 2004
Town Car	Luxury Sedan	Jun 2005	Jun 2005	Jun 2005	Jun 2005
Navigator	SUV	Jun 2005	Jun 2005	Jun 2005	Jun 2005

Control Group	
SUV	(CH:Cherokee,Liberty,Durango) (BMW:X3,X5) (CH:JeepWrangler) (GM:Blazer,Aztek,Trailblazer) (GM:Tracker) (LR:Discovery) (LR:Freelander,RangeRover) (MB:ML,G) (NI:Pathfinder,Frontier,X-trail,X-terra)
Luxury Sedan	(FO:Lincoln LS,Thunderbird)(FO:CrownVictoria)(AU:A3,A4,A6,A8,TT) (BMW:S3,S5,S7,S8,Z4) (JA:XJ,X,S) (MB:A,C,E,S,SLK,CLK) (NI:Maxima,InfinityQ30,InfinityQ45) (PE:405,406,407,607) (VO:S40,V40/V50,S60/S70,V70,S80,C70)
Compact	(CH:Neon) (HO:Civic) (NI:Sentra,Almera,Tsubame,Lucino) (PE: 306,307) (PE:206) (RE:Clio) (SE:Ibiza,Cordoba) (SE:Toledo) (VW:Jetta,Beetle,Golf,Cabrio,PointerWagon)
Minivan	(CH:Voyager,Ram Wagon) (VW:Sharan) (NI:Quest) (SE:Alhambra) (VW:Combi,Eurovan) (VW:Sharan) (GM:Venture,CadillacEscalade,Express) (HO:Odyssey)
Sedan	(CH:Stratus,Cirrus,Cruiser) (HO:Accord) (NI:Altima) (VW:Passat) (RE:Megane,Scenic) (GM:Malibu,Grandam,Grandprix,Vectra,Tigra) (GM:Cavalier,Sunfire, Astra,Chevy SW,Meriva,Zafira)
Subcompact	(CH:Atos) (FO:Fiesta,Ikon,Ka) (VW:OldBeetle) (VW:Derby,Pointer,Polo) (GM:Chevy,Monza,Corsa,Matiz)
Sports car	(GM:Corvette) (SE:Leon)
Truck	(CH:Pickup,Chassis) (FO:Ranger,Courier) (FO:150,250,350,450,550) (GM:1500,2500,3500,Avalanche,Luv,ChevyPickup,S10) (NI:Pickup,Chassis,Estacas) (VW:Pointer,PointerVan) (FO:Econoline,ClubWagon) (NI:Urvan)

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Variable	Mean	Std. Dev.	Min	Max
Panel A: All Observations (N=36,406)					Panel D: Lojack Equipped (N=235)				
Thefts	3.5	24.6	0	1,502	Thefts	2.97	6.02	0	37
Stock	619.0	1,767.5	1	32,940	Stock	558.74	648.01	1	2,725
Age Car	1.95	1.70	0	6	Age Car	0.72	0.84	0	4
Lojack	0.0064	0.080	0	1	Lojack	1	0	1	1
Panel B: Lojack Models (N=7,550)					Panel E: Non Lojack Models (N=28,856)				
Thefts	1.08	5.25	0	125	Thefts	4.15	27.54	0	1,502
Stock	225.9	462.9	1	7,704	Stock	721.85	1,958.23	1	32,940
Age Car	1.97	1.70	0	6	Age Car	1.94	1.70	0	6
Lojack	0.031	0.173	0	1	Lojack	0	0	0	0
Panel C: Lojack States (N=6,554)					Panel F: Non Lojack States (N=29,852)				
Thefts	16.21	56.25	0	1,502	Thefts	0.72	2.11	0	61
Stock	1,702.73	3,757.26	1	32,940	Stock	381.07	629.86	1	8,427
Age Car	1.93	1.70	0	6	Age Car	1.95	1.70	0	6
Lojack	0.035	0.18	0	1	Lojack	0	0	0	0

An observation unit is a quadruplet: (state, car model, year made, year stolen). Thefts and Stock are in car units. Thefts refers to events of thefts of insured vehicles. Stock refers to cumulative sales in the specified (state, car model, year made) combination. Age of car is in terms of completed years since sale (0 if the car is up to 12 months old, etc.) The Lojack variable equals one if the car model was equipped with Lojack when the vehicle was sold. Lojack Models refers to the 13 Ford vehicle models that participated in the Lojack program at some point between 1999 and 2005 (Panel B). Lojack states are the 4 states where Lojack was implemented between 1999 and 2005 (Panel C). Lojack Equipped refers to vehicles that were equipped with Lojack when the vehicle was sold (Panel D).

Table 3: Mean Theft Rates

	Lojack States (4)		Nearby Non Lojack States (19)		Distant Non Lojack States (9)	
	Lojack Model	Non Lojack Model	Lojack Model	Non Lojack Model	Lojack Model	Non Lojack Model
before	0.846***	0.884***	0.214***	0.236***	0.259***	0.383***
	(0.046)	(0.025)	(0.018)	(0.009)	(0.030)	(0.021)
	[692]	[3,960]	[2,652]	[12,478]	[1,073]	[5,265]
after	0.468***	0.953***	0.241***	0.220***	0.193***	0.352***
	(0.060)	(0.061)	(0.044)	(0.016)	(0.027)	(0.031)
	[197]	[1,229]	[713]	[3,777]	[300]	[1,556]
Difference over time:	−0.378***	0.069	0.027	−0.015	−0.066	−0.030
	(0.076)	(0.066)	(0.048)	(0.018)	(0.035)	(0.037)
	[889]	[5,189]	[3,365]	[16,255]	[1,373]	[6,821]

Theft rates defined as $(Thefts/StockofCars) * 100$. The table reports mean (unweighted) theft rates for the specified group. Robust standard errors in parentheses, and number of observations in brackets. "After" defined as vehicles produced in the year 2003 and beyond. Excludes models that got Lojack in 2004 and 2005. All observations in which the stock of cars was less than five were dropped from the calculations in the table because of small denominators driving results. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Geographical Externalities of Lojack

Poisson Regression Dep. Var: Number of Thefts	All Cars			Lojack Cars			Non Lojack Cars		
	Coeff	IRR	Count	Coeff	IRR	Count	Coeff	IRR	Count
Non Lojack States Contiguous to Lojack States									
After Lojack	0.2307***	1.259***	89.88***	0.7932***	2.210***	22.19***	0.2256***	1.253***	83.03***
	(0.0617)	(0.077)	(26.94)	(0.2727)	(0.602)	(11.05)	(0.0604)	(0.0758)	(24.86)
(State, Car Model) Dummies		YES			YES			YES	
Sales Exposure Control		YES			YES			YES	
State Specific Time Trend		YES			YES			YES	
Age of Car Dummies		YES			YES			YES	
Observations		12,296			2,549			9,747	
(State, Car Model) Groups		475			94			381	
α		0.139			0.018			0.139	
Non Lojack States Adjacent to Contiguous States									
After Lojack	0.2572**	1.293**	68.51**	0.6428***	1.901***	19.69***	0.2476**	1.281**	59.48**
	(0.1135)	(0.146)	(34.28)	(0.1267)	(0.241)	(5.260)	(0.1149)	(0.147)	(31.18)
(State, Car Model) Dummies		YES			YES			YES	
Sales Exposure Control		YES			YES			YES	
State Specific Time Trend		YES			YES			YES	
Age of Car Dummies		YES			YES			YES	
Observations		8,704			1,828			6,876	
(State, Car Model) Groups		335			69			266	
α		0.241			0.156			0.240	
All Other Non Lojack States									
After Lojack	0.1946	1.214	61.47	0.5613	1.752	15.31	0.1869	1.205	54.61
	(0.1342)	(0.163)	(46.65)	(0.3925)	(0.688)	(13.99)	(0.1331)	(0.1605)	(42.66)
(State, Car Model) Dummies		YES			YES			YES	
Sales Exposure Control		YES			YES			YES	
State Specific Time Trend		YES			YES			YES	
Age of Car Dummies		YES			YES			YES	
Observations		8,852			1,882			6,970	
(State, Car Model) Groups		337			71			266	
α		0.278			0.252			0.275	

Observations weighted by sales. Robust bootstrapped standard errors clustered at the state level in parentheses. The Poisson regression coefficient estimate is reported under the Coeff column, while the incidence rate ratio column (IRR) reports the coefficient in its exponentiated form. An IRR is interpreted as the ratio of expected number of thefts with Lojack implemented to the number of thefts if Lojack had not been implemented. The Count column is a transformation of the coefficient in the IRR column that, together with data on total thefts before Lojack, estimates the impact of the intervention in terms of annual thefts generated (if positive) or prevented (if negative). α is the estimated conditional over(+)/underdispersion(−) in the dependent variable. The regressions use data from Non Lojack states only. The top panel only uses data from Non Lojack states contiguous to Lojack ones, the middle one only uses data from Non Lojack states adjacent to the ones in the top panel, and the third panel uses data from all other Non Lojack states. Lojack is dummy variable equal to one for years after Lojack was introduced in the nearest Lojack state.
* significant at 10%; ** significant at 5%; *** significant at 1% for the test $H_0 : \beta = 0$ in the Coeff and Count columns, and $H_0 : e^{(\beta)} = 1$ in the IRR column.

Table 5: Externalities of Lojack in Lojack States: Impact on Non-Lojack Models and Old Lojack Models

Poisson Regression Dep. Var: Number of Thefts	Externalities on Non Lojack Models			Externalities on Old Lojack Models		
	Coeff	IRR	Count	Coeff	IRR	Count
After Lojack	0.1458	1.157	762.21			
	(0.1328)	(0.153)	(745.99)			
Old Lojack Model				−0.0551	0.946	−21.56
				(0.0932)	(0.088)	(35.46)
(State, Car Model) Dummies		YES			YES	
Sales Exposure Control		YES			YES	
State Specific Time Trend		YES			YES	
Age of Car Dummies		YES			YES	
Observations		12,233			2,295	
(State, Car Model) Groups		476			107	
α		0.115			0.081	

Observations weighted by sales. Robust bootstrapped standard errors clustered at the state level in parentheses. The Poisson regression coefficient estimate is reported under the Coeff column, while the incidence rate ratio column (IRR) reports the estimated coefficient in its exponentiated form. An IRR is interpreted as the ratio of expected number of thefts with Lojack implemented to the number of thefts if Lojack had not been implemented. The Count column is a transformation of the coefficient in the IRR column that, together with data on total thefts before Lojack, estimates the impact of the intervention in terms of annual thefts generated (if positive) or prevented (if negative). α is the estimated conditional over(+)/underdispersion(−) in the dependent variable. The first regression uses data from Non Lojack models in Lojack states and in distant Non Lojack states. The second regression uses data from Old Lojack models from Lojack states and distant states. $AfterLojack$ is dummy variable equal to one for years after Lojack was introduced into the state. *OldLojackmodel* is a dummy variable equal to one once Lojack was implemented in the state.
* significant at 10%; ** significant at 5%; *** significant at 1% for the test $H_0 : \beta = 0$ in the Coeff and Count columns, and $H_0 : e^{(\beta)} = 1$ in the IRR column.

Table 6: Impact on Lojack Models and Effect as Lojack Cars Aged

Poisson Regression Dep. Var: Number of Thefts	Impact on Lojack Models			Impact as Car Ages		
	Coeff	IRR	Count	Coeff	IRR	Count
Lojack Equipped	−0.7987***	0.4498***	−151.87***			
	(0.1346)	(0.0605)	(16.73)			
Lojack equipped & Age=1				−0.7597***	0.4677***	−146.94***
				(0.1713)	(0.080)	(22.13)
Lojack equipped & Age=2				−0.6988***	0.4971***	−138.82***
				(0.1688)	(0.0839)	(23.18)
Lojack equipped & Age=3				−0.9896***	0.3717***	−173.46***
				(0.2868)	(0.1066)	(29.43)
(State, Car Model) Dummies		YES			YES	
Sales Exposure Control		YES			YES	
State Specific Time Trend		YES			YES	
Age of Car Dummies		YES			YES	
Observations		3,173			3,173	
(State, Car Model) Groups		119			119	
α		0.100			0.102	

Observations weighted by sales. Robust bootstrapped standard errors clustered at the state level in parentheses. The Poisson regression coefficient estimate is reported under the Coeff column, while the incidence rate ratio column (IRR) reports the estimated coefficient in its exponentiated form. An IRR is interpreted as the ratio of expected number of thefts with Lojack implemented to the number of thefts if Lojack had not been implemented. The Count column is a transformation of the coefficient in the IRR column that, together with data on total thefts before Lojack, estimates the impact of the intervention in terms of annual thefts generated (if positive) or prevented (if negative). α is the estimated conditional over(+)/underdispersion(−) in the dependent variable. Both regressions use data from Lojack models in Lojack states and in distant Non Lojack states. $LojackEquipped$ is a dummy variable equal to one for car models that were sold with Lojack. $LojackEquipped\&Age = k$ is a dummy variable equal to one if the car was sold with Lojack and is aged between $(k-1) \cdot 12$ and $k \cdot 12$ months old.
* significant at 10%; ** significant at 5%; *** significant at 1% for the test $H_0 : \beta = 0$ in the Coeff and Count columns, and $H_0 : e^{(\beta)} = 1$ in the IRR column.

Table 7: Mean Theft Rates: Using All Lojack Models

	Lojack States (4)		Nearby Non Lojack States (19)		Distant Non Lojack States (9)	
	Lojack Model	Non Lojack Model	Lojack Model	Non Lojack Model	Lojack Model	Non Lojack Model
before	1.036***	.887***	.233***	.237***	.352***	.384***
	(.054)	(.026)	(.017)	(.009)	(.034)	(.021)
	[1000]	[3943]	[3362]	[12439]	[1429]	[5243]
after	.560***	.958***	.251***	.222***	.301***	.354***
	(.066)	(.061)	(.038)	(.016)	(.048)	(.031)
	[278]	[1223]	[908]	[3752]	[399]	[1548]
Difference over time:	-.476***	.070	.018	-.014	-.050	-.030
	(.0856)	(.066)	(.042)	(.019)	(.059)	(.037)
	[1278]	[5166]	[4270]	[16191]	[1828]	[6791]

Theft rates defined as $(Thefts/Sales) * 100$. The table reports mean (unweighted) theft rates for the specified group. Robust standard errors in parentheses, and number of observations in brackets. "After" defined as vehicles produced in the year 2003 and beyond. All observations in which the stock of cars was less than five were dropped from the calculations in the table because of small denominators driving results. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Effect of Lojack on Insurance Coverage

Dep. Var: Proportion of Cars Insured Nationally

	(1)	(2)
Lojack Equipped	0.0232	0.0362
	(0.2502)	(0.2251)
Year Dummies	YES	YES
Age of Car Dummies	YES	YES
Model Group Dummies	NO	YES
Data used	$t \geq 2003$	$t \in [1999, 2005]$
Observations	354	1510
R^2	0.04	0.07

Dependent variable is the proportion of cars in a (model group, year made) combination that are insured nationally in a given year, divided by the number of cars sold nationally for the same (model group, year made) duplet. The regression in the first column uses data for 2003 on, when Lojack had been implemented for most Lojack vehicles. The regression in the second column has model specific fixed effects and uses all observations. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Robustness Checks: Geographical Externalities of Lojack

Dep. Var: Number of Thefts		All Cars		Lojack Cars		Non Lojack Cars	
Regressor	Specification	Coeff	IRR	Coeff	IRR	Coeff	IRR
Non Lojack States Contiguous to Lojack States							
After Lojack	Main Specification	0.2307***	1.259***	0.7932***	2.210***	0.2256***	1.253***
		(0.0617)	(0.077)	(0.2727)	(0.602)	(0.0604)	(0.0758)
	Negative Binomial	0.2069***	1.2299***	0.7711***	2.1622***	0.2010***	1.222***
		(0.0739)	(0.0909)	(0.2854)	(0.6172)	(0.0721)	(0.088)
	Non Linear Least Squares	0.3982***	1.4892***	1.5550***	4.7354***	0.3976***	1.4882***
		(0.0731)	(0.1089)	(0.5575)	(2.6404)	(0.0735)	(.1095)
	Inflated Thefts	−0.4458	0.6403	1.4212**	4.1423**	−0.4523	0.6361
		(0.4227)	(0.2707)	(0.7240)	(2.9900)	(0.4240)	(0.2698)
	Unconstrained Exposure	0.2487***	1.2825***	0.7894***	2.2020***	0.2439***	1.2763***
		(0.0610)	(0.0783)	(0.2754)	(0.6066)	(0.0600)	(0.0766)
Exposure	Unconstrained Exposure	0.6791***		1.0443***		0.6715***	
		(0.0793)		(0.1463)		(0.0786)	
Non Lojack States Adjacent to Contiguous States							
After Lojack	Main Specification	0.2572**	1.293**	0.6428***	1.901***	0.2476**	1.281**
		(0.1135)	(0.146)	(0.1267)	(0.241)	(0.1149)	(0.147)
	Negative Binomial	0.2559***	1.291***	0.6807***	1.975***	0.2425***	1.274***
		(0.0881)	(0.1138)	(0.1366)	(0.2699)	(0.0868)	(0.1106)
	Non Linear Least Squares	0.3779*	1.4592*	1.4695***	4.3473***	0.3729*	1.4520*
		(0.2047)	(0.2978)	(0.3503)	(1.5229)	(0.2101)	(.3051)
	Inflated Thefts	0.4972	1.6441	1.2637**	3.5387**	0.4975	1.6448
		(0.3883)	(0.6385)	(0.1245)	(0.4408)	(0.3869)	(0.6365)
	Unconstrained Exposure	0.2631**	1.3010**	0.6740***	1.9621***	0.2549**	1.2904**
		(0.1126)	(0.1466)	(0.1245)	(0.2444)	(0.1143)	(0.1475)
Exposure	Unconstrained Exposure	0.8785***		1.3569***		0.8580***	
		(0.0658)		(0.2647)		(0.0683)	
All Other Non Lojack States							
After Lojack	Main Specification	0.1946	1.214	0.5613	1.752	0.1869	1.205
		(0.1342)	(0.163)	(0.3925)	(0.688)	(0.1331)	(0.1605)
	Negative Binomial	0.2288***	1.257***	0.5237	1.688	0.2224***	1.249***
		(0.0757)	(0.0952)	(0.3275)	(0.553)	(0.0776)	(0.0970)
	Non Linear Least Squares	0.1862	1.2047	0.7265	2.0680	0.1863	1.2047
		(0.2882)	(0.3472)	(0.8088)	(1.6726)	(0.2894)	(0.3486)
	Inflated Thefts	−0.5292	0.5891	0.8137	2.2563	−0.5199	0.5946
		(0.9122)	(0.5374)	0.7186	(1.6216)	(0.9136)	(0.5432)
	Unconstrained Exposure	0.1972	1.2180	0.5746	1.78	0.1891	1.2082
		(0.1394)	(0.1698)	(0.4172)	(0.7413)	(0.1394)	(0.1685)
Exposure	Unconstrained Exposure	0.6019***		1.3926***		0.5611***	
		(0.1478)		(0.1330)		(0.1670)	

Observations weighted by sales. Robust bootstrapped standard errors clustered at the state level in parentheses. All specifications include (State,Car Model) dummies, Stock Exposure Control, state specific time trend, and Age of Car Dummies. The Poisson regression coefficient estimate is reported under the Coeff column, while the incidence rate ratio column (IRR) reports the estimated coefficient in its exponentiated form. An IRR is interpreted as the ratio of expected number of thefts with Lojack implemented to the number of thefts if Lojack had not been implemented. The regressions use data from Non Lojack states only. The top panel only uses data from Non Lojack states contiguous to Lojack ones, the middle one only uses data from Non Lojack states adjacent to the ones in the top panel, and the third panel uses data from all other Non Lojack states. Lojack is dummy variable equal to one for years after Lojack was introduced in the nearest Lojack state. Exposure refers to the Stock of Vehicles control.
* significant at 10%; ** significant at 5%; *** significant at 1% for the test $H_0 : \beta = 0$ in the Coeff columns, and $H_0 : e^{(\beta)} = 1$ in the IRR column.

Table 10: Robustness Checks: Impact on Non-Lojack Models and Old Lojack Models

Dep. Var: Number of Thefts		Externalities on Non Lojack Models		Externalities on Old Lojack Models	
		Coeff	IRR	Coeff	IRR
Main Specification	After Lojack	0.1458	1.157		
		(0.1328)	(0.153)		
	Old Lojack Model			−0.0551	0.946
				(0.0932)	(0.088)
Negative Binomial	After Lojack	0.1922	1.211		
		(0.1162)	(0.1409)		
	Old Lojack Model			0.0089	1.009
				(0.0879)	(0.0887)
Non Linear Least Squares	After Lojack	0.0685	1.0710		
		(0.1428)	(0.1529)		
	Old Lojack Model			−0.1817	0.8338
				(.1905)	(0.1588)
Inflated Thefts	After Lojack	0.5083**	1.6625**		
		(0.2493)	(0.4146)		
	Old Lojack Model			−0.3888**	0.6778**
				(0.1526)	(0.1035)
No Control Observations	After Lojack	0.1458	1.157		
		(0.1374)	(0.159)		
	Old Lojack Model			−0.0556	.9458
				(0.1025)	(.0969)
Unconstrained Exposure	After Lojack	0.1454	1.1565		
		(0.1314)	(0.1520)		
	Old Lojack Model			−0.0083	0.9917
				(0.0899)	(.0892)
	Exposure	1.0170***		1.9838***	
		(0.1272)		(0.2777)	

Observations weighted by sales. Robust bootstrapped standard errors clustered at the state level in parentheses. All specifications include (State,Car Model) dummies, Stock Exposure Control, state specific time trend, and Age of Car Dummies. The Poisson regression coefficient estimate is reported under the Coeff column, while the incidence rate ratio column (IRR) reports the estimated coefficient in its exponentiated form. An IRR is interpreted as the ratio of expected number of thefts with Lojack implemented to the number of thefts if Lojack had not been implemented. The first regression uses data from Non Lojack models in Lojack states and in distant Non Lojack states. The second regression uses data from Old Lojack models from Lojack states and distant states. $AfterLojack$ is a dummy variable equal to one for years after Lojack was introduced into the state. *OldLojackmodel* is a dummy variable equal to one once Lojack was implemented in the state. Exposure refers to the Stock of Vehicles control.
* significant at 10%; ** significant at 5%; *** significant at 1% for the test $H_0 : \beta = 0$ in the Coeff columns, and $H_0 : e^{(\beta)} = 1$ in the IRR column.

Table 11: Robustness Checks: Impact on Lojack Models and Effects as Lojack Cars Aged

Dep. Var: Number of Thefts		Impact on Lojack Models		Impact as Car Ages	
		Coeff	IRR	Coeff	IRR
Main Specification	Lojack Equipped	−0.7987***	0.4498***		
		(0.1346)	(0.0605)		
	Lojack equipped & Age = 1			−0.7597***	0.4677***
				(0.1713)	(0.080)
	Lojack equipped & Age = 2			−0.6988***	0.4971***
				(0.1688)	(0.0839)
	Lojack equipped & Age = 3			−0.9896***	0.3717***
				(0.2868)	(0.1066)
Negative Binomial	Lojack Equipped	−0.7709***	0.4625***		
		(0.1386)	(0.0641)		
	Lojack equipped & Age = 1			−0.7692***	0.4633***
				(0.1457)	(0.0675)
	Lojack equipped & Age = 2			−0.7426***	0.4758***
				(0.2164)	(0.1029)
	Lojack equipped & Age = 3			−0.7325***	0.4806***
				(0.2109)	(0.1013)
Nonlinear Least Squares	Lojack Equipped	−1.2665***	0.2818***		
		(0.2373)	(0.0668)		
	Lojack equipped & Age = 1			−1.2232***	0.2942***
				(0.2097)	(0.0617)
	Lojack equipped & Age = 2			−1.2036***	0.3000***
				(0.3280)	(0.0984)
	Lojack equipped & Age = 3			−1.4593***	0.2323***
				(0.4308)	(0.1001)
Inflated Thefts	Lojack Equipped	−1.5173***	0.2193***		
		(0.0762)	(0.0167)		
	Lojack equipped & Age = 1			−1.487745***	0.2258***
				0.2301793	(0.0520)
	Lojack equipped & Age = 2			−1.400944***	0.2463***
				0.2669831	(0.0657)
	Lojack equipped & Age = 3			−1.642465***	0.1935***
				0.3875504	(0.0749)
No Control Observations	Lojack Equipped	−0.8071***	0.4461***		
		(0.1556)	(0.0694)		
	Lojack equipped & Age = 1			−0.7675***	0.4641***
				(0.1751)	(0.0812)
	Lojack equipped & Age = 2			−0.7072***	0.4929***
				(0.1737)	(0.0856)
	Lojack equipped & Age = 3			−0.9955***	0.3695***
				(0.2635)	(0.0973)
Unconstrained Exposure	Lojack Equipped	−0.5478***	0.5781***		
		(0.1262)	(0.0729)		
	Lojack equipped & Age = 1			−0.5184**	0.5954***
				(0.2223)	(0.1324)
	Lojack equipped & Age = 2			−0.4371***	0.6458***
				(0.1538)	(0.0993)
	Lojack equipped & Age = 3			−0.7326***	0.4806***
				(0.2405)	(0.1156)
	Exposure	1.6634***		1.6692***	
		(0.1829)		(0.1750)	

Observations weighted by sales. Robust bootstrapped standard errors clustered at the state level in parentheses. All specifications include (State,Car Model) dummies, Stock Exposure Control, state specific time trend, and Age of Car Dummies. The Poisson regression coefficient estimate is reported under the Coeff column, while the incidence rate ratio column (IRR) reports the estimated coefficient in its exponentiated form. An IRR is interpreted as the ratio of expected number of thefts with Lojack implemented to the number of thefts if Lojack had not been implemented. Both regressions use data from Lojack models in Lojack states and in distant Non Lojack states. *LojackEquipped* is dummy variable equal to one for car models that were sold with Lojack. *LojackEquipped&Age* $= k$ is a dummy variable equal to one if the car was sold with Lojack and is aged between $(k-1)\cdot 12$ and $k \cdot 12$ months old. Exposure refers to the Stock of Vehicles control.
* significant at 10%; ** significant at 5%; *** significant at 1% for the test $H_0: \beta = 0$ in the Coeff columns, and $H_0: e^{(\beta)} = 1$ in the IRR column.