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An Evaluation of the Effectiveness of Automobile Parts Marking and Anti-Theft Devices on Preventing Theft

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Executive Summary

Problem Statement

The Motor Vehicle Theft Law Enforcement Act of 1984 required automobile manufacturers, based on standards established by the U.S. Department of Transportation (DOT), to mark 14 component parts of selected high-theft automobile lines with identifying numbers. The Federal Anti-Car Theft Act of 1992 required manufacturers to mark an additional 50 percent of their remaining lines. Both statutes permitted the DOT to grant a limited number of exemptions for new automobile lines equipped with factory-installed anti-theft devices.

The 1992 legislation also required the U.S. Attorney General to conduct two assessments of the DOT rules:

> Evaluate the effectiveness of the parts marking and, if found to be effective in inhibiting chop shop operations and deterring motor vehicle theft, extend parts marking to all remaining vehicle lines; and,
>
> Evaluate (a) whether parts marking has been effective in substantially inhibiting the operation of chop shops and motor vehicle theft and (b) whether the anti-theft devices for which the DOT has granted exemptions are an effective substitute for parts marking in substantially inhibiting motor vehicle theft.

U.S. Department of Justice's National Institute of Justice contracted with Abt Associates to conduct this evaluation.

Methodology

Data comprised a cross-section time-series of the number of stolen automobiles, the number of registered automobiles, and hence, the automobile theft rate. The study sought to learn whether or not the introduction and use of automobile parts marking and factory installed anti-theft devices have reduced that automobile theft rate. Automobiles that never received either parts marking or anti-theft exemptions provide a measure of control, helping to distinguish between prevailing trends and the effectiveness of parts marking and anti-theft devices.

Analysis used statistical procedures, based on Generalized Linear Least Squares and Maximum Likelihood Poisson regression models, to estimate the reduction in automobile theft attributable to parts marking and factory-installed anti-theft devices. The application of benefit cost criterion required that the estimated reduction in theft be valued at the costs of a stolen car and compared with the cost of marking automobiles and equipping them with anti-theft equipment during the production process.

Conclusions

Parts marking is cost-beneficial. This conclusion rests on the following findings:

- The value of preventing the theft of an automobile by parts marking exceeds $6,000 per automobile.

- The cost of marking an automobile is somewhere between $0.50 and $2.50 per car per year, with the former figure being a better reflection of marking cars given current technology.

- According to one estimate, parts marking reduces automobile theft by 138 to 207 cars per 100,000 registered automobiles. According to another estimate, parts marking reduces car theft by 220 to 300 automobiles per 100,000 registered automobiles.

- Given the benefit from preventing an automobile theft ($6,000 on average), and assuming the cost of marking automobiles at $0.50 per car per year, parts marking would be cost-beneficial if it prevented 9 thefts per 100,000 registered automobiles. Assuming that parts marking costs as much as $2.50 per car per year, parts marking would be cost-beneficial if it prevented 42 thefts per 100,000 registered automobiles. Statistical analysis suggests that the effectiveness of parts marking exceeds both thresholds.

Anti-Theft Devices are a cost-effective way of reducing automobile thefts. This conclusion rests on the following findings:

- The value of preventing the theft of an automobile using anti-theft devices is probably less than $6,000 per automobile, but this does not include the theft of articles from the car.

- The cost of an anti-theft device is difficult to establish because of variation in the quality and nature of such devices and the fact that when automobile manufacturers offer anti-theft devices as optional equipment, the option is bundled with an electronic accessories package. Excluding car location systems, however, anti-theft devices probably add less than $20 cost per car per year.

- By one estimate, anti-theft devices reduce automobile thefts by between 311 and 445 per 100,000 registered cars per year. By another estimate, they reduce thefts by between 413 and 475 per 100,000 registered cars per year.

- Assuming a $6,000 average loss per car, and assuming that anti-theft devices cost $20 per car per year, anti-theft devices would have a favorable benefit-cost ratio if those devices prevented 330 thefts per 100,000 registered automobiles per year. By this criterion, anti-theft devices would appear to have benefits that exceed costs.

To some extent the Motor Vehicle Theft Law Enforcement Act of 1984 may displace crime from cars that are less attractive targets (because of parts marking and anti-theft devices) to cars that are less protected or even to other forms of criminal activity. This report provides evidence that displacement does not offset the favorable reduction in theft rates for high-theft-rate cars that have component parts marked and anti-theft devices installed.

Nothing in this argument says that parts marking is better than anti-theft devices. Nothing says the opposite. Parts marking and anti-theft devices seem to serve different purposes. Anti-theft devices are intended to harden a vehicle target, making it more difficult to steal the car. They probably discourage theft for joyriding and some professional thieves. In contrast, parts marking is intended to assist law enforcement in identifying stolen cars and their parts and to promote prosecution by building stronger cases. Anti-theft devices are not a substitute for parts marking; both play important roles deterring automobile theft.

1.0 Introduction

The nature of car theft changed significantly beginning in the 1970's, from joyriding to theft for profit, partly due to a proliferation of so-called "chop shops" that engaged in the volume sale of stolen car parts to body shops, to auto repair shops, and directly to car owners. Because auto theft investigators were often unable to identify from which vehicles the stolen parts came or whether the parts were stolen at all, the Federal Government enacted the Motor Vehicle Theft Law Enforcement Act of 1984. That Act required automobile manufacturers, based on standards established by the U.S. Department of Transportation (DOT), to mark 14 component parts of selected high-theft automobile lines with identifying numbers. The Federal Anti-Car Theft Act of 1992 required manufacturers to mark an additional 50 percent of their remaining lines. Both statutes permitted the DOT to grant a limited number of exemptions for new automobile lines equipped with factory-installed anti-theft devices.

The 1992 legislation also required the U.S. Attorney General to conduct two assessments of the DOT rules:

(1) conduct by 1997 an initial evaluation of the effectiveness of the parts marking and, if found to be effective in inhibiting chop shop operations and deterring motor vehicle theft, extend parts marking to all remaining vehicle lines by December 1997; and,

(2) conduct by 1999 a long-range review of (a) whether parts marking has been effective in substantially inhibiting the operation of chop shops and motor vehicle theft and (b) whether the anti-theft devices for which the DOT has granted exemptions are an effective substitute for parts marking in substantially inhibiting motor vehicle theft.

Pursuant to the first of these two requirements, the U.S. Department of Justice's National Institute of Justice contracted with Abt Associates to evaluate the legislation's impact. The Abt researchers estimated that between 33 and 158 fewer cars were stolen by professional thieves per 100,000 cars that were marked between 1987 and 1995. They also estimated (conservatively) that the cost of a car theft is $6,000 per car, and that the cost of marking each car is 50 cents per year. Using the estimated 33 per 100,000 reduction in stolen cars, they estimated the benefits from marking 100,000 high theft-rate cars as being almost $200,000, which compares favorably with paying $50,000 per year to mark those cars (Rhodes, Johnston and McMullen, 1999). A survey of law enforcement offered a supportive assessment of these findings (Finn, Truitt and Buron, 1996).

The Department of Justice also asked the Abt researchers to evaluate whether or not anti-theft exclusions were a good substitute for parts marking. They could not make that judgment because the data were inadequate to support an inference. Moreover, they questioned the logic of using anti-theft devices as substitutes for parts marking because marking and anti-theft devices serve different purposes. Anti-theft devices are intended to harden a vehicle target, making it more difficult to steal the car. They probably discourage theft for joyriding and some professional thieves. In contrast, parts marking is intended to assist law enforcement in identifying stolen cars and their parts and to promote prosecution by building stronger cases. Anti-theft devices seem to be a complement to, not a substitute for, parts marking.

There were two notable limitations to the first study. One limitation was that parts marking was introduced incrementally over eight years, so the length of the time-series available to the researchers may have been too short to provide reliable estimates. A second limitation was that data did not indicate whether or not an automobile had a factory-installed anti-theft device. Data only indicated that a car had an exemption from parts marking. The presence of the exemption meant that the car had a factory-installed anti-theft device, but the absence of an exemption did not imply that it lacked one.

The present study is an improvement over the previous study in three ways. First, the current study has expanded the time-series by six years, so it can replicate and extend the earlier study with more data. Second, the current study had data about whether or not a model line had a factory-installed anti-theft device, although only for the last five years (1997-2001). Third, statistical procedures and computing software have improved since the earlier evaluation, and the current study takes advantage of those improvements.

Section 2.0 explains the analysis plan. Then section 3.0 describes data assembly. Results are reported in section 4.0 and conclusions are drawn in section 5.0.

2.0 Analysis Plan

Data comprised a cross-section time-series of the number of stolen automobiles, the number of registered automobiles, and hence, the automobile theft rate. The study sought to learn whether or not the introduction and use of automobile parts marking and factory installed anti-theft devices have reduced that automobile theft rate. Automobiles that never received either parts marking or anti-theft exemptions provide a measure of control, helping to distinguish between prevailing trends and the effectiveness of parts marking and anti-theft devices.

The null hypotheses are:

- Within a model line, the proportion of registered automobiles that are marked has no effect on the rate at which automobiles are stolen, and

- Within a model line, the proportion of registered automobiles that have factory installed anti-theft devices has no effect on the rate at which automobiles are stolen.

These null hypotheses are refined, and suitable statistical tests are introduced, in subsequent arguments.

2.1 Notation and Restatement of the Null Hypotheses

The logic behind the Motor Vehicle Theft Law Enforcement Act of 1984 is that making automobiles less attractive targets can deter automobile theft. Many cars are stolen and delivered to chop-shops, where the cars are disassembled and their parts sold as replacement parts for cars of the same model. By putting a vehicle identification mark on major automobile parts, the Act helps police to identify stolen parts, and the Act helps prosecutors to build stronger cases. By increasing the risk of reselling stolen parts, the Act reduces the value of stolen cars, and hence the incentive to steal them. Of course, the Act provides no disincentive for thieves who steal cars for their own use, and it provides no deterrent for thieves who steal cars for export. Parts marking is aimed at chop shops.

Anti-theft devices, by making the theft of a car more difficult, are aimed at all forms of automobile theft. This study is concerned with factory-installed anti-theft devices. Although these take many forms, essentially they are relatively inexpensive devices intended to lock cars automatically, to disable them when an unauthorized driver attempts to take control, and to sound an audible alarm. Anti-theft devices include less expensive mechanisms (such as physically independent bar-locks for steering wheels) and more expensive devices (such as LOJACK, which is used to track stolen cars with a GIS system), but this study is not concerned with those latter devices because they are not “factory-installed,” the concern of the Motor Vehicle Theft Law Enforcement Act of 1984.

Anti-theft devices and parts marking both increase the difficulty and risk of being a car thief. Rational thieves will take one of several course of action. Some will continue to steal automobiles that are marked and otherwise protected by anti-theft devices. Some others will continue to steal cars, but they will switch to those that lack protective devices. Still other thieves will switch to other forms of crime, or they may abandon crime altogether. The utility of the Act requires that it not just displace crime, so the concern of this analysis is whether or not the Act provides a favorable benefit-cost ratio once displacement is taken into account. For this purpose, displacement is limited to automobile theft; the study does not attempt to measure displacement to other forms of crime.

This simple theory leads to a statistical model used to test for the effectiveness of parts marking and anti-theft devices. Notation will be convenient for formalizing the null hypotheses and explaining statistical testing. Define:

T_{ijk} the automobile theft rate. The subscript i identifies the state; the District of Colombia is included as a state. The subscript j identifies an automobile model. The definition of model is narrower than the industry definition. Given the present interest in chop-shops, a model is defined as automobile types that have interchangeable parts. That is, if body parts could be removed from car A and installed without modification on car B, then A and B are deemed the same model. The subscript k represents calendar years. Thus T_{ijk} is the automobile theft rate during year k, for model j, in state i. Parts of the analysis decompose this rate into:

N_{ijk} the number of model j cars stolen during year k in state i.

R_{ijk} the number of model j cars registered during year k in state i.

$$T_{ijk} = \frac{N_{ijk}}{R_{ijk}}$$

Y_k dummy variables for each year. The specific years vary across parts of the analysis, but they are never earlier than 1986 and never later than 2001. Manufacturers introduce models over time, so a model has no representation in these data before its introduction date. For example, a model introduced in 1986 has sixteen years of representation in these data; a model introduced in 1990 has twelve years of representation; and so on.[1]

M_{ijk} the proportion of registered automobiles from model line j that have their parts marked in state i during year k. Parts are marked during the manufacturing process so automobiles do not have their parts marked retrospectively. For model lines that always had their parts marked, M equals 1 from the date those model lines were introduced. For model lines that never had their parts marked, M is 0 for every year. Otherwise, M increases if parts marking had been introduced on a model line over time, and it decreases if parts marking had been removed from that model line over time.

MY_{ijk} an interaction variable, computed by multiplying M by the number (YEAR-1997)/14. The interaction was zero before parts marking began in 1997, it was zero for 1997, and it equaled M for 2001.[2]

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[1] A year T model is typically introduced during year T-1. For reasons explain in this paper's section on data assembly, year T cars registered and stolen in year T-1 do not enter into the analysis. In fact, year T cars registered and stolen in year T do not enter into the analysis. We presume that the slight misstatement in the text will facilitate reading by those who do not seek details, and that readers who seek precision in language can modify the text accordingly.

[2] This model specification, which was adopted after some testing, accounts for a trend in the effectiveness of parts marking. There are at least two reasons to anticipate a trend. First, thieves may have adjusted to the technology behind parts marking, for example by removing the original labels and substituting counterfeited labels. At least partially offsetting what would therefore be a negative trend is both an improvement in the technology of parts marking and expanded use of parts marking by police and prosecutors. Second, there may be some displacement in automobile theft resulting from parts marking. For example, when 10 percent of a model line has been marked, thieves could in theory target the other 90 percent that had not yet been marked. Were displacement a significant phenomenon, then, we would not expect parts marking to reduce thefts for that model line until the percentage of marked automobiles passes a threshold.

F_{ijk} the proportion of registered automobiles from model line j that have factory installed anti-theft devices in state i during year k. For some of the analysis, F is equivalent to having an anti-theft exemption to parts marking; for the rest of the analysis, F is equivalent to having a factory-installed anti-theft device. As was true of M, F may be constant at 0, constant at 1, or increase/decrease over time.

FY_{ijk} an interaction variable, computed by multiplying F by (YEAR-1997)/14.[3]

C a row vector of dummy variable that represent the automobile models. This size of this vector varies slightly across the states and over the various analyses presented here because (1) not all automobiles entered each part of the analysis, and (2) some models were excluded when there was insufficient data. These exclusions were the rare exceptions, however, and they will be explained in the context of reporting results. Up to 670 model lines enter the analysis for each state. Some of these model lines have as many as 16 years of data; the analysis used model lines with 6 years or more of data for a model line.[4] This means that model lines that were introduced after 1995 did not enter the analysis.

X_{ijk} A row vector of control variables. The control variables, which vary across parts of the analysis, were:

- Number of automobile registrations, R_{ijk} from above
- The average age of cars of model j registered in state i during year k.

For some of the analyses, the number of registrations enters as a scale variable; that is, the number of thefts should be proportional to the number of registered automobiles. The average age of automobiles enters the model because some analysts have reported that theft rates increase as the stock of automobiles age.

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3 Over time, an increasing proportion of the control models (e.g., those that had not received anti-theft exemptions) were sold with factory-installed anti-theft devices. The larger the proportion of control models produced with anti-theft devices, the more diluted the estimate of the effectiveness of anti-theft devices based on anti-theft exemptions to parts marking. Displacement provides another reason for introducing nonlinearity into the model. When few cars have factory-installed anti-theft devices, those devices may appear especially efficacious because thieves stop stealing cars with anti-theft devices and start stealing cars that lack such devices. As an increasing number of automobiles have anti-theft devices, however, thieves will face a decreasing opportunity to steal cars that lack such devices. Without crime displacement, the apparent effectiveness of factory-installed anti-theft devices would be lower.

4 As explained later in the analysis, the analysis used adjustments for auto-correlation that relied on group-wise analysis of regression residuals for adjustments. These adjustments required at least two data points per model line, and it seemed prudent to allow for more. Otherwise there was no special reason for requiring at least six years in the time-series for each model line.

The basic model can be written:

$$[1] \qquad E(T_{ijk}) = G(Y\alpha_i + C\beta_i + M_{ijk}\delta_{i1} + MY_{ijk}\delta_{i2} + F_{ijk}\gamma_{i1} + FY_{ijk}\gamma_{i2} + X_{ijk}\tau_i)$$

G() denotes an unspecified mean function that translates a linear combination of the independent variables into an expectation. The α, β and τ parameters are conformable column vectors whose expected values may vary across the states—hence the i subscripts. The δ are parameters associated with parts marking, and the γ parameters are associated with factory installed anti-theft devices. Interest is focused on the δ and γ; the rest are nuisance parameters associated with control variables. The study estimates these parameters by running separate regressions, one for each state that enters the analysis.

Many variables that might affect theft rates do not appear in this model specification. Any variable that is specific to a state would not enter into this analysis because the regressions are state-specific. For example, states may have different experiences with parts marking/anti-theft devices, but those differences would be captured by variations in the δ and γ parameters.[5] Some other variables are specific to an automobile model and their effects will be captured by the fixed-effects represented by the β parameters. For example, Ford Explorers and Chevrolet Cameros may have different latent theft rates, but that fact would be taken into account by the β. Still other variables that are specific to a year will be captured by the fixed-effects represented by the α parameters. For example, the year variables will capture the effect of general crime trends in a state. It would also capture the effectiveness of special anti-theft programs that are introduced in some states but not others.

In fact, parameters associated with variables that are specific to any state, model or period could not be estimated by this fixed effect model. They might be estimated using random effects models (hierarchical modeling procedures), but such random effects models rest on assumptions that do not hold in this analysis. (We justify this assertion later.) At any rate, those other parameters are not the interest here.

Some parts of the analysis add greater flexibility to the statistical modeling:

Model lines can be assigned to types. Types that entered into this analysis are:

- compact

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5 Automobile theft rates are especially high on the West Coast and along the Texas border (LaVigne, Fleury and Szakas, 2000), and near ports and the Canadian border (National Insurance Crime Bureau, 2002). These concentrations suggest that both the level and nature of automobile theft varies over states and imply that enforcement based on parts marking technology would have a varying effect over the states. Furthermore, local and state police vary in the sophistication they bring to anti-theft programs (see Finn, Truitt and Buron, 1996; Ethridge and Gonzales, 1996), also implying that the effectiveness of part marking will vary across the states.

- luxury
- near luxury
- mid-size and full-size
- sport
- sports-like coups

The above analysis can be replicated across model types, effectively allowing the effect of parts marking and anti-theft exemptions to vary by those model types.

In addition, the definition of automobile theft can be limited to automobiles that were stolen and not recovered. Such a measure may be better when investigating thefts by professional thieves because cars stolen for joy-riding are typically recovered.

The specification is easily modified to accommodate other variables and interactions. For some analysis, we introduced the square of M and F; for other analysis we introduced an interaction between M and F.

The null hypotheses can be restated in terms of the δ and γ parameters, averaged across the states to provide best estimates of the effectiveness of parts marking and anti-theft devices. Evaluating the null hypothesis when M percent of automobiles are marked and time is fixed to some specific year, we reject the null hypothesis that parts marking is ineffective by rejecting the statement:

Ho_1: $Md_1 + MYd_2 = 0$

Likewise, evaluating the null hypothesis when F percent of automobiles have anti-theft devices and time is set to some year, we would reject the null hypothesis that factory installed anti-theft devices are ineffective by rejecting the statement:

Ho_2: $Fg_1 + FYg_2 = 0$

The following two subsections explain how we estimated the above parameters and their standard errors, and how we used the results from estimation to test the two null hypotheses.

2.2 Statistical Models

Equation [1] provides a basic structure for the statistical model. Given that the parameters vary across the states, the model represented by [1] was estimated separately for each of the states, and results were combined to test the null hypothesis. The nature of that combined test is the subject of the following subsection (2.3). There are various ways to refine and estimate the model represented by [1]. Specification and estimation is the topic of this section.

One approach is to treat the expectation as a linear function of the variables that appear on the right-side of [1] and introduce an assumption about the distribution of T about E(T). In this linear model, error terms are expected to be both heteroscedastic and autocorrelated.[6] Assuming within group autocorrelation, the analysis applied a partial differences method to transform the data.[7] Then it used a sandwich estimator to correct the estimated parameter covariance matrix for heteroscedasticity.[8] This approach, called Feasible Generalized Least Squares (FGLS), is expected to provide consistent estimates of the slope parameters (α, β, δ, γ and τ) and their standard errors.

The linear model is problematic in one respect. For some models, relatively few automobiles are registered and none are stolen. This problem is worst in small states. To assure that results were not sensitive to this problem, the analysis also used a Poisson counterpart to the GLS model. The Poisson model was estimated by maximum likelihood; hence, we call this the ML Poisson model. For reasons that will be discussed, the ML Poisson counterpart had its own problems, including the fact that software is not readily available for Poisson models that deal with autocorrelation (Durbin and Koopman, 2001).

Turning to a Poisson model, the counterpart to equation [1] becomes:

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6 Heteroscedasticity is to be expected for three reasons. First, the number of registered automobiles varies widely over model lines. Holding theft rates constant, the residual variance should vary with the inverse of the number of registrations. Second, for some model lines in certain states, no automobiles were stolen during a specified year. This is a frequent occurrence in small states and less frequent in large states. Putting a lower limit on the theft rate will induce heteroscedasticity in the error distribution. Third, specifying an additive effect (instead of a multiplicative effect) for parts marking/anti-theft devices will likely induce heteroscedasticity. We have no strong reasons to expect autocorrelation but, in fact, testing showed strong positive autocorrelation.

7 Transformation requires estimating the residuals from the OLS regression on untransformed data. Those residuals provide an estimate of the autocorrelation term, r, which is specific to each model and state. The r is then used to transform every variable, v, so that when t=1 (the first observation in the time-series), $v_t^{'} = \sqrt{1 - r^2} v_t$, and for any other time after t, $v_t^{'} = v_t - r v_t$.

8 We considered two alternative approaches to estimating the covariance matrix. One alternative approach was to apply FGLS after assuming groupwise heteroscedasticity. To apply this alternative approach, we used the residual from the regression correcting for autocorrelation to estimate the sampling variance within each group, and we applied feasible generalized least squares (FGLS) to get final estimates. The resulting standard errors were less that half their counterparts based on the robust covariance matrix estimator. This seemed unrealistic and led to some anomalous results. The problem seems to be that groupwise heteroscedasticty is untenable because the number of registrations increases markedly during the first few years of a model line's production, so heteroscedasticity should decrease during those early years. A second alternative is to argue that that the residual variance should be inversely proportional to the number of registrations provided that theft rate does not vary much from model to model. In fact, the theft rate does vary significantly from model to model, so there is some question about the assumption of proportionality. Our choice was to use the sandwich estimator, which provides a conservative (relatively large) variance estimate.

[2] $$E(N_{ijk}) = \exp(Y\boldsymbol{a}_i + C\boldsymbol{b}_i + M_{ijk}\boldsymbol{d}_{i1} + MY_{ijk}\boldsymbol{d}_{i2} + F_{ijk}\boldsymbol{g}_{i1} + FY_{ijk}\boldsymbol{g}_{i2} + X_{ijk}\boldsymbol{t}_i + \ln(R_{ijk}))$$

First, the dependent variable is N (the number of thefts) rather than T (the theft rate). Second, the logarithm of the number of registered automobiles enters the model specification; its parameter is constrained to equal 1 because it is a scale effect. To explain this constraint, note that [2] could be manipulated algebraically and rewritten as:

$$E(N_{ijk}) = R_{ijk}\exp(Y\boldsymbol{a}_i + C\boldsymbol{b}_i + M_{ijk}\boldsymbol{d}_{i1} + MY_{ijk}\boldsymbol{d}_{i2} + F_{ijk}\boldsymbol{g}_{i1} + FY_{ijk}\boldsymbol{g}_{i2} + X_{ijk}\boldsymbol{t}_i)$$
$$E\left(\frac{N_{ijk}}{R_{ijk}}\right) = \exp(Y\boldsymbol{a}_i + C\boldsymbol{b}_i + M_{ijk}\boldsymbol{d}_{i1} + MY_{ijk}\boldsymbol{d}_{i2} + F_{ijk}\boldsymbol{g}_{i1} + FY_{ijk}\boldsymbol{g}_{i2} + X_{ijk}\boldsymbol{t}_i)$$

Thus, a principal difference between the FGLS and ML Poisson models is that the mean function is linear for the FGLS model and log-linear in the Poisson. This seemingly subtle difference has in at least one important implication: The FGLS model is an additive model; the ML Poisson is a multiplicative model. Of course, assumptions about the distributions about these mean functions also differ materially between the FGLS model and the ML Poisson model.[9]

Diagnostic testing showed that one crucial assumption of the Poisson model does not hold. The problem is that the model is over-dispersed, meaning that the variance of N is larger than the mean of N. (The expectation and variance are equal in the Poisson statistical model.) This complication may seem trivial, but it has serious consequences for hypothesis testing. Provided the mean function is correctly specified, the estimates of the slope coefficients are consistent, but they are inefficient, and worst, their estimated standard errors are biased and inconsistent. In practice it appears that the Poisson grossly underestimates the standard errors.

A way to deal with this problem is to treat efficiency as a secondary consideration and use a robust covariance matrix estimator to correct the standard errors. In this approach, the analysis used the results from a Poisson regression to estimate the slope parameters, which are after all consistent although inefficient. It then used a consistent estimate of the covariance matrix based on what is sometimes called the “sandwich” estimator or the “empirical covariance matrix” estimator. Cameron and Trivedi (1998, p. 65) describe this estimator. One version of this estimator makes no assumptions about the variance function; others make explicit assumption about how the variance is related to the mean. The analysis employed the more general form.

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9 Saying that an automobile has a small probability of being stolen during any year and a near zero probability of being stolen more than once, thefts are generate according to a Bernoulli process. This process will be approximately Poisson for a model line, and it will be approximately normal when R is large. Thus there may be little practical difference in assumptions regarding the error terms in [1] and [2].

To summarize, we estimated two statistical models in each of 49 states:

- A FGLS linear regression that accounted for heteroscedasticity and first-order serial autocorrelation.

- A ML Poisson model using a robust covariance matrix estimator to deal with overdispersion but with no special adjustment for autocorrelation.

Both approaches to estimation suffer from some problems, so a finding that findings are invariant with respect to methodology would enhance confidence in the conclusions. Results from both approaches are presented later.

2.3 Hypothesis Testing

As noted, estimates of δ and γ lead to tests of the null hypotheses. This subsection explains those tests for parts marking. The tests for anti-theft devices are similar.

Let:

$\hat{d}_{i1}, \hat{d}_{i2}$ represent the parameter estimates for δ for each of the states.

Let V_i represent their estimated covariance matrix, such that:

$$V_i = \begin{matrix} s_{i1}^{2} & s_{i12}^{2} \\ s_{i12}^{2} & s_{i1}^{2} \end{matrix}$$

Consider the linear model [1]. When M automobiles are marked at time T, the effect of interest is:

[3] $$\Delta_{iFGLS} = 100{,}000 \bullet (Md_{i1} + MYd_{i2})$$

Multiplication by 100,000 provides a reduction in automobile theft per 100,000 registered automobiles. Using the delta method, [3] has an estimated variance of:

[4] $$s_{\Delta_{iFGLS}}^{2} \approx 100{,}000^{2} \bullet [M \quad MY\ ] V_i \begin{bmatrix} M \\ MY \end{bmatrix}$$

Holding time constant, the estimates from specification [1] are linear functions of the proportion of automobiles that are marked.

The ML Poisson model raises an additional complication. Because the ML Poisson model is nonlinear, the effects must be evaluated at some base level of theft. Call this base level T_{Bi}. Then the estimated effect is:

[5] $$\Delta_{iMLPOISSON} = 100{,}000 \bullet T_{Bi}(e^{Md_{i1}+MYd_{i2}} - 1)$$

The term $e^{Md_{i1}+MTd_{i2}} - 1$ will be zero when marking has no effect on theft rates and it will equal the *proportional* reduction in the theft *rate* when marking reduces that theft rate. Multiplying that proportionate reduction in the theft rate by the prevailing base level theft rate T_{Bi} provides the estimated reduction in the theft rate attributable to parts marking. Multiplying that reduction in the theft rate by 100,000 provides an estimate of the reduction in the number of stolen cars per 100,000 registered cars.

Using a Taylor-series approximation, the estimated variance for [5] is:

[6] $$s^2_{\Delta_{iMLPOISSON}} \approx 100{,}000^2 T^2_{Bi} \bullet [M \quad MY] V_i \begin{bmatrix} M \\ MY \end{bmatrix}$$

Given [3] through [6], there are several ways to derive an average estimate of the effect of parts marking across the states. This study sets weights proportional to the number of automobiles registered in a state, because this weighting comes closest to representing the average effect that parts marking/anti-theft devices have on automobile thefts. Thus the weight for the ith state is:

$$w_i = \frac{\sum_j \sum_k R_{ijk}}{\sum_i \sum_j \sum_k R_{ijk}}$$

Those weights are used to estimate:

[7] $$\hat{\Delta}_{FGLS} = \sum_{i=1}^{49} w_i \hat{\Delta}_{iFGLS} \text{ or } \hat{\Delta}_{MLPOISSON} = \sum_{i=1}^{49} w_i \hat{\Delta}_{iMLPOISSON}$$

[8] $$s^2_{\hat{\Delta}_{FGLS}} = \sum w_i^2 s^2_{\Delta_{iFGLS}} \text{ or } s^2_{\hat{\Delta}_{MLPOISSON}} = \sum w_i^2 s^2_{\Delta_{iMLPOISSON}}$$

Holding time constant, this approach produces a grand estimate for every value of M. To present findings, this study sets MY = 0.5M (that is, time is roughly 1994 for the sixteen-year series) and graphs $E[\hat{d}_M]$ against M. Confidence intervals are two standard errors from the mean. Results will show that the effectiveness of parts marking/anti-theft devices decrease over time (the parameters associated with the interaction terms are positive), so setting time equal to 0.5 provides an average of the span of time observed in this study.

3.0 Data Assembly

This analysis requires a combination of data from many different sources. The main elements are automobile thefts, automobile registrations, factory-installed anti-theft device information, parts marking and anti-theft exemption information, body style change information, and to which segment of the consumer market each make and model is targeted.

The previous analysis (Rhodes, Johnston and McMullen, 1999) generated analysis data for the calendar years 1984 to 1995. Abt's task was to update these data old with the newest available data and improve upon them. We discuss the old data, each piece of new data, and address issues of combining them all.

3.1 Automobile Thefts

The FBI's National Crime Information Center (NCIC) database maintains a record of all automobiles stolen in the United States. When an automobile is stolen, the law enforcement agency to which the theft is reported records the vehicle's Vehicle Identification Number (VIN) and any other relevant information about the theft case. The FBI receives this information and records it in the NCIC database.

Through the Department of Justice, we asked the FBI for access to the data for the calendar years 1995-2001. Though the older data already gave us the number of thefts in 1995, we wanted to make sure our methodology of processing these data was comparable to the previous contractor. The FBI graciously provided the data, and all the support we needed to understand the NCIC database.

The NCIC database contains a number of necessary analytic fields, such as the automobile's VIN, make, model, model year, theft status, date and state from which it was stolen, and date found if it was recovered. For model years 1981 forward, the Department of Transportation standardized VINs to decode information about the vehicle's make, model, model year, country of manufacture, and a serial number corresponding to when it was produced.

The NCIC considers an automobile theft case "open" for 5 years from the date of theft. After that time, the case is closed. We consider these closures unrecovered vehicles. Additionally, if a VIN number cannot be entered for a theft case within 60 days, the NCIC will indicate a closure of this type. There are few of these cases in the data, so we drop them from our analysis. Since we are using newer data that have thefts less than five years old, we do observe some open cases. We assume these cases are unrecovered thefts, as recoveries usually occur within months of theft.

Deciphering the make, model, and model year was the main task with these data. We began by decoding VINs. A VIN is a cryptic 17 character identifier. To decipher this volume of VINs, we licensed the VinPower Software Developer Kit from ESP Data Solutions Inc.

However, the VIN has an internal method of checking its validity, and some of them were incorrectly recorded. Fortunately, the NCIC uses its own coding scheme to identify make, model, and model year of the data, documented in the vehicle data codes portion of the "NCIC 2000 Code Manual" (FBI, 2000). We could not rely exclusively on this, however, since many of these fields were either blank or did not correspond to published codes.

3.2 Automobile Registrations

RL Polk, an automotive industry consultant, is the sole source of automobile registration information for each State and the District of Columbia. For July 1 of each year, they collect registration information from the various Departments and Registries of Motor Vehicles around the country. We purchased these data aggregated by state, make, model, and model year for the calendar years 1996 to 2001. The data are expensive, and though we would have liked to confirm our data processing methodology with the older data by purchasing 1995 registrations, we could not justify the cost. Fortunately, since these data are cleaned and provided by RL Polk to many different automotive analysts, there is little reason to suspect differences between the pre-1996 and post-1996 registrations.

3.3 Production Numbers for Factory-Installed Anti-theft Devices

Ideally we would have found the percentage of automobiles that have anti-theft devices installed for each state, make, model, and model year. Anti-theft devices are defined as alarms, tracking systems, and engine or fuel cutoff designs. However, through both our own research and talks with automotive analysts, this information seems impossible to compile.

Instead, we found that DRI-WEFA collects anti-theft device installation data for all automobiles produced in North America, and a limited number of those that are produced elsewhere but sold here. Unfortunately, they had begun limited data collection in 1996 and full collection in 1997. As these were the only possible data we found to use in our analysis, we purchased them.

3.4 Parts Marking/Anti-theft Device Exemption Information

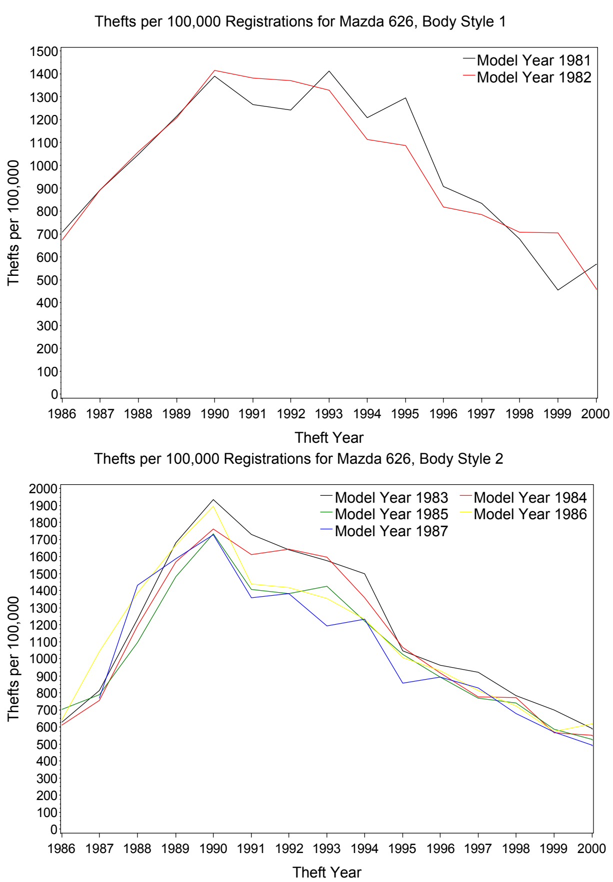
Since 2000, the National Highway Transportation Safety Administration (NHTSA) has published the "Parts-Marking Quick Reference Guide for the Law Enforcement Community" (NHTSA 2001). This report outlines all makes, models, and model years of automobiles that are subject to parts marking or have an anti-theft device exemption.

3.5 Body Style Change Information

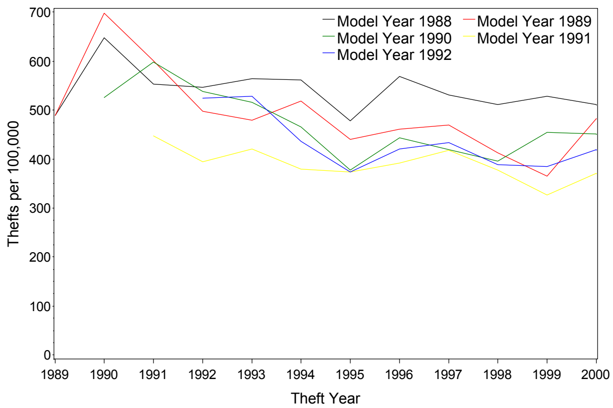
Automobile manufacturers frequently redesign their automobiles to update technology or styling. Between redesigns, the model lines go through so few changes that different model years can be considered substitutes. For example, a 1987 Ford Mustang is essentially the same car as a 1988, but is a much different car than the 2001. Therefore, in our analysis we aggregate automobiles of like technologies, styling, etc. The web site www.consumerguide.com, an automotive review site, was useful to determine in which year a make and model's body style had changed for automobiles manufactured since 1990. For models produced before then, a mixture of manufacturer, review, and enthusiast web sites provided the necessary body style change information.

One example that similar body styles are substitutes is shown in Figure 3. It depicts the number of thefts per 100,000 for 4 different body styles of the Mazda 626 for each calendar year. The selection of the 626 is illustrative of the time path of theft rates for most other makes, models, and body types. The top left pane shows the 1981-1982 models, followed by panes representing models with different body styles. Note that the time paths of the theft rates for each model year within a body style are remarkably similar.

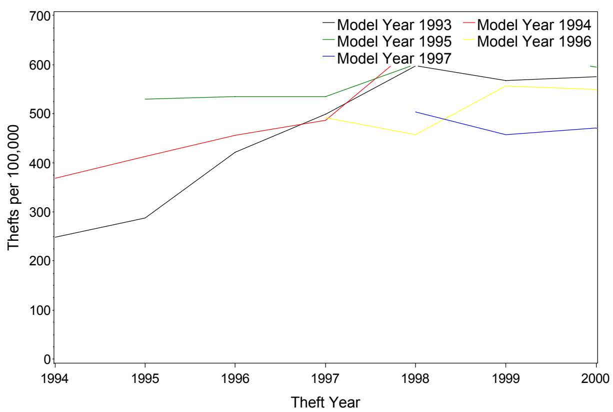
Figure 3 — Theft Rate Time Path for 4 Body Styles of Mazda 626



Thefts per 100,000 Registrations for Mazda 626, Body Style 3



Thefts per 100,000 Registrations for Mazda 626, Body Style 4



3.6 Market Segment Information

One additional piece of new information is the consumer segment in which a make and model belongs. It may be that certain segments, such as sports cars, garner more attention from thieves, and marking or anti-theft devices may have a larger deterrence effect for those segments than for other, less popular segments. Again, the consumerguide.com web site is a useful resource for classifying segments. Segments we identified for the analysis are:

- Compact — an amalgam of compact and sub-compact autos
- Pickup — an amalgam of compact and full-size pickups
- SUV — an amalgam of compact, mid-size, full-size, and luxury Sport Utility Vehicles
- Mid-Size/Full-Size — amalgam of mid-size and full-size passenger cars
- Van — contains both full-size and minivan
- Luxury — e.g., Mercedes-Benz S-Class
- Near Luxury — e.g., Volvo 740
- Sports — e.g., Chevrolet Corvette
- Sporty Coupe — a coupe with sports styling, e.g., Dodge Avenger

For some segments, automobiles that comprise those segments never had anti-theft exemptions and, consequently, they never entered into the segment analysis.

3.7 Previous Analysis File

To assemble data for the earlier evaluation of the effectiveness of parts marking, KRA Corporation compiled automobile registration and theft data for the calendar years 1984-1995. For reasons outlined in Rhodes, Johnston and McMullin, 1999, we discard the 1984-1985 data. For the other years, we used the number of registrations, thefts, and theft recoveries, and added our newly collected data about parts marking and body style changes.

Since two contractors (KRA and Abt) compiled data from different time periods, we are concerned about comparability between them. Using the compilation of 1995 NCIC data assembled by both contractors, we examined numbers of thefts between like makes, models, and model years. The differences in number of thefts between our methodology and theirs were negligible. Figure 3 above provides a visualization of the comparability between the data sets; the pre-1996 data are from KRA, the data from 1996 forward are our updates. There are no obvious breaks in the time paths for theft rates between 1995 and 1996. To the extent there are differences, we presume that the time variables in equation [1] provide adequate control for those differences.

3.8 Analysis File Data Creation

We spent a great deal of time merging all of these data pieces together. These data files are large and require lengthy processing times; furthermore, assuring that all makes and models merge together is time-consuming.

Before aggregation we removed any data where the model year was greater than or equal to the theft year. For example, both thefts and registrations for a 1997 Ford Explorer stolen in 1996 or 1997 were deleted from the analysis file. The problem is that RL Polk's census occurs on July 1 while the FBI reports thefts for the entire calendar year. Thus, for 1997 Ford Explorers, we could not know how many Explorers were registered during 1996 or 1997; nor could be know how long on average each of those Explorers were at risk of being stolen. This problem disappears for 1998 and later registrations of 1997 Ford Explorers.

Once a data set containing all of the pieces was created with one observation indicating a theft year, state, make, model, and model year, within a theft year, state, make, and model we aggregated across model years within a body style.

4.0 Findings

As noted, this study estimated regressions using two methods:

- FGLS that adjusted for auto-correlation and heteroscedasticity, and
- ML Poisson with a robust covariance matrix estimator.

Using each technique, the study specified different models and used different data.

- It varied the definition of automobile theft. For most of the analysis, the dependent variable was the number of automobile thefts; for other parts of the analysis it was the number of automobile thefts that were not recovered.

- The study used different data. For some of the analysis, it used the sixteen-year data series, for which factory-installed anti-theft devices were inferred from the fact that an automobile had an anti-theft exemption. For the rest of the analysis, it used the six-year data series, for which factory-installed anti-theft devices were identified from industry data.

- The study estimated the same statistical models for different automobile segments.

- The study experimented with different ways of specifying the model including:

    - Introducing powers of M and F;
    - Introducing interactions between M and F.

- Furthermore, each of these statistical models and variations were estimated for each state.

A reader would almost certainly be overwhelmed by a needlessly detailed presentation of findings, so subsections 4.1 through 4.3 are selective in their reporting. To outline the remainder of this section:

Subsection 4.1 reports regression results from the FGLS and Poisson model for a single state (Florida) where:

- the dependent variable is automobile thefts;
- the data are from the sixteen-year series;
- the data are for all model segments;
- the statistical model specifications correspond to [1] and [2].

Subsection 4.2 reports summary estimates of the effectiveness of parts marking. It provides:

- Table 4.2A reports estimates of the effectiveness of parts-marking and anti-theft devices for each state.
- Figures 4.2A and 4.2B show the best estimate of the effectiveness of parts-marking based on the results reported in table 4.2A.
- Table 4.2B summarizes results across model segments.
- Table 4.2C summarizes results across model segments when M2 and F2 are used in place of MY and FY.

Subsection 4.3 has the same organization as 4.2, but 4.3 reports results from anti-theft exemptions.

4.1 Estimation in a Single State

Table 4.1 reports detailed regression results for a single state (Florida). Although Florida is one of the largest states with respect to automobile registration, there was no special reason for choosing it to illustrate the regressions, and there is no reason to believe that findings based on Florida are "representative" of findings for other states. The purpose of presenting table 4.1 is simply to show the nature of the regressions that underlie the rest of the analysis.

For the FGLS regressions, the dependent variable is automobile thefts per registered automobiles, the data are from the sixteen-year series, and the model corresponds to equation [1]. For the maximum likelihood Poisson regressions, the dependent variable is automobile thefts, the data are from the sixteen-year series, and the model corresponds to equation [2].

The first column of table 4.1 identifies the independent variables, which were defined earlier. None of the fixed-effects associated with model line appear in this table.[10] Columns 2 and 3 report the parameter estimates and their t-scores from the FGLS estimation. A t-score is the parameter estimate divided by its estimated standard error. Columns 4 and 5 provide parameter estimates and t-scores from the maximum likelihood Poisson model. A t-score in excess of 2 (absolute value) might be considered to be statistically significant.

[10] There are just over 660 fixed effects. They are not reported to conserve space, but this loses little of value because the fixed effects are of no direct interest to this analysis.

Table 4.1 — Illustrative Regression Results for Florida

	Estimation Methodology			
	FGLS autocorrelation heteroscedasticity (robust covariance estimator)		Maximum Likelihood Poisson (robust covariance estimator)	
	parm.	t-score	parm.	t-score
YEAR86	0.00223	3.59	***	
YEAR87	0.00291	4.45	0.1538	4.87
YEAR88	0.00449	6.22	0.4008	7.63
YEAR89	0.00460	5.77	0.4676	6.91
YEAR90	0.00471	5.42	0.4762	6.19
YEAR91	0.00421	4.45	0.4429	4.68
YEAR92	0.00497	4.87	0.5705	4.94
YEAR93	0.00569	5.17	0.6845	5.14
YEAR94	0.00661	5.62	0.7308	4.73
YEAR95	0.00603	4.82	0.6043	3.45
YEAR96	0.00640	4.69	0.6355	3.41
YEAR97	0.00638	4.46	0.6146	3.07
YEAR98	0.00575	3.77	0.5729	2.61
YEAR99	0.00496	3.07	0.4214	1.75
YEAR20	0.00508	2.99	0.3715	1.44
YEAR21	0.00533	2.98	0.3902	1.37
MARKED (M)	-0.00271	-3.86	-1.0894	-2.33
INTERACTION (MT)	0.00144	2.80	0.789	1.57
ANTITHEFT	-0.00386	-2.78	-2.1786	-3.48
INTERACTION (FT)	0.00057	0.54	0.3658	1.06
AGESTOCK	-0.00026	-2.69	0.0063	0.27
R-Square (corrected)	0.51			
Observations	6347			
50% marked	-99	+/-71.5	-221	+/-160
50% exemptions	-179	+/-149	-476	+/-176

Notes: The regressions are from Florida. Data are from the 1986 through 2001 time-series. All automobile models enter the analysis. Thefts are all automobile thefts.
*** The Poisson model includes a constant, so the first year was excluded from the regression specification

Estimation based on an OLS model, before variable transformations, explains 51 percent of the variance after adjusting for degrees of freedom. The parameter associated with parts marking, and the parameter associated with the interaction between parts marking and time, are both statistically significant with t-scores in excess of 2 in the FGLS regression. Setting time equal to 0.5, parts marking prevented an estimated 99 thefts per 100,000 automobiles when 50 percent of those automobiles were marked. The formula is 99 = 100,000x(-0.00271x0.5+0.5x0.00144x0.5). The parameter associated with parts marking is statistically significant in the maximum likelihood Poisson regression, but the interaction effect is not quite significant. Setting time equal to 0.5, and using a base theft rate of 754 thefts per

100,000 cars, parts marking prevented an estimated 221 thefts per 100,000 cars. The formula is 221=754x[exp(-1.0894x0.5+0.5x0.789x0.5)-1].[11] Although these two estimates seem very different, their confidence intervals overlap. Of course these results show that estimates from a single state are not very precise. Combining estimates across the states will increase precision.

The parameter associated with anti-theft devices is statistically significant, but the parameter associated with the interaction term is not, for both the FGLS and the maximum likelihood Poisson models. The FGLS model implies that anti-theft devices prevented about 179 thefts per 100,000 cars when half those cars had anti-theft devices. According to the maximum likelihood Poisson model, the reduction is 476 per 100,000 cars. The confidence intervals overlap for these two estimates.

Although the FGLS model treats parts marking and anti-theft devices as additive, a few automobiles had both parts marking and anti-theft exemptions, and an interaction term between M and F (not included in the model reported in Table 4.1) is negative, suggesting that an interaction term would improve the model. Nevertheless, the study did not include the interaction term because the overlap between parts marking and anti-theft exemptions was modest; addition of an interaction would have had little substantive importance while needlessly complicating the modeling. The ML Poisson model is a multiplicative model, so an interaction would play an even less important role.

Table 4.1 has provided illustrations of the regressions used to estimate the effectiveness of both parts marking and anti-theft devices at preventing automobile theft. Of course, these two regressions were repeated for each of the states. They were then replicated for each of the automobile model segments, run on both the long time-series from 1986 through 2002 and the short time-series from 1996 through 2002, and estimated after defining thefts as "unrecovered" thefts. Furthermore, the models were repeated with somewhat different specifications before settling on the specification reported here.[12] Reporting all this analysis would generate too much output for a manageable report, but the next section will summarize how these changes affected results.

4.2 Estimates: Effectiveness of Parts Marking

Table 4.2A shows state-by-state estimates of the theft reduction per 100,000 registered cars. The calculations assume that 50 percent of the cars were marked and the estimates are for 1994. Estimates are based on the 1986–2001 time-series and use all thefts in constructing the dependent variable.

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[11] Unlike the FGLS estimator, the Poisson estimator is non-linear. Some baseline must be factored into the estimation. We chose the number of thefts in 1994 as the baseline.

[12] One competitor specification included M^2 and F^2 in the regression but dropped MT and FT. Another specification included an interaction between M and F. We selected the simplest specification both for ease of reporting and because other specification did not materially change conclusions.

The first column identifies the state and the second column reports the national percentage of cars registered in that state over the period of this study. Column 3 reports an estimate of the number of thefts prevented per 100,000 cars (50 percent marked), and column 4 reports a t-statistic suitable for testing whether or not parts marking was effective in that state. Both columns come from the FGLS model. Columns 5 and 6 report similar statistics from the ML Poisson model. Some states are excluded from this table because colinearity problems precluded estimation.

Figure 4.2A — Summary Statistics for the Effectiveness of Parts Marking (FGLS and Maximum Likelihood Poisson)

		FGLS		ML Poisson	
	registrations	estimate	t-statistic	estimate	t-statistic
AK	0.22%	109.6	0.63	-222.2	-4.58
AL	1.76%	-67.6	-2.45	-79.2	-2.45
AR	0.96%	94.5	1.12	-49.3	-1.90
AZ	1.39%	-39.7	-0.63	-177.8	-2.20
CA	10.89%	-77.5	-2.05	-242.5	-2.17
CO	1.43%	5.7	0.14	-118.1	-3.29
CT	1.47%	-124.2	-1.48	-119.7	-1.67
DC	0.15%	-512.0	-2.25	-316.9	-1.31
DE	0.34%	-74.9	-1.41	-108.3	-3.28
FL	5.81%	-99.3	-2.78	-221.2	-2.76
GA	2.73%	-17.5	-0.38	-84.6	-1.04
IA	1.22%	-25.0	-0.77	-42.6	-3.85
ID	0.43%	-1.1	-0.03	-22.9	-2.25
IL	4.73%	-82.0	-2.65	-204.4	-3.78
IN	2.41%	-108.2	-3.65	-111.3	-2.92
KS	1.05%	-13.0	-0.32	-95.8	-2.95
KY	1.51%	42.5	1.25	-29.4	-1.30
LA	1.65%	-43.9	-0.93	-100.1	-1.66
MA	2.61%	-128.6	-2.13	-245.3	-2.71
MD	2.07%	-393.4	-5.81	-161.4	-2.37
ME	0.53%	-208.0	-5.42	-29.9	-3.30
MI	4.27%	-150.0	-3.36	-124.5	-2.34
MN	1.96%	-27.7	-0.73	-82.9	-2.37
MO	2.13%	105.5	1.95	-100.0	-2.98
MS	0.88%	-251.8	-1.74	-35.1	-0.85
MT	0.34%	-15.3	-0.23	-4.0	-0.27
NC	2.87%	-70.1	-2.15	-63.9	-3.25
NE	0.55%	-14.3	-0.26	-91.1	-2.68
NH	0.59%	-14.9	-0.51	-27.8	-2.21
NJ	3.33%	-232.0	-3.39	-277.0	-3.18
NM	0.64%	80.5	0.98	56.5	0.87
NV	0.51%	-120.6	-1.65	-158.6	-2.18
NY	6.01%	-123.6	-2.22	-379.0	-3.77
OH	4.74%	-92.3	-3.78	-75.6	-3.07
OR	1.18%	-59.2	-1.48	-101.0	-1.24
PA	4.78%	-153.9	-4.26	-139.4	-3.01
RI	0.40%	-220.3	-2.38	-293.4	-3.89
SC	1.38%	-28.2	-0.70	-77.8	-3.00
SD	0.31%	16.1	0.30	-21.8	-1.22
TN	2.08%	-23.9	-0.32	-107.2	-2.16
TX	6.98%	-83.6	-2.26	-126.9	-1.81
UT	0.66%	-61.0	-1.60	-29.3	-1.26
VA	2.80%	-49.6	-2.26	-63.2	-2.15
VT	0.28%	56.5	0.96	-1.2	-0.07
WA	1.90%	-71.9	-1.54	-131.0	-1.59
WI	2.16%	-38.2	-1.11	-80.6	-3.03
WV	0.72%	-95.7	-2.51	-9.8	-0.58
WY	0.20%	127.1	1.95	19.9	0.71

The estimates associated with parts marking typically are negative and often statistically significant. Whether or not this table demonstrates variation across the states in the effectiveness of parts marking is unclear, because there is considerable sampling variability in the estimates, both across the states and between the two estimation techniques.

After weighting across the states, figure 4.2A shows the confidence intervals for the estimated reduction in automobile thefts per 100,000 cars when M percent of cars are marked. This figure is based on the FGLS model. When 50 percent of a model line has been marked, the reduction in automobile theft rates is estimated to be between 67 and 101 per 100,000 automobiles. When 100 percent of a model line has been marked, the reduction is estimated to be between 138 and 207 per 100,000 automobiles. The latter confidence interval, evaluated at 100 percent marking, should be accepted with caution because 100 percent marking is beyond the support point for these regressions. Nevertheless these results are consistent with concluding that parts marking has prevented an appreciable number of automobile thefts.

Figure 4.2A — Estimated Effectiveness of Parts Marking As a Function of Percentage Marked Based on the FGLS Model

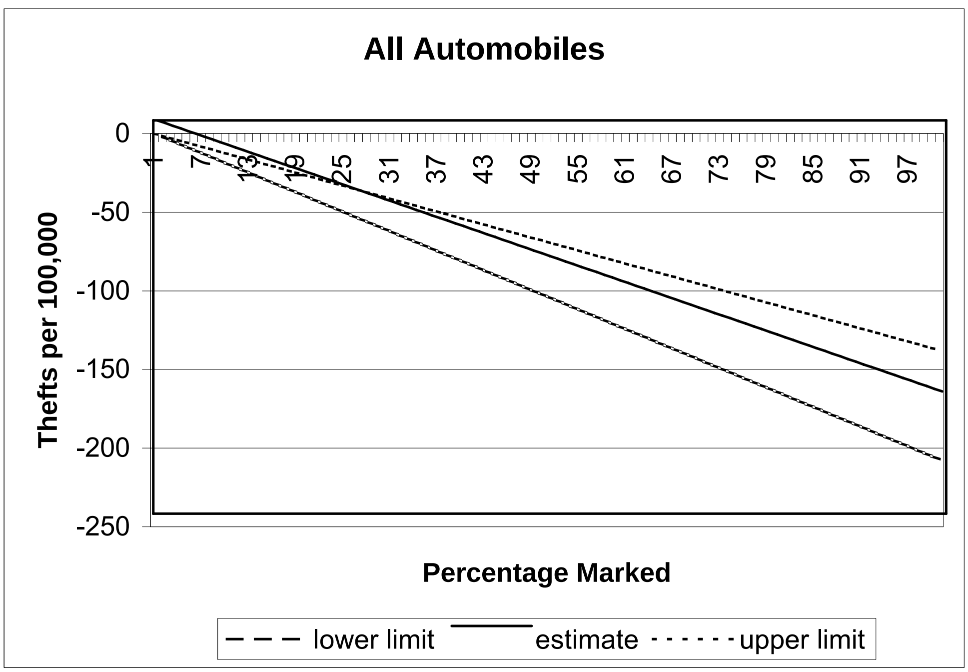
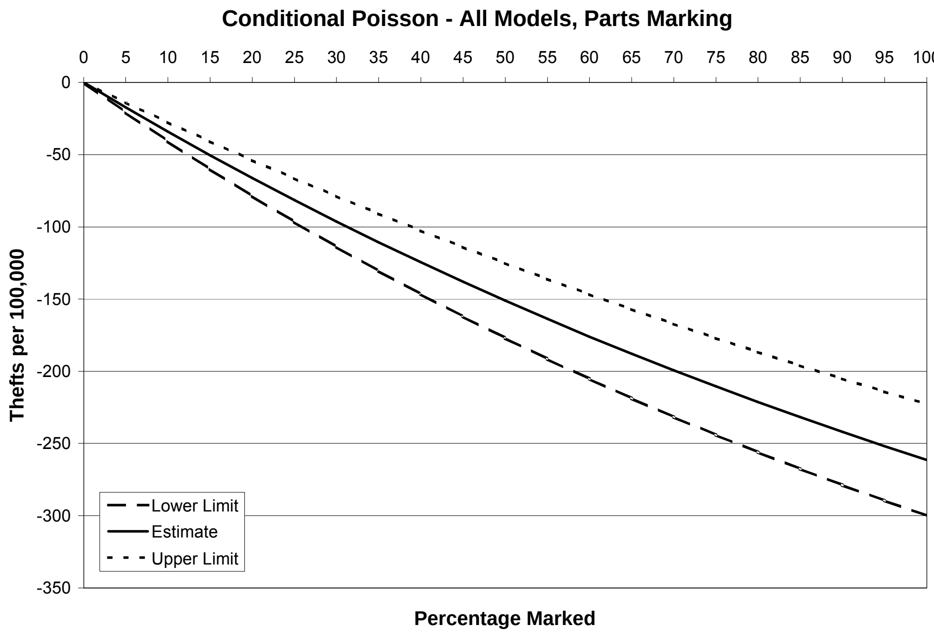


Figure 4.2B shows similar statistics based on the Maximum Likelihood Poisson model. The Poisson model seems to show a somewhat larger effect from parts marking—somewhere between 220 and 300 reduced thefts per 100,000 registered cars. These differences might result from the way that the estimates are calibrated, however. Had we used a different base

for computing the estimates based on the ML Poisson model, or had we selected a different year for the FGLS model, such comparisons could have been different.

Figure 4.2B — Estimated Effectiveness of Parts Marking As a Function of Percentage Marked Based on the ML Poisson Model



Inferences based on model segments are broadly consistent with the inferences based on all automobiles combines. Table 4.2C provides a summary of the confidence intervals, by model segment, evaluated when 100 percent of automobiles were marked.

Table 4.2B — Estimated Effect of Parts Marking by Model Segment

	FGLS Confidence Intervals			ML Poisson Confidence Intervals		
Type	**Lower Limit**	**Estimate**	**Upper Limit**	**Lower Limit**	**Estimate**	**Upper Limit**
All	-207.1	-172.3	-137.6	-299.9	-261.3	-222.8
Compact	-441.6	-376.4	-311.2	-173.6	-85.6	2.4
Mid/Full	-321.0	-255.2	-189.4	-260.2	-193.0	-125.8
Luxury	-31.2	103.8	238.9	-48.3	103.1	254.5
Near Luxury	107.6	190.0	272.4	175.3	325.8	476.4
Sports	-818.2	-411.4	-4.5	-1001.3	-716.1	-431.0
Sports Coup	-620.5	-445.7	-270.8	-635.3	-479.3	-323.4

For compact cars, mid-size and full-size cars, sports cars and sports coups, the FGLS model indicates that parts marking has decreased automobile thefts. The effect for compacts is not significant in the ML Poisson model. The confidence intervals vary over these segments, presumably for two reasons. The first is that the amount of data about thefts within these segments is less than the amount of data across all cars, and this likely causes wider confidence intervals for estimates based on segment data. The second reason is that the automobiles that comprise the different segments have different latent theft rates. Presumably the size of the estimated reduction in thefts is larger when the latent theft rate is large.

For luxury cars and near luxury cars, the results are anomalous: Automobile thefts seem to have *increased* with the introduction of parts marking. Perhaps the findings for luxury cars should be discounted given that it lacks statistical significance. Findings for near luxury cars are not so easily dismissed because the effects are both statistically significant and substantively large. The reason for this perverse effect is unknown.

The study also estimated the above model using M^2 in place of MT and using F^2 in place of FT. Results are summarized in Table 4.2C.

Table 4.2C — Estimated Effect of Parts Marking by Model Segment (with M^2 and F^2)

	FGLS Confidence Intervals			ML Poisson Confidence Intervals		
Type	**Lower Limit**	**Estimate**	**Upper Limit**	**Lower Limit**	**Estimate**	**Upper Limit**
All	-92.8	-73.5	-54.2	-78.7	-52.1	-25.5
Compact	-137.9	-102.3	-66.7	-15.0	21.7	58.4
Mid/Full Size	-167.8	-132.7	-97.6	-141.7	-90.0	-38.3
Luxury	-100.3	-20.5	59.4	-100.9	-30.1	40.7
Near Luxury	-7.9	37.8	83.4	-25.2	22.3	69.7
Sports	-334.9	-116.8	101.3	-799.7	-601.0	-402.3
Sports Coups	-294.6	-206.9	-119.2	-319.0	-218.6	-118.3

A problem with introducing the power of M into this specification is that the relationship between thefts and M is no longer monotonic. In some of the regressions, thefts first decrease with M, reach a minimum, and then increase with M. This nonsense result probably occurs because most of the data is concentrated around values of M that are considerably less than 100 percent marking, so the regression may do a poor job of predicting in the area of 100 percent marking. Table 4.2C consequently shows estimates when 50 percent of the automobiles are marked.

Estimates for all automobiles are somewhat less than half what they were in Table 4.2B. This seems reasonable because the estimates are evaluated at 50 percent marking in Table 4.2C and at 100 percent marking in 4.2B. Results based on the segments are consistent for compact (except for the ML Poisson), mid-sized and full-sized, and sports coups. The estimates are not statistically significant for luxury, near luxury and sports cars.

As noted earlier, the regressions were repeated after limiting thefts to cars that were not recovered. The effect was not significant: the confidence interval was –10 to 17 fewer thefts per 100,000 marked cars. Note that a "recovered" car may have been recovered after it had been damaged or even destroyed. This means that the failure to recover a car is a relatively rare event, and this fact may account for failure to detect an effect from parts marking for unrecovered cars while it was detected for all stolen cars.[13]

Also as noted earlier, the analysis was repeated using the shorter time-series from 1996 through 2001. For this analysis, anti-theft devices were determined from industry data rather than being inferred from anti-theft exemptions. The FGLS model provided little evidence that parts marking had deterred an appreciable amount of automobile theft. The confidence interval was -2 to -15 for the model with interaction terms (evaluated at 100 percent marking). For the ML Poisson models, estimates were positive. The problem with the short time-series is that there is scant variation in M within a model over time. That is, M is typically 0 or 1 for all years; even when it is between 0 and 1, it typically does not change much over the five years that comprise these data. The shorter time-series data provide too little information to derive a credible estimate of the effectiveness of parts marking.

To summarize this section, there is a statistically significant and substantively meaningful inverse relationship between the percentage of automobiles that have parts marking and the proportion of automobiles that are stolen. The findings seem robust with respect to model specification, but there are some contrary findings. At least in one instance, the relationship between marking and thefts was positive, and no ready explanation is apparent. The findings could not be replicated when the automobile theft rate was based on unrecovered car thefts. The five-year time series showed small effects, but failure to find a larger effect can be attributed to inadequacies of those five-year data.

4.3 Estimates: Effectiveness of Anti-Theft Devices

There is also a logical problem when judging the effectiveness of anti-theft devices. There is no specific anti-theft *device*; there are instead a variety of anti-theft *devices*. Some are audible alarms, which seem to vary widely in quality. Others are electronic vehicle immobilizers. Of this latter type, some require purposeful intervention by drivers to activate and deactivate; others are passive devices that set and unset themselves without driver interaction. There are also vehicle locator systems, but the analysis does not consider these because the manufacturers do not typically install them. Furthermore, this technology has evolved over time, as have counter technologies used by criminals.[14]

[13] The earlier data file had defined an unrecovered automobile as one that had not been recovered within five years. A better definition would have been to define an unrecovered automobile as having been unrecovered within a 60 days or some other period. After 60 days, we would expect an automobile to have sustained significant damage, perhaps having been stripped of its parts, so that "recovery" implies that not more than a shell was identified and returned to the owner or, more likely, to the owner's insurance company as the owner's agent. Although we would have used such a definition for the more recent data, we lacked any means to convert the older data to this preferable specification.

[14] For example, some immobilizer systems work by sending infrared signals between the key and the automobile's computer. Electronic supply stores now sell low-cost devices that are able to intercept and

Table 4.3A, which pertains to anti-theft devices, is the counterpart to 4.2A, which pertained to parts marking. As before we report separate estimates for the FGLS and ML Poisson methods.

then emulate the infrared signal, thereby defeating the anti-theft device. Alternatives rely on radio signals. (Texas Instruments, undated.)

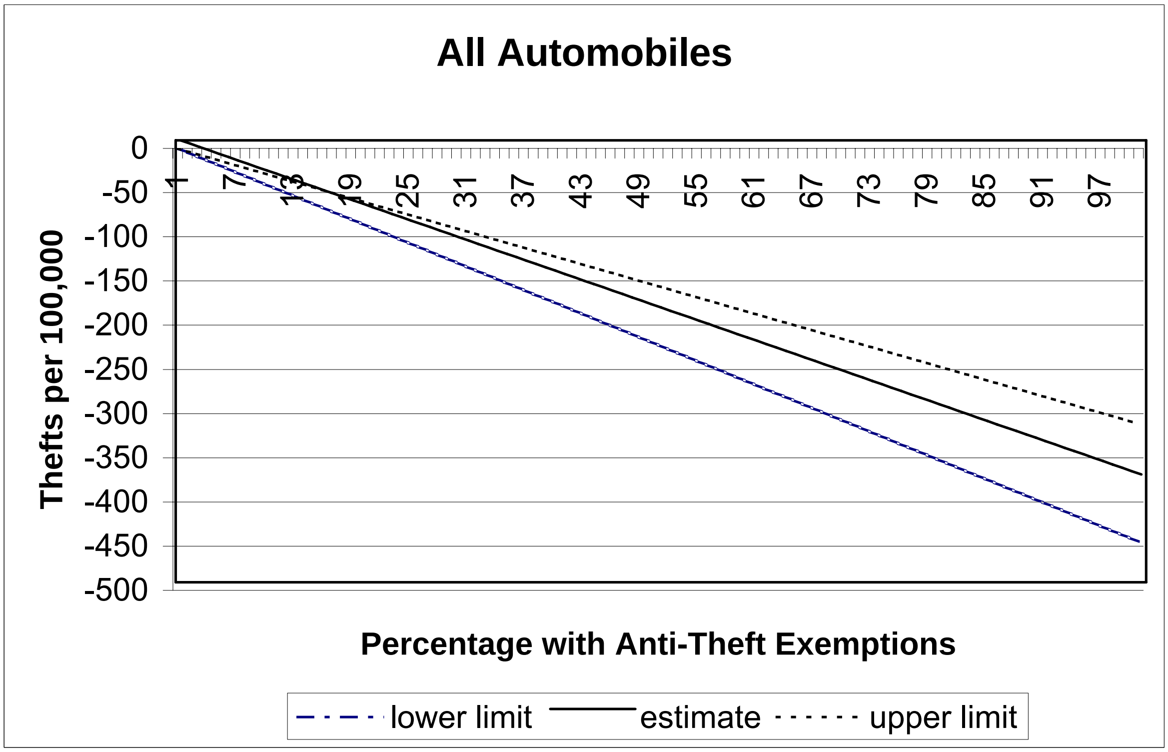
Figure 4.2b – Summary Statistics for the Effectiveness of Anti-Theft Devices (FGLS and ML Poisson)

	registrations	FGLS		ML Poisson	
	(national percentage)	estimate	t-statistic	estimate	t-statistic
AK	0.22%	505.3	1.47	-144.2	-0.59
AL	1.76%	-273.9	-4.58	-157.6	-3.32
AR	0.96%	203.6	1.27	-135.4	-4.09
AZ	1.39%	-102.0	-1.04	-484.2	-5.06
CA	10.89%	-116.6	-1.76	-307.8	-3.62
CO	1.43%	-360.7	-4.41	-233.6	-5.41
CT	1.47%	-87.7	-0.58	-342.1	-6.22
DC	0.15%	-773.8	-1.90	-227.3	-0.62
DE	0.34%	-143.8	-1.34	-232.8	-4.77
FL	5.81%	-178.7	-2.40	-475.8	-5.42
GA	2.73%	-41.4	-0.48	-229.6	-1.71
IA	1.22%	-179.7	-3.05	-64.8	-4.38
ID	0.43%	-55.6	-0.98	-28.6	-1.44
IL	4.73%	-187.7	-3.14	-386.8	-6.24
IN	2.41%	-185.7	-3.04	-234.5	-5.70
KS	1.05%	-85.0	-1.01	-180.7	-4.32
KY	1.51%	-84.0	-1.09	-98.9	-2.99
LA	1.65%	-84.5	-1.00	-316.3	-5.42
MA	2.61%	-113.7	-0.96	-512.2	-4.32
MD	2.07%	-211.9	-1.61	-189.5	-1.70
ME	0.53%	-366.7	-5.38	-51.0	-3.68
MI	4.27%	-332.5	-3.58	-266.1	-2.93
MN	1.96%	23.4	0.33	-170.9	-5.35
MO	2.13%	-87.7	-0.85	-248.2	-5.36
MS	0.88%	-7353.8	-21.70	-119.4	-1.66
MT	0.34%	-9.0	-0.07	2.3	0.06
NC	2.87%	31.9	0.50	-117.3	-3.74
NE	0.55%	83.7	0.61	132.6	1.14
NH	0.59%	-94.8	-1.60	-86.5	-4.62
NJ	3.33%	-103.6	-0.81	-484.1	-4.34
NM	0.64%	-50.5	-0.33	-85.7	-2.01
NV	0.51%	-264.1	-2.03	-118.3	-1.19
NY	6.01%	63.6	0.59	-578.6	-3.29
OH	4.74%	-174.8	-3.18	-198.7	-5.64
OR	1.18%	-36.0	-0.47	-216.7	-3.93
PA	4.78%	-139.1	-1.93	-324.6	-6.14
RI	0.40%	-1296.2	-6.33	-412.1	-6.17
SC	1.38%	-88.9	-1.21	-159.2	-3.72
SD	0.31%	106.3	0.91	-62.3	-3.61
TN	2.08%	-113.2	-0.75	-272.5	-6.31
TX	6.98%	-168.7	-2.38	-356.7	-4.76
UT	0.66%	-42.1	-0.61	-91.9	-4.63
VA	2.80%	-22.3	-0.50	-132.1	-3.24
VT	0.28%	-227.4	-1.88	-18.6	-0.45
WA	1.90%	-68.5	-0.82	-262.5	-7.19
WI	2.16%	-267.1	-3.96	-135.9	-4.27
WV	0.72%	-76.0	-1.03	-63.5	-3.42
WY	0.20%	24.2	0.18	12.2	0.23

Both models tend to show fewer thefts after the introduction of anti-theft devices. The state-specific estimates are often statistically significant, and it appears that the effect was more likely to be detected by the ML Poisson model.

Figure 4.3A shows the estimated relationship between reductions in thefts per 100,000 automobiles and the presence of anti-theft devices as inferred from the presence of exemptions. This figure was based on the FGLS model.

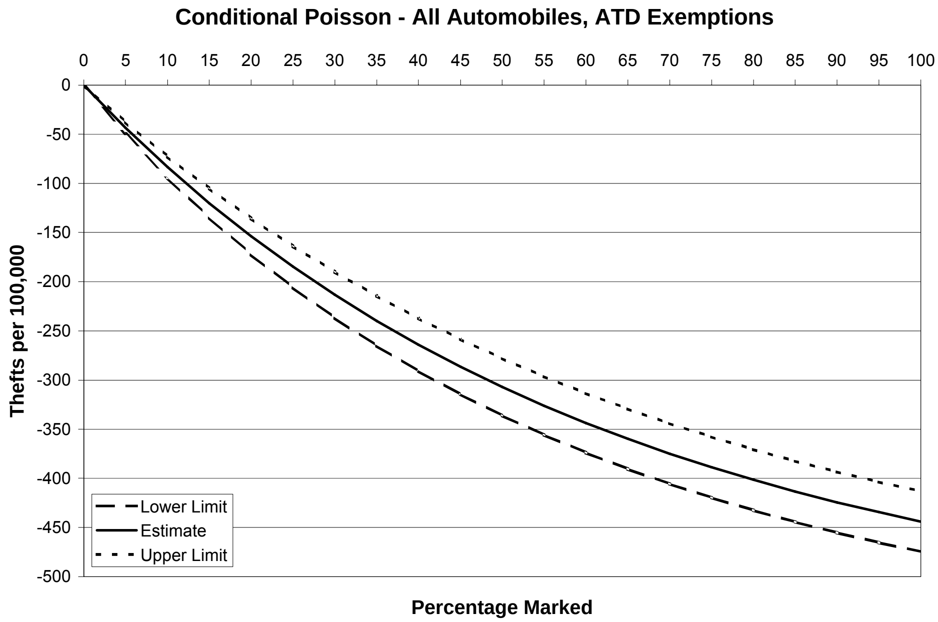
Figure 4.3A – Estimated Effectiveness of Anti-Theft Devices As a Function of Percentage with Devices Based on the FGLS Model



According to this analysis, anti-theft devices reduce automobile thefts by between 156 and 222 cars per 100,000 when 50 percent of those 100,000 cars have anti-theft devices. Anti-theft devices reduce thefts by between 311 and 445 cars per 100,000 when 100 percent of those cars have anti-theft devices.

Figure 4.3B, based on the ML Poisson model, is the counterpart to 4.3A, based on the FGLS model. It tells a similar story. Anti-theft devices seem to reduce thefts by between 413 and 475 cars per 100,000 automobiles. As before, we are cautious about inferences about the consequences of having 100 percent of automobiles have anti-theft exemptions, because the estimates are outside the range of the data.

Figure 4.3B – Estimated Effectiveness of Anti-Theft Devices As a Function of Percentage with Devices Based on the ML Poisson Model



We repeated this analysis for each segment. Results are summarized in Table 4.3A.

Table 4.3A — Estimated Effect of Anti-Theft Devices by Model Segment

	FGLS Confidence Intervals			ML Poisson Confidence Intervals		
	lower limit	estimate	upper limit	lower limit	estimate	upper limit
All	-444.9	-378.0	-311.2	-474.7	-443.9	-413.1
Compact	-9.7	174.9	359.5	142.8	254.6	366.4
Mid/Full	-280.0	-181.5	-83.0	-341.0	-257.3	-173.6
Luxury	-73.3	170.4	414.1	-249.0	96.2	441.4
Near Luxury	48.3	168.5	288.6	-346.8	-53.4	239.9
Sports	-1880.9	-1257.4	-633.8	-1219.3	-1026.6	-834.0
Sports Coup	-1493.4	-1185.4	-877.3	-1388.4	-687.2	14.1

Analysis of the segment data supports inferences drawn from the combined data for mid-sized and full-sized cars, sports cars and sports coups. (The confidence interval based on two standard deviations overlaps zero for sports coups according the to ML Poisson model.) The estimated effects were not statistically significant for compacts and luxury cars. In fact, the estimate for compact cars is perverse when based on the ML Poisson model. For the FGLS model, the evidence was perverse for near luxury cars, a finding for which there is no ready explanation.

The study repeated the above analysis using the model with quadratic terms, M^2 and F^2 instead of MY and FY. Results are summarized in Table 4.3B. Effects are evaluated when 50 percent of the cars have anti-theft devices.

Table 4.3B — Estimated Effect of Parts Marking by Model Segment (FGLS with M^2 and F^2)

	FGLS Confidence Intervals			ML Poisson Confidence Intervals		
	lower limit	estimate	upper limit	lower limit	estimate	upper limit
All	-201.8	-182.3	-162.8	-280.2	-249.8	-219.5
Compact	74.2	109.8	145.4	66.7	95.3	123.9
Mid/Full Size	-147.5	-111.7	-75.9	-167.7	-115.0	-62.3
Luxury	-11.7	61.3	134.4	207.8	667.1	1126.3
Near Luxury	119.4	165.6	211.7	-17.4	167.9	353.2
Sports	-969.9	-748.7	-527.6	-912.3	-609.3	-306.3
Sports Coups	-877.7	-788.7	-699.6	-370.9	-171.5	27.8

Results for mid-sized and full-sized cars, for sports cars and for sports coups are consistent with findings for all cars combined. Anti-theft devices reduce automobile theft by between 163 and 201 per 100,000 when half those cars have anti-theft devices (FGLS) and by 220 to 280 per 100,000 (ML Poisson). Confidence intervals are for all cars combined. Yet there is an unsettling finding that thefts seem to increase with the introduction of antitheft devices for compact cars and for near luxury and luxury cars.

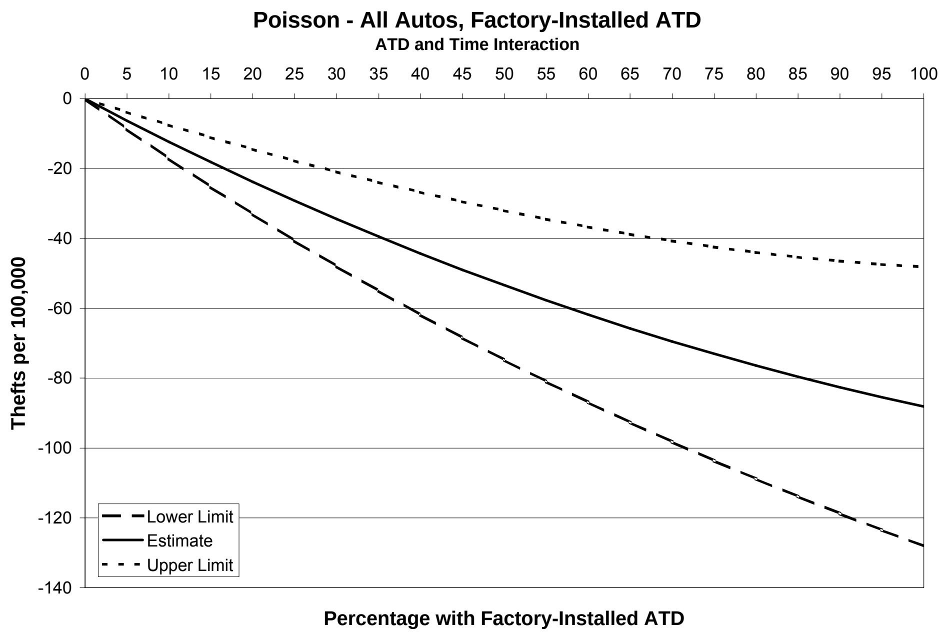
When unrecovered cars is the dependent variable, the effect of anti-theft devices was not statistically significant (-31 to 24). The smaller file, representing thefts from 1997 through 2001, is especially useful because the data report the proportion of automobile models that actually had factory-installed anti-theft devices. These data are in contrast to the data from 1986 through 2001, where an anti-theft device was inferred from an exemption to parts marking. Table 4.3C reports findings for the ML Poisson model. As before, the table identifies the state. The first two columns report the estimate and t-score for a model that includes the M^2 and F^2 terms. The last two columns report a model with the interaction MT and FT.

Table 4.3C – Summary Statistics for the Effectiveness of Anti-Theft Devices (ML Poisson)

	Square term		Time Interaction where Time=.5	
State	**Estimate**	**z-score**	**Estimate**	**z-score**
AK	370.2	0.60	118.5	0.61
AL	-77.6	0.85	-32.6	0.62
AR	153.2	0.95	63.9	1.06
AZ	-338.9	2.52	-158.3	1.40
CA	-80.3	0.77	-67.5	1.43
CO	-127.0	1.50	-55.9	1.26
CT	-180.7	2.28	-74.8	1.28
DC	-462.0	0.46	-197.3	0.23
DE	-55.2	0.34	-99.8	1.45
FL	-134.0	1.21	-22.1	0.30
GA	-83.3	1.00	-37.1	0.83
IA	-46.7	0.68	-26.9	0.77
ID	-77.6	1.35	-26.0	0.39
IL	-202.8	2.41	-77.2	1.41
IN	-130.3	1.77	-7.5	0.13
KS	243.5	1.00	41.6	0.54
KY	8.5	0.16	12.5	0.34
LA	-182.5	2.58	-145.5	2.93
MA	-97.9	1.07	-45.2	0.66
MD	-298.4	4.12	-110.8	1.04
ME	-48.7	1.15	-10.1	0.20
MI	-198.8	1.56	-170.1	1.70
MN	-109.7	2.87	-83.5	3.14
MO	-230.4	3.51	-73.8	1.49
MS	-161.5	1.63	-18.8	0.22
MT	-43.3	0.54	46.5	0.61
NC	-104.8	2.43	-25.4	0.83
ND	-65.6	3.52	-21.9	0.59
NH	-44.3	0.94	-12.5	0.38
NJ	-312.9	4.11	-211.0	3.64
NM	-6.7	0.04	-100.4	1.47
NV	-237.1	1.12	104.8	0.76
NY	-168.8	2.76	-60.3	1.60
OH	68.7	0.56	1.1	0.03
OK	-171.8	2.53	-99.2	2.87
OR	33.0	0.24	13.8	0.19
PA	-182.0	2.87	-41.7	0.86
RI	-274.1	2.62	-108.4	1.28
SC	-149.6	2.77	-81.9	2.06
SD	-78.8	2.52	-41.4	1.31
TN	-116.5	2.49	-9.7	0.18
TX	-129.1	1.33	-133.8	2.87
UT	-1.2	0.01	17.1	0.21
VA	-65.5	1.29	-30.5	0.99
VT	-68.9	2.79	-49.4	1.99
WA	-151.1	0.64	-136.3	1.46
WI	79.0	0.65	65.7	1.13
WV	282.3	1.20	167.2	2.10
WY	-64.7	1.27	7.9	0.08

The estimates are typically negative, as we would expect if anti-theft devices were effective deterrents to theft. The effects are occasionally statistically significant. When they are averaged across the states, that average is statistically significant and appreciable. Figure 4.3C, which is based on the interaction model, illustrates.

Figure 4.3C – Estimated Effectiveness of Anti-Theft Devices As a Function of Percentage with Devices



When 100 percent of automobiles have anti-theft devices, we estimate that thefts will be reduced by roughly 90 cars per 100,000 registrations. (For the FGLS model, the confidence intervals was –5 to –33) This is a smaller deterrence effect than was estimated using the longer time-series, but there are problems with this shorter time-series. Many model lines always have anti-theft devices; many others never have anti-theft devices. Inferences are based on the relatively few automobile models for which provision of anti-theft devices changed materially over time. Still, these findings are consistent with a conclusion that anti-theft devices have decreased automobile theft, and they might provide evidence that the previous estimates (based on the 1996-2001 data) are not seriously biased toward zero.

The previous statement about "serious bias" notwithstanding, the analysis of the effectiveness of anti-theft devices suffers from a measurement problem. Most of the analysis is based on the presence of an anti-theft exemption to parts marking, from which we inferred the presence of an anti-theft device. In truth, many automobiles that lack an anti-theft exemption nevertheless have factory installed anti-theft devices as standard equipment. This has significance for the analysis, specifically: the estimate of the effectiveness of anti-theft devices is almost certainly understated.

Essentially the inference about the effectiveness of anti-theft devices is based on a simple comparison. The analysis presumes that cars that lacked anti-theft exemptions also lacked anti-theft devices. We observed the trend in theft rates for those cars over a sixteen-year period. In contrast, we assumed that cars that received anti-theft exemptions lacked anti-theft devices prior to receiving exemptions, but they had anti-theft devices after receiving anti-theft exemptions. The inferences about the effectiveness of anti-theft devices is based on the observation that the theft rate fell more (or increased less) for cars that had exemptions than it did for cars that lacked exemptions. Furthermore, the difference was greatest for those models that had the largest proportion of registered cars with exemptions (e.g. anti-theft devices).

Assuming equivalence between having an anti-theft exemption and having a factory-installed anti-theft device is surely incorrect. We can observe that during the period 1997-2001, a sizable proportion of cars that had anti-theft devices did not have anti-theft exemptions. (Most cars that had anti-theft exemptions also had anti-theft devices, and we are uncertain why this is not 100 percent.) How does a mistaken assumption affect the analysis and the inferences based on that analysis?

Table 4.3D provides some evidence about trends in factory-installed anti-theft. The table shows the status of automobile models that were manufactured in the specified year—1997 through 2001. It would be useful to extend this table into earlier years, but as noted earlier, the earliest available data commence in 1997. For each year, the table shows the percentage of automobile models that fall into each of four categories:

- Exemptions — these are automobiles that received exemptions from parts marking. We presume that all have factory installed anti-theft devices, although curiously a few (7 of 42 in 2001) do not have such a device according to our data.

- 100% anti-theft devices — the complete model line has factory-installed anti-theft devices but no exemption.

- 1 to 99% anti-theft devices — part of the model line has factory-installed anti-theft devices. This happens because the manufacturer offered an anti-theft device as optional equipment, typically as part of a larger package of electronic equipment such as power windows.

- No anti-theft device

Table 4.3D – Introduction of Factory-Installed Anti-Theft Devices through Time

	1997	1998	1999	2000	2001
Exemptions	24.0%	24.4%	24.1%	22.4%	22.8%
100% anti-theft devices	14.3%	18.3%	18.8%	21.3%	26.1%
1-99% anti-theft devices	20.1%	25.0%	30.0%	27.9%	28.8%
no anti-theft device	41.6%	32.3%	27.1%	28.4%	22.3%
	100%	100%	100%	100%	100%

Notes: The columns denote the year that an automobile line was produced. Thus, if model A were produced in 1997 but not thereafter, it would only affect the statistics reported in column 1997. The percentages are the percentages of models produced during the designated year that had a specified anti-theft device installed at the factory.

Trends are apparent. Almost 42 percent of the models lacked any anti-theft devices in 1997, but by 2001 that percentage had shrunk to 22 percent. Manufacturers offered anti-theft devices as standard equipment even without acquiring an exemption from parts marking on more than 14 percent of their models in 1997 compared with over 26 percent of their models in 2001. Anti-theft devices were offered as optional equipment on over 20 percent of the models in 1997 compared with nearly 29 percent of the models in 2001, and even that increase hides a larger trend, because over time an increasing proportion of buyers choose the anti-theft option.

Projecting these trends backwards suggests that the presence of anti-theft devices without an exemption was probably relatively rare prior to the middle 1990s (Gomez, 1998; Vitty, undated). That is one reason why we chose to make our estimates of the effectiveness of anti-theft devices as of 1994. Note that theft rates for 1994 were based on automobile manufactured before 1994, and given that cars stay in use for ten to fifteen years, coupled with the trend shown in table 4.3D, we would expect anti-theft exemptions to be a reasonably good proxy for the presence of a factory-installed anti-theft device and the absence of an anti-theft exemption to be a reasonable proxy for the absence of an anti-theft device, for 1994.

Nevertheless, we would expect the effectiveness of anti-theft devices to be underestimated by the analysis reported in this subsection. If some of the cars assumed to lack an anti-theft device actually had one, then the time-series for automobiles that we mistakenly deemed to lack anti-theft devices would understate the theft rate for cars that in fact lacked anti-theft devices. This would then bias downward the comparison between automobile deemed to have an anti-theft device, based on the presence of an anti-theft exemption, and automobiles deemed to lack anti-theft devices, based on the absence of an anti-theft exemption.

4.4 Displacement as an Alternative Explanation

Criminologists who study the effectiveness of crime prevention have been concerned that crime prevention programs may shift criminal activity from hardened and hence less desirable target to more desirable ones (Hesseling, 1995; Eck, 1993). From this perspective, thieves may stop stealing marked cars and shift their attention to unmarked ones; they may stop stealing automobiles with anti-theft devices and switch their attention to cars that lack alarms and locking mechanisms. The benefit-cost analysis would overstate the cost effectiveness of parts marking and anti-theft devices to the extent that displacement causes thieves to shift the focus of their attentions.

This theory of displacement, when applied to the theft of automobiles, presumes that thieves decide to steal a car and then search for an automobile that is relatively unprotected. However, Rice and Smith (2002) argue that planning is not the modus operandi of not-for-profit thieves, whom Rice and Smith considered to typify automobile thieves. These two researchers argue that most auto theft depends on opportunity, the flow of traffic of motivated offenders, and other factors. From this perspective, displacement would be modest, because target hardening removes opportunity. In contrast, the automobile theft rings described by Mulmat et. al. (2000) clearly have a profit motive and whether or not Rice and Smith are correct that theft ring members are a minority of thieves, professionals steal a disproportional number of automobiles. For them, displacement is a realistic possibility.

Nevertheless, even for professional thieves, there is no reason to believe that crime displacement completely or materially offsets prevention. Target hardening may cause thieves to shift their attentions from the most desirable targets (before hardening) to less desirable automobiles, but still, this implies that the reward from stealing cars has been decreased. As a consequence, we would expect the number of thefts to fall as a result, although the decrease in total thefts is uncertain.

Furthermore, the phenomenon of displacement is not universal. Some criminologist point out that target hardening can have a beneficial spillover effect (Clark and Weisburd, 1994), and at least one study seems to show that *reverse* displacement can apply to automobile anti-theft devices (Ayres and Levitt, 1998). The logic of the spillover effect is that thieves cannot easily tell which cars have anti-theft devices and which do not. Therefore, once anti-theft devices are widely used, the risk of unwittingly stealing a car with an anti-theft device poses a prohibitive risk for a significant proportion of potential thieves.

The underlying criminological theory points all ways: Target hardening may increase, have no effect on, or decrease crime for targets that are not hardened. Whether or not a significant amount of positive or negative displacement exists for parts marking and factory-installed anti-theft devices is thus an empirical question, for which strong evidence is unfortunately lacking. This is not to say that available evidence is unworthy of consideration, however.

With respect to parts marking, a thief's ability to shift his or her attention to alternative targets is limited. If there is a demand for Cadillac hoods, then there is no gain from stealing Ford doors. From the thief's perspective, the Government has imposed parts-marking on especially desirable models, specifically, those that are worth the most to chop-shops. The thieves might shift to less desirable models, of course, just as counterfeiters might respond to an increased quality of twenty-dollar bills by manufacturing one-dollar bills. But given the altered incentive structure, the thieves might better switch to other crimes (such as robbery or burglary), or earn a legitimate income.

Still, this is an empirical question, and some of the evidence from this study provides insight. Recall that the regression specification was non-linear, allowing us to determine whether the incremental effect of marking an additional Cadillac increased or decreased as more Cadillacs were marked. When just a few automobiles are marked, and if displacement is operable, then we would not see any effect from part marking. A thief would simply steal an unmarked Cadillac from the same model line as the marked one. As additional Cadillacs are marked, however, the thief would have fewer choices; either he or she would steal marked Cadillacs or else he or she would switch to some other model or some other crime. In fact, when we examine the relationship between theft rates and the percentage of marked Cadillacs, we see that thefts decrease after even a small percentage of Cadillacs get marked, suggesting that even professional thieves are opportunistic in the sense that Rice and Smith used this term. Displacement does not seem to account for the results from the parts marking analysis.

With respect to anti-theft devices, Ayres and Levitt (1998) report that LOJACK has had a spillover effect on reducing all automobile theft. LOJACK is not a factory-installed anti-theft device, however, and while we might suspect that factory-installed anti-theft devices have similar spillover effects (for the same reason that LOJACK does), we cannot be sure.

Evidence that displacement has been minimal comes from noting that, over time, an increasing percentage of automobiles were receiving factory-installed anti-theft devices. (See table 4.3D and the previous discussion about that table.) If displacement were the explanation for earlier findings about the effectiveness of anti-theft devices, then we would expect the effectiveness of parts marking to decrease materially over time as anti-theft devices appeared on a majority of cars. In fact, figure 4.3B shows that the *marginal* effectiveness of installing anti-theft devices is smaller as anti-theft devices are extended to more cars, suggesting displacement. But the extent of that displacement is overwhelmed by the apparent effectiveness of those anti-theft devices.

The displacement hypothesis must be taken seriously and this study cannot altogether rule out the possibility that displacement accounts for findings. Nevertheless, concluding that displacement probably accounts for these findings, or is likely to account for these findings, would be unwarranted. From a logical perspective, the fact that part marking and anti-theft devices deter criminals from stealing desirable (to the thief) cars is a victory for law enforcement, as fewer cars, especially fewer expensive cars, will be stolen. From an empirical standpoint, the evidence points toward a finding that if displacement occurs, it does not come close to offsetting the salutary effect of part marking and anti-theft devices.

5.0 Conclusions

Evaluation results released in 1998 caused the National Highway Traffic Safety Administration to provide a qualified endorsement of the effectiveness of parts marking (NHTSA, 1998). Neither the NHTSA report nor the Abt report were seen as compelling by the insurance industry (Alliance of American Insurers et. al., 2002), who nevertheless called for improvement in the parts marking technology and expansion of parts marking to all cars. The automobile industry judged the evidence differently (Card, 1997;Technical Affairs Committee, 2002), calling for eliminating parts marking. As noted, the law enforcement community has expressed support for the continuation and expansion of parts marking (Finn, Truitt and Buron, 1997).

There is less disagreement about the effectiveness of anti-theft devices although formal evaluations are lacking. NHTSA (1998) reports that "The system installed by a domestic manufacturer as standard equipment in various car lines during 1989-94 was associated with an immediate, and persistent 70 percent reduction in the theft rate and a 58 percent reduction in the unrecovered-theft rate." Others have referred to statistics published by the Highway Loss Data Institute (HLDI, 2000) that seem to show that passive immobilizing anti-theft devices had a dramatic reduction on insurance losses. From the HLDI report, the reductions in claims after the introduction of passive immobilization devices was:

- 380/100,000 for Nissan Maxima (midsize car)
- 0/100000 for Ford Ranger 4Wd (small pickup)
- 100/100,000 for Ford F-150 (large pickup)
- 10/100,000 for Chevrolet Venture (large passenger van)
- 30/100,000 for all passenger cars

There is considerable variation in these numbers. Furthermore, they are based on claims data, which includes theft of the vehicle and theft from the vehicle. Finally with respect to published studies, Ayres and Levitt (1998) reported that LOJACK reduced automobile theft, but the LOJACK technology is very different from the anti-theft technology considered in this evaluation. In short, the published literature provides few evaluations of standard anti-theft technology that are likely to pass rigorous scientific scrutiny.

This current evaluation provides evidence that parts marking has reduced automobile theft. Perhaps the magnitude of the decrease is uncertain, but we can ask the question: How large must the effect be to justify the cost of marking cars?

First, the answer depends on the cost of marking cars, and there is some disagreement about that figure. NHTSA estimated the average cost of marking a car as $4.92 in 1995 (NHTSA, 1998). Because the average automobile is in use for ten to fifteen years, this implies a cost of less than $0.50 per car per year, the figure used in the earlier Abt calculations. An improved system, recommended by the insurance industry (Alliance of American Insurers et. al., 2002), would cost about $24.86, so a high estimate would seem to be about $2.50 per car per year. This estimate would likely exceed the costs of marking cars using the technology assessed in this current evaluation.

Second, the answer depends on the dollar loss from a stolen car. The earlier Abt calculations were based on an assumption of $6,000 per car. (See Rhodes, Johnston and McMullen, 1999, for an explanation.) According to HLDI (2000), the average loss payment per claim was about $5,500 for passenger cars during 1999. Taking deductions into account, and figuring that claims from thefts by professional thieves would be higher than this $5,500 average, an assumption of $6,000 loss is probably conservative. Furthermore, it does not account for the non-pecuniary costs to car owners, or for any prorated administrative costs of the automobile insurance system, or for police, prosecutorial and court costs (see Field, 1993).

If these estimates are true, how many automobile thefts must be deterred to justify the cost of parts marking? If parts marking costs $0.50 per car, then preventing 9 thefts per 100,000 cars (9x$6000=$54,000) would offset the yearly cost of marking those 100,000 cars (100,000x$0.50=$50,000). Suppose the cost of marking were increased to $2.50 per year per car. Then preventing 42 thefts per 100,000 marked cars ($6,000x42=$252,000) would justify the cost of marking those 100,000 cars (100,000x$2.50).

Our best estimates for the reduction in the number of thefts per 100,000 marked cars is between 54 and 93 cars. Such estimates seem to justify parts marking from a benefit-cost standpoint. Of course these estimates do not include the costs of training police to use parts marking effectively or other costs associated with incorporating parts marking into investigations and prosecution, but if parts marking is a productivity enhancement, there is little reason to suppose that police and prosecution costs would increase.

The benefits may be understated for another reason. Possibly parts marking increases the rates at which automobiles are recovered without significant damage once stolen. If that is true, the benefits from parts marking would be understated, but we lack any means to assess the evidence for this surmise.

What about factory-installed anti-theft devices? We are uncertain of the costs of such devices. As noted earlier, factory-installed anti-theft devices vary widely both in quality and in methodology used to protect a vehicle. When factory-installed anti-theft devices are standard equipment, their costs cannot be factored from the total cost of a vehicle. When they are optional equipment, they are typically offered as part of a package of electronic devices, so their costs cannot be extracted from the total cost of the package. Audible alarms and electronic immobilizers can be purchased from secondary sources, and a check of prices provided on the Internet shows that alarms and immobilizers can both be purchased for under $100. Installation would be extra, of course, although the installation does not appear complicated. We tentatively set the cost of an anti-theft device at $200 per car.

Assuming that a car will be operational for ten years, the yearly cost of an anti-theft device is about $20 per year or $2 million for 100,000 automobiles. At such prices, how many thefts must be deterred to justify the cost? If a stolen car results in a $6000 loss, then anti-theft devices must prevent about 330 thefts per 100,000 cars. This is in the range of estimates provided by our analysis of the effectiveness of anti-theft devices.

For several reasons, these estimates may be conservative. We are uncertain about the cost of anti-theft devices, and as noted, $200 may higher than the actual cost to consumers. Also as noted earlier, the effectiveness of anti-theft devices might be underestimated, because some automobiles that had anti-theft devices were classified as lacking such devices, a fact that would bias downward our estimates of the effectiveness of anti-theft devices. Furthermore, the benefit from anti-theft devices is not limited to automobile theft per se. By hindering access to automobiles, anti-theft devices also reduce the theft of detachable parts (i.e., radios) and possessions that are in a car but not part of the car (i.e., shopping packages).

On the other hand, the estimated $6000 may be too high as an estimate for the loss from automobile theft when applied to car theft prevented by anti-theft devices, because many of those deterred thefts are likely to be by nonprofessional thieves, in which case the car is typically returned to the owner with at most minor damage. Still, this estimate excludes losses of items from the car. When that is the case, the stolen car is likely to be recovered without serious damage within a few days of the theft.

Nothing in this argument says that parts marking is better than anti-theft devices. Nothing says the opposite. We remain convinced that parts marking and anti-theft devices serve different purposes. They are complements rather than substitutes. One might be effective while the other is not or, more likely based on the analysis presented here, both are cost-effective ways of reducing automobile theft. We hold to our earlier recommendations that anti-theft exemptions be eliminated. If parts marking and anti-theft devices are cost-effective, they should act in concert to reduce the cost of automobile theft.

References

Alliance of American Insurers, American Insurance Association, National Association of Independent Insurers and the National Association of Mutual Insurance Companies (2002) Letter submitted to the Docket Section, National Highway Traffic Safety Administration, August 23, 2002.

Ayres, I. And Levitt, S. (1998) Measuring Positive Externalities from Unobserved Victim Precaution: An Empirical Analysis of LOJACK. The Quarterly Journal of Economics: 43-77.

Bowers, K. and Johnson, S. (2003) Measuring the Geographical Displacement and Diffusion of Benefit Effects of Crime Prevention Activity. Journal Of Quantitative Criminology, Vol 19 (3): 275-301.

Cameron, A. and Trivedi, P (1998) Regression Analysis of Count Data. Cambridge University Press, Cambridge, U.K.

Card, A. (1997) Statement of the American Automobile Manufacturers Association Before the Telecommunications, Trade and Consumer Protection Subcommittee of the House Commerce Committee on May 22, 1997.

Clark, R. and Weisburd, D. (1994) Diffusion of Crime Control Benefits: Observations on the Reverse of Displacement. In Clark, R. (ed) Crime Prevention Studies (Vol 3) Willow Tree Press, Monsey, NY.

Durbin, J. and Koopman, S. (2001) Time Series Analysis by State Space Methods. Oxford Statistical Series no. 24. Oxford University Press, Oxford, England.

Eck, J. (1993) The Threat of Crime Displacement. Criminal Justice Abstracts, 25: 527-546.

Ethridge, P. and Gonzales, R. (1996) Combating Vehicle Theft Along the Texas Border. Abstract downloaded from the Internet abstractsdb.ncjrs.org/content/AbstractsDB_Details.asp?index=21&perpage=25&ncjnu on 12/11/2002.

Finn, P., Truitt, L. and Buron, L. (1996) Opinions of 47 Auto Theft Investigators Regarding Automobile Components Parts Anti-Theft Labels. National Institute of Justice, Washington, D.C. NCJ Number 171693.

Field, S. Crime Prevention and the Costs of Auto Theft: An Economic Analysis. Reprinted from Criminal Justice Press. Downloaded from the Internet.

Gomez, J. (1998) Vehicle Security Industry Surmounts Speed Bumps, CE Visions Magazine, Consumer Electronics Association, downloaded from the Internet from www.ce.org/publications/vision/1998/mayjun/pg18.asp?bc=bak&year=1998 on December 12, 2002.

Harris, P. and Clarke, R. (1991) Car Chopping, Parts Marking and Motor Vehicle Theft Law Enforcement Act of 1984. Sociology and Social Research, volume 75, issue 4: 228-233.

Hesseling, R. (1995) Displacement: A Review of the Empirical Literature. In: Clark, R. (ed) Crime Prevention Studies (Vol 2), Criminal Justice Press, Monsey, NY: 187-230.

Highway Loss Data Institute (2000) Theft Losses Decline by Half when Cars Are Equipped with Immobilizing Antitheft Devices. Press release. Downloaded from the Internet at www.hwysafety.org/news_releases/2000/pr2000/pr071900.htm on 12/11/2002.

La Vigne, N., Fleury, J. and Szakas, J. (2000) Auto Theft and Detecting Chop Shop Locations in Atlas of Crime: Mapping the Criminal Landscape, p. 60-67. Oryx Press, Phoenix, AZ.

Mulmat, D., Rienick, C., Melton, R. and Pennell, S. (2000) Targeting Auto Theft with a Regional Task Force and Mapping Technology. Report submitted to the National Institute of Justice by the San Diego Association of Governments. NCJRS document number 94-IJ-CX-0027.

National Insurance Crime Bureau (2002) Vehicle Theft Booming in Port and Border Communities. Downloaded from the Internet at www.nicb.org/services/hotspotsrelease.html on 12/11/2002.

NHTSA (1998) Auto Theft Recovery: Effects of the Anti Car Theft Act of 1992 and the Motor Vehicle Theft Law Enforcement Act of 1984: Report to Congress. NHTSA Report Number DOT HS 808 761. Executive Summary. Downloaded from the Internet at www.nhtsa.dot.gov/cars/rules/regrev/evaluate/808761.html.

Potchak, M.; McGloin, J. and Zgoba, K. (2002) Spatial Analysis of Criminal Effect: Auto Theft in Newark, New Jersey. Criminal Justice Policy Review Volumne 13 (3): 257-285.

Rhodes, W., Johnston, P. and McMullen, Q. (1999) Evaluation of the Effectiveness of Automobile Parts Marking on Preventing Theft: Revised Final Report. National Institute of Justice/NCJRS. Rockville, MD.

Rice, K. and Smith, W. (2002) Socioecological Models of Automotive Theft: Integrating Routine Activity and Social Disorganization Approaches. Journal of Research in Crime and Delinquency Volume 39 (3): 304-336.

Texas Instruments (undated) Automobile Immobilizers Anti-Theft Systems Experience Rapid Growth in 1999. downloaded from the Internet at www.ti.com/tiris/docs/news/news_releases/90s/rel06-01-99.shtml on 12/12/2002.

Vittym K. (undated) Security Equipped Vehicles. Downloaded from the Internet at www.sterlingis.com/vatsequipped.htm on 12/12/2002.