ABSTRACT

COLLETT-SCHMITT, KRISTEN ELIZABETH. Alarming Behavior: Crime Displacement and Observable Private Precaution. (Under the direction of Charles R. Knoeber.)

Homeowners engage in private precaution when public protection is inadequate. When this precaution is observable to criminals, as in the case of a home burglar alarm system advertised with a sign or sticker, it has the beneficial effect of decreasing the probability of burglary of alarmed homeowners. However, because a burglar is rational in his criminal activity, he will avoid protected homes and target homeowners without alarms, increasing their probability of burglary. Observable private precaution therefore incorporates both the deterrence (Clotfelter 1978) and diversion (Shavell 1991) effects. Even though burglar alarms have been identified as effective deterrents, little research has been devoted to determining if they also divert crime. In this dissertation, I examine the diversion effect associated with burglar alarms. In chapter three, I estimate the net effect, or combined deterrence and diversion effects, of burglar alarms on burglary rates and find that burglary rates fall only slightly with increases in burglar alarm use. Assuming that burglar alarms deter, this finding suggests the presence of the diversion effect muting deterrence. In chapters four and five, I present two methods for measuring the diversion effect associated with burglar alarms using data from the homeowner's insurance industry. Since companies with more non-alarmed customers face larger costs due to diversion, chapter four measures the diversion effect as the relationship between the market shares of homeowner's insurance companies and the protective device discounts they offer. Chapter five's approach is based on the empirical method of Berry, Levinsohn, and Pakes (1995) and uses supply and demand parameters in an oligopolistic framework to measure the diversion effect as the difference in

the probabilities of burglary of non-alarmed homeowners when some homes install alarms and when no homes are alarmed. Both methods show that diversion can be measured. When empirically tested, they also yield estimates of the diversion effect. Although the social effects associated with burglar alarms are likely to be positive on balance, I expose the hidden costs that may be associated with observable precautionary measures.

Alarming Behavior: Crime Displacement and Observable Private Precaution

by
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DEDICATION

To my parents, who taught me the star was not too high to reach;

and to my husband, who helped me reach that star.

BIOGRAPHY

Kristen Elizabeth Collett-Schmitt was born to John and Marcy Collett on December 31, 1980 in Cincinnati, Ohio. She attended high school at Notre Dame Academy in Park Hills, Kentucky and graduated Valedictorian of the Class of 1999. Kristen attended Bellarmine University in Louisville, Kentucky, where she served three years on the nationally-ranked mock trial team, participated in the Brown Scholars Leadership Program, was active in student leadership, and worked as both a research and teaching assistant. She graduated from Bellarmine University in 2003 as Valedictorian and earned a Bachelor of Arts in economics and sociology, with minors in mathematics and psychology. Shortly after, Kristen began the Ph.D. program in economics at North Carolina State University, focusing primarily on the research fields of applied microeconomics and law and economics. She earned a Master of Economics in 2004. On July 29, 2006, she married David Schmitt in Fort Wright, Kentucky. While a graduate student, Kristen served as both a teaching assistant and graduate student instructor, and was awarded the "Outstanding Graduate Teaching Assistant Award" in 2007. Upon graduation from North Carolina State University, Kristen will begin a faculty appointment in the Department of Finance at the University of Notre Dame in Notre Dame, Indiana.

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CHAPTER 1

INTRODUCTION

Property rights facilitate socially efficient use of resources. By providing individuals with the exclusive right to use resources as they see fit, property rights generate incentives for owners to take full account of the costs and benefits of employing those resources. Property rights related to homeownership are no different. Public protection of residential property is often inadequate and owners find it in their interest to engage in private precautionary measures. Empirically, private protection is important and growing. According to a Wall Street Journal report cited by Sherman (1995), the security guard industry grew eleven percent in 1994, which is more than twice the rate of growth of police expenditures in recent years (Ayres and Levitt 1998).

Homeowners engage in private precaution in various ways, including installing burglar alarms or deadbolt locks, placing bars on windows, or even staying home during the day. Rational burglars will respond to such measures (Blackstone and Hakim 1997). Homeowners benefit from employing private precaution because it decreases the likelihood that their homes are victimized. However, homeowners also incur the costs of taking these measures. A homeowner will increase the use of private precaution until marginal benefit equals marginal costs.

The social effects of private precautionary measures are two-fold. Precautionary measures benefit homeowners because they deter criminals, thereby lowering the expected loss due to crime. Precaution can also be costly to others if it diverts crime to property that is not protected. Precautionary measures that are visible to a burglar, such as burglar alarm

systems, incorporate both the beneficial and costly effects of private protection by not only reducing crime for protected homes, but also displacing it to unprotected homes. Such measures exhibit what have been identified by the literature as the deterrence (Clotfelter 1978) and diversion (Shavell 1991) effects. Unobservable (but known) measures, such as hidden video cameras, generally only have the beneficial effect of reducing crime and therefore exhibit the deterrence effect alone. Clearly, the overall effect of private precautionary measures on the level of crime in a community is largely determined by the type of precaution taken by households.

Although considerable literatures in the fields of criminology, sociology, and economics agree on the existence of the diversion and deterrence effects associated with observable private precaution, measuring the size of each effect is notoriously difficult. I contribute to the existing literature on the diversion and deterrence effects by analyzing the social effects associated with a common form of observable private precaution - burglar alarm systems. This analysis includes three different empirical approaches to assessing the significance and prevalence of the diversion effect when burglar alarms are used.

In the first empirical approach, I produce an estimate of the net effect of burglar alarms on county burglary rates in the United States. Since most burglar alarms are observable to burglars, their net effect encompasses both the diversion and deterrence effects. This research follows the econometric analysis of Levitt and Ayres (1998) on the social effects of Lojack, a form of unobservable private precaution for automobiles. Lacking data on burglar alarms, I use security system services sales by county as a proxy for burglar alarm adoption and estimate the net effect for a large sample of U.S. counties using Bayesian

estimation. While it is not possible to separate the deterrence and diversion effects using this technique, I find a small but significant, negative net effect of burglar alarms on burglary rates. This finding is consistent with a large deterrence effect and a diversion effect that is nearly as large. However, it is also consistent with a small deterrence effect and a negligible diversion effect. By measuring a small overall social effect associated with burglar alarm use, this first empirical method provides motivation for measuring the diversion effect alone.

The second approach measures the diversion effect alone using a unique dataset consisting of homeowner's insurance company market shares, base premiums, and protective device discounts collected at the zip-code level from the state of Illinois, where insurance pricing has been deregulated. Homeowner's insurance companies have some customers who install burglar alarms to protect their properties, and others that do not. Because these companies benefit when burglars are deterred from alarmed homes, they offer protective device discounts to those customers installing burglar alarms. However, homeowner's insurance companies also face a cost when burglary is diverted to its non-alarmed customers. Assuming that competition in the insurance industry leads to a zero-profit equilibrium, simple cost/benefit analysis suggests that an insurance company should be willing to offer protective device discounts to alarmed customers if the savings generated by the deterrence effect are greater than the costs generated by the diversion effect. Furthermore, since companies insuring more non-alarmed customers likely face larger costs due to diversion, larger companies should offer smaller discounts. In this chapter, I measure the diversion effect associated with burglar alarm installation by regressing the dollar value of the discounts offered to homeowners who install burglar alarms on the product of homeowner's

insurance company market shares and the average insured loss due to burglary. Estimation cannot establish that the 38 homeowner's insurance companies in my sample individually face statistically significant diversion effects. However, my findings suggest that these companies face a negative and statistically significant average diversion effect with the use of all burglar alarm types by both frame and masonry homeowners. Support for a statistically significant and positive average deterrence effect is also found. Additionally, the relative sizes of the two different average effects for all alarm types are consistent with the small net effect of burglar alarms on burglary rates found in the first empirical approach.

The final empirical approach provides another method for measuring the diversion effect associated with private precautionary measures, again using the Illinois homeowner's insurance company data. It is based on the influential work in the field of Industrial Organization by Berry, Levinsohn, and Pakes (1995), who estimate supply and demand parameters in an oligopolistic, differentiated product setting without using consumer-level data. The benefit of using this empirical approach over the second approach is that it measures the diversion effect in an oligopolistic setting and does not require generally unavailable data on the number of homeowners installing burglar alarms. In this chapter, I construct a structural model of equilibrium in the oligopolistic homeowner's insurance industry and measure supply and demand parameters to predict probabilities of burglary of non-alarmed homes in two cases. In the first case, some homes install burglar alarms; the second case is a counterfactual where no homes are alarmed. The difference in these predicted probabilities represents the change in the probability of burglary of non-alarmed homes due to an increase in alarm installation, or the diversion effect. Although this method

cannot generate a precise estimate of the fraction of the market installing burglar alarms, results show that both diversion and deterrence effects are likely to be present with burglar alarm use. This method even suggests that for some types of housing construction and burglar alarms, the diversion effect may outweigh the deterrence effect. Coupled with the success of the second method in measuring the diversion effect, the main contribution of this chapter is that it provides evidence that crime displacement associated with burglar alarms can, in fact, be measured.

This paper is organized as follows: chapter two justifies interest in the social effects of burglar alarms by providing an overview of the literature regarding observable private precaution, the diversion and deterrence effects, and protective device discounts offered by homeowner's insurance companies. The three different methods for assessing the diversion effect associated with burglar alarm use are presented separately in chapters three, four and five. A brief conclusion ends the paper. Although the social effects associated with burglar alarms are likely to be positive on balance, this dissertation exposes the hidden costs that may be associated with observable precautionary measures.

CHAPTER 2

LITERATURE REVIEW

Observable precautionary measures are those that are visible to a burglar contemplating entry, as when an alarm system is advertised in the form of a sign or sticker on a window or mailbox. A rational burglar will tend to avoid homes that are protected by this form of security. By increasing both the probability of apprehension and the difficulty of entry for the burglar, observable security measures increase the expected cost of criminal activity to the burglar and therefore engender the deterrence effect. Despite its ability to deter criminals, not all homeowners engage in observable private precaution (Hakim, Rengert, and Schachmurove 1995). Blackstone and Hakim (1997) estimate the range of alarm ownership to be just 11-15% of all homes and businesses. A rational burglar will find unprotected homes more attractive and tend to make them his target. Therefore, as the fraction of protected homes within a community increases, the likelihood of burglary of unprotected homes in that community also increases. This is the diversion effect, a negative externality, associated with observable security measures.

Private precautionary measures that are unobservable are unlikely to be associated with the diversion effect. Unobservable measures, such as silent alarms, do not allow a burglar to determine a household's level of protection. Assuming that rational burglars gain a general idea of how many households are protected, unobservable private precaution serves two purposes: one is to stop the burglary of protected homes, and the second is to deter the burglary of unprotected homes (Hakim, Rengert, and Schachmurove 1995). Because such measures leave potential criminals unaware of which households are protected, unobservable

private security does not divert crime, but rather generates positive externalities for the community. Unobservable precautionary measures exhibit only the deterrence effect, and therefore unambiguously lead to an overall decrease in crime. This general deterrence of unobservable security is estimated empirically by Ayres and Levitt (1998). Adjusting for the fact that Lojack is disproportionately installed in central cities, they show that a one percentage-point increase in the installation of the unobservable car retrieval system reduces the rate of auto theft by 7% or more (Ayres and Levitt 1998).

There are several types of diversion described in the literature, including temporal, tactical, target, crime type, spatial, and perpetrator (Bowers and Johnson 2003). These types refer to diversion by time of day, modus operandi, target, type of crime, location, and offender, respectively. Due to the nature of housebreaking, residential burglars are less likely to shift to other types of crime when faced with an increase in burglar alarm use. For example, residential burglars are unlikely to switch from houses to banks because of the greater risks associated with bank breaking. House burglars are also unlikely to switch from residential burglary to street robbery because of the personal confrontation involved in work on the street. The type of diversion that is likely to be associated with burglar alarm use is a change in modus operandi or a change in target (Home Office Research Study No. 34). By changing targets, burglars seek out unprotected houses. Previous ethnographic studies (Cromwell et al. 1991; Rengert and Wasilchick 1995; Wright and Decker 1994) reveal that burglars prefer to avoid targets with alarms. Bowers and Johnson (2003) show that burglars seek out unprotected properties located near protected properties, as well as areas that are similar to protected households in external characteristics and income. Burglars may also try

to adopt techniques that neutralize the effects of burglar alarms.

Although an independent measure of the deterrence effect associated with burglar alarms does not exist, evidence of their deterrence has been documented. Blackstone and Hakim (1997) describe a burglar alarm system as "the single most effective precaution one can take" because of its ability to deter, prevent, and detect burglary. They also establish burglar alarm installation as a necessary condition for an effective security package. Using a household questionnaire and review of police files in Philadelphia's metropolitan area in 1992, Buck and Hakim find that among homeowners who take at least three minor private precautionary measures, such as deadbolt locks, non-alarmed homeowners are 5.2 times more likely to be burgled than alarmed homeowners. This is an especially informative statistic regarding deterrence because it controls for the fact that some homeowners may be more careful than others, as well as for differences between neighborhoods that may make homeowners more likely to take minor precautionary measures. A separate study in Cedar Rapids, Iowa in 1972 shows that there is a 55% percent reduction in burglaries and a reduction in financial losses in alarmed residences, compared to non-alarmed homes. Between 1979 and 1981, a police department in the affluent Scarsdale, New York finds that 90% of burgled homeowners do not have alarm systems; the other 10% have disabled or incomplete systems.

Blackstone and Hakim (1997) insist that a major factor in the deterrence generated by burglar alarms is the visibility of a sign advertising them. A survey of burglars conducted by Wright and Logie (1987) suggests that burglars look for an exterior indicator of the presence of an alarm. A survey of homeowners in Greenwich, Connecticut by Blackstone and Hakim

reports that 40% of alarmed homeowners that were burgled had no sign, while only 33% of non-burgled alarmed homeowners did not have a sign.

Perhaps the best evidence of the effectiveness of burglar alarms and their ability to deter is that homeowners are willing to incur the private costs of employing them. A study of alarmed homeowners in Tredyffrin Township by Buck and Hakim (1992) estimates the annual nominal costs of burglar alarms to the entire community to be $1,066,576. This figure includes residential installation costs, monthly service costs, and the cost of the local police department responding to false alarms. Despite their significant costs, the total benefits accruing to homeowners from the use of burglar alarms tend to be larger. Benefits to the entire community, including the non-monetary and monetary costs of burglary, costs of residential property stolen, and demoralization costs that are avoided when a burglar alarm is installed, are estimated to be $1,551,888. Again in the Tredyffrin Township study, Buck and Hakim find that 94% of alarmed respondents are satisfied with their decision to install, 83% say that a burglar alarm makes them/their family feel safe, and 12% claim that an alarm has prevented a burglary.

According to Blackstone and Hakim (1997), alarms tend to deter myopic or "narrow-minded" burglars. Professional burglars avoid alarmed properties, especially those reporting to a central station, because alarms limit the time they can spend in a house before being caught. A burglar alarm connected to a central station limits the burglar to 15 minutes to complete the burglary and escape from the premises. This is a constraint that burglars do not face in non-alarmed homes. A sample of incarcerated burglars (Dimitz and Huff 1988) indicates that burglar alarms connected to central stations and police stations are the most

effective deterrents, and that local burglar alarms are the least effective. When asked about the most effective measures they would take in their own homes, burglars list dogs and alarm systems. Blackstone and Hakim (1997) cite the example of a retired, professional burglar who preferred to switch to non-alarmed targets when faced with burglar alarms. The burglar claims that as far as a residential target was concerned, he avoided alarmed homes [or ones with a large dog] and switched to other homes that lacked both.

Although burglar alarms are widely described as deterrents, empirical evidence of the diversion effect is rare and informal. Clarke, Hough, Mayhew, and Sturman (Home Office Research Study No. 34) compare the fraction of stolen new cars in 1969, when some new cars were fitted with steering column locks, with the same fraction in 1973, when all new cars had locks. Steering column locks are a form of observable private precaution for automobiles. The authors find that new cars represented a smaller portion of stolen cars in 1973, when more cars were equipped with the locks, than in 1969. Despite the fact that more new cars were protected and fewer protected cars were vandalized, an increase in the number of offenses related to vehicle theft occurred. Clarke et al. attribute the increase in crime to a redirection of thieves to vehicles without steering column locks. In another study, LeBeau and Vincent use evidence that criminals do not attempt to burgle alarmed homes more than once as reason to suggest that alarmed premises may be responsible for diverting crimes to non-alarmed locations.

While empiricism is rare, diversion has been examined theoretically by a number of researchers. Shavell (1991) shows that the level of observable precaution taken by households will be higher than the level of unobservable precaution, due to the negative

externality that diversion imposes. Since unobservable private precaution benefits the entire community, not just those homeowners who incur the costs of engaging in protection, fewer homeowners are likely to protect when security is unobservable. Clotfelter (1978) argues that since successful crimes result in losses to victims that are probably not offset by gains to criminals, the negative externality from the diversion effect results in an inefficiently large number of households employing security measures. What is the efficient number when the diversion effect is present? De Meza and Gould (1992) suggest that social efficiency requires all or no households to install burglar alarms. This result follows from their assumption that the expected loss from burglary is an increasing function of the number of households installing burglar alarms.

Of course, there are also arguments against the concern that burglar alarms displace crime. Blackstone and Hakim (1997) claim that their own and other research efforts find little support for the existence of displacement, citing Hakim and Rengert (1981). They fail to attribute any of the aforementioned differences in the probabilities of burglary of homeowners to diversion, and use the fact that only a small percentage of homeowners are actually alarmed as evidence that displacement is unlikely to occur until alarm ownership reaches a greater number of establishments. These arguments, however, primarily refer to temporal and crime type diversion. Furthermore, the work of Hakim and Rengert focuses on public enforcement. Since burglar alarms are a form of private precaution that are likely to cause target displacement, these arguments do not provide convincing evidence against the diversion effect.

Some economists argue that if in fact observable private precaution generates the

diversion effect, efforts should be made to either reduce the use of observable precaution or incentivize the use of unobservable precaution in order to eliminate the negative externality. Landsburg (1997) goes as far as calling observable precautionary measures, "socially wasteful." Di Tella, Galiani, and Schargrodsky (2002) suggest taxation or regulation of the private security industry as a way to eliminate the diversion effect. However, despite this suggestion, the use of some burglar alarm systems is actually subsidized. Homeowner's insurance companies subsidize the use of private security by offering their customers discounted homeowner's insurance premiums for employing the use of protective devices.

On average, homeowner's insurance companies offer protective device discounts that range between 1% and 25%. A survey by Hakim and Gaffney (1994) shows that homeowner's insurance companies enjoy net gains from offering these discounts. Hakim and Gaffney suggest that homeowner's insurance companies are willing to offer protective device discounts in order to attract customers, compete effectively with other companies, and encourage burglar alarm installation in order to lower the average insured loss due to burglary. Hakim (1996) describes a discount as being effective from an insurance company's perspective if two conditions are met: the value of claims saved from alarm systems outweighs the cost of offering discounts, and alarm buyers are aware of discounts prior to purchasing alarm systems.

CHAPTER 3

MEASURING THE NET EFFECT OF BURGLAR ALARMS ON BURGLARY RATES

My purpose in this chapter is to estimate the net effect, or the combined deterrence and diversion effects, of burglar alarms on burglary rates. This estimation is the motivation for teasing out the separate diversion effect associated with burglar alarms in chapters four and five.

3.1 Empirical Specification and Data Sources

The empirical specification I use to measure the net effect of burglar alarms on burglary rates is:

$$ln(BURGLARY_i) = \alpha + \beta ALARM_i + \lambda' CONTROL_i + \varepsilon_i \quad , \qquad (1)$$

where i indexes county. Analysis is conducted at the county level in the United States because crime displacement is likely to occur within short distances (Bowers and Johnson 2003). BURGLARY represents the per-capita burglary rate, α is the intercept, ALARM represents the fraction of homes with burglar alarms, CONTROL is a vector of control variables affecting the likelihood of residential burglary, λ is a conformable vector of parameters, and ε_i is an error term. Because BURGLARY is logged, β is interpreted as the percentage change in the per-capita burglary rate associated with a one percentage-point change in the fraction of homes using burglar alarms. For example, if β is estimated to be -2, a change from 0.50 to 0.51 in the fraction of homes using burglar alarms results in a 2% decrease in burglaries. β is the measure of the net effect of burglar alarms on burglary rates.

While previous research does not provide an independent measure of the actual deterrence effect, chapter two outlines convincing evidence that burglar alarms deter. The cited statistic that non-alarmed homeowners are burgled 5.2 times more than alarmed homeowners (Buck and Hakim 1992) suggests that the deterrence effect might even be quite large. Using this evidence to assume the existence of a significant deterrence effect associated with burglar alarms, two different findings regarding the net effect are possible if the diversion effect also exists. One possible finding is that ALARM is statistically significant and negatively related to burglary rates. In this case, it is the size of the net effect that offers support for whether or not diversion is present. A finding of a small net effect, converted to an elasticity for ease of interpretation, suggests that the overall effect of burglar alarms on burglary rates is small because diversion is muting the deterrence effect. However, without an independent estimate of the deterrence effect, I cannot rule out the possibility that a small net effect also suggests the presence of a small deterrence effect and negligible diversion effect. The other finding regarding the net effect that is possible if the diversion effect exists is that ALARM is statistically insignificant in determining burglary rates. This finding suggests that the presence of the diversion effect may be neutralizing the deterrence of burglar alarms, making the overall effect of burglar alarms on crime insignificant. Since it is improbable that the diversion effect is larger than the deterrence effect, β is unlikely to be positive.

To measure BURGLARY, I employ per-capita burglary rates, which are calculated using total number of burglaries and total population from Uniform Crime Reports County Data. Per the Uniform Crime Report, burglary is defined as "the unlawful entry of a

structure to commit a felony or theft, where the use of force is not necessary for entry." The FBI does not distinguish between residential and commercial burglaries.

Data on ALARM, the primary variable of interest, are not readily available. Previous empirical studies on the effectiveness of burglar alarms, including those mentioned in chapter two, rely on burglar alarm data from household questionnaires and police files. Such data are not available for my research. Contact with trade associations for the licensed security alarm industry and companies that insure households installing burglar alarms also failed to generate data sources. Therefore, as a proxy for the fraction of homes with burglar alarms in each county, I employ data on the nominal sales of security system services (in $1,000's) from the U.S. Census, Business and Industry Statistics Sampler, North American Industry Classification System (NAICS) 56162. NAICS 56162 is the industry classification that is comprised of establishments "engaged in selling security systems, such as burglar and fire alarms and locking devices, along with installation, repair, or monitoring services or remote monitoring of electronic security alarm systems." Data on security system services sales do not distinguish between the sale of residential and commercial security systems, between fire and burglar alarms, or between observable and unobservable devices. However, previous studies have found that a significant amount of revenue from security sales originates from residential burglar alarms: 58% of revenue comes from burglar alarms (Blackstone and Hakim 1997) and roughly 60% of new burglar alarms installed each year is residential (Blackstone, Hakim, and Spiegel 2000).

I face two significant obstacles when using U.S. Census data on security system services sales as a proxy for burglar alarm use. Because it is unlikely that all security system

services used throughout the year are purchased that year, total sales is not a direct measure of burglar alarm use. I specify that burglar alarm use is related to security system services sales through the following relationship:

$$ALARM\_STOCK_{it} = SALES_{it} + (1-\delta)\, ALARM\_STOCK_{it-5} \quad , \qquad (2)$$

where i refers to county and t refers to year. ALARM_STOCK[1] represents the total number of homes with burglar alarms installed, δ is the five-year depreciation rate (assumed to be 0.3[2]), and SALES represents the annual real receipts of establishments selling security system services. ALARM_STOCK is lagged by five on the right-hand side because of the frequency with which U.S. Census data on sales are available. Equation (2) suggests that the current year's use of burglar alarms is the sum of the current year's security system services sales and last period's use, taking depreciation into account. Recursively substituting $ALARM\_STOCK_{it-5}$, …., $ALARM\_STOCK_{it-5n}$ into (2), where n is the number of years prior to time t for which data are available, (2) becomes:

$$ALARM\_STOCK_{it} = SALES_{it} + (1-\delta)\, SALES_{it-5} + \ldots\ldots + (1-\delta)^n\, SALES_{it-5n} \ . \qquad (3)$$

I convert data on nominal security system services sales from the U.S. Census to real sales using the CPI (1982-84 dollars). ALARM_STOCK is divided by the total number of housing units in each county to obtain ALARM, which represents the fraction of protected homes[3]. Data on the total number of housing units are available only from decennial 100-percent U.S. Census reports, so annual data are linearly interpolated. The U.S Census

[1] ALARM_STOCK is the ALARM variable before it is converted to the fraction of homes using burglar alarms.
[2] Other values for the five-year depreciation rate are considered, as discussed in section 3.2.
[3] Gaffney and Hakim (1994) quote the average nominal price of a custom-designed alarm system to be $2,000. Using the CPI (1982-84 dollars), a nominal price of $2,000 converts to a real price of just slightly more than $1,000. Since SALES are denominated in $1,000, I can therefore approximate ALARM as the "fraction" of protected homes.

defines a housing unit as "a house, an apartment, a mobile home, a group of rooms, or a single room that is occupied (or, if vacant, is intended for occupancy) as separate living quarters." Because Business and Industry Statistics are only available every five years, the calculation of (3) is limited to the years of 2002, 1997, and 1992.

The second obstacle I face in using U.S. Census data to measure burglar alarm use is that in order to use (3), all U.S. counties in the sample are required to have security system services sales data in 2002, 1997, and 1992. However, sales data from NAICS 56162 are only available for the years of 2002 and 1997 because the industry classification did not exist until 1997. Furthermore, only 109 counties have sales data in both 2002 and 1997. The unavailability of sales data for all counties in both years is primarily due to the fact that security system services establishments do not operate in all counties in the United States. Data are also suppressed for counties with few sales in order to maintain company anonymity.

To overcome the problem of a small sample size, I employ a straightforward method for estimating security system services sales at the county level using murder rates in 2002, 1997, and 1992. This approach focuses on the perception that homeowners have of the prevalence of violent crime. The evening news and local newspaper are more likely to broadcast violent, rather than property, crime. Violent crimes are also more likely to shock homeowners into thinking that they live in a dangerous neighborhood, inducing the employment of private precautionary measures, such as burglar alarms. Using murder to predict SALES is econometrically sound because I do not use murder as a CONTROL variable in my specification measuring the net effect of burglar alarms on burglary rates.

Employing this argument, as well as the sample of 109 U.S. counties for which I am able to obtain data on security system services sales from the U.S. Census in both 2002 and 1997[4], I estimate the following specification to measure the effect of murder rates on burglar alarm sales:

$$ln(SALES_i) = \zeta + \varphi \ ln(MURDER_i) + \theta INCOME_i + \gamma UNITS_i + \nu_i \quad , \qquad (4)$$

where i corresponds to county, SALES represents real security system services sales, ζ is the intercept, MURDER is the number of murders, INCOME is per-capita real personal income, UNITS represents the number of housing units, and ν_i is an error term. Each of the three explanatory variables should be positively related to burglar alarm sales. Data on MURDER are obtained from Uniform Crime Reports County Data. Per the Uniform Crime Report, murder is considered to be a violent crime and is defined as "the willful (non-negligent) killing of one human being by another." Data on the total number of housing units are linearly interpolated from 100-percent U.S. Census reports. Per-capita nominal personal income data are available from the Regional Economics Information System, Bureau of Economics Analysis, and are converted to real values using the CPI (1982-84 dollars).

Table 3.1 presents the parameters obtained from (4) via Ordinary Least Squares (OLS) estimation. Although these results are not the focus of this chapter, it is interesting to note that murder is statistically significant and positively related to security system services sales[5]. The coefficient on MURDER is an elasticity measure of the responsiveness of SALES to instances of murder. Focusing only on those U.S. counties with SALES data in

[4] The observations from 2002 and 1997 are pooled without year-indicator variables.
[5] MURDER is found to be statistically insignificant when represented by the per-capita murder rate in the data.

2002, 1997, or both[6], I use the parameters in Table 3.1, in conjunction with data on MURDER, INCOME and UNITS in 2002, 1997, and 1992, to predict SALES for counties without U.S. Census sales data in the same years.

Literature on property crime and security dictate several control variables to be included in the specification measuring the net effect of burglar alarms on burglary rates. According to the literature on private security, determinants of residential burglary include home value, race of the homeowner, and age of the home. Buck, Hakim, and Rengert (1993) suggest that homes of higher value are more likely to be burgled, as well as newer houses and those owned by African Americans (Hakim and Gaffney 1995). Data on median age of housing units, nominal median value of housing units, and the number of African American homeowners are obtained from decennial sample U.S. Census reports. Annual data are linearly interpolated. Data on real median value of housing units are preferred, but an annual housing price index at the county level is difficult to obtain. Data on the number of African American homeowners are converted to a percentage of the population using population data from Uniform Crime Reports County Data.

Explanatory variables suggested by property crime literature include the unemployment rate and age distribution. Chiricos (1987) and Freeman (1996) argue that property crime is negatively related to employment, and Blumstein et al. (1986) suggest that the prevalence of criminal involvement drops after the teen years. Data on the unemployment rate are obtained from the Bureau of Labor Statistics. To represent age

[6] This sample includes 219 counties. It is different than the smaller sample of 109 counties used to generate Table 3.1 results because it includes counties with at least one observation of SALES data in 2002, 1997, *or* both.

distribution, I use the percentage of the population aged 0-17, 18-24, and 25-44. The percentage of the population aged 44+ is omitted from the sample. Annual data are linearly interpolated from decennial data from County and City Data Books. In addition to these CONTROL variables, dummy variables are included to represent the geographical region of the counties in the sample because FBI statistics show that the prevalence of burglary differs between national regions. According to the 2004 FBI publication of "Crime in the United States," the South, West, Midwest, and Northeast regions of the U.S. account for 45.2%, 23.9%, 19.8%, and 11% of all burglaries, respectively. The boundaries of the geographical regions are defined by the FBI. The dummy variable for the Western region is omitted.

It is important to note that previous literature also establishes the theoretical importance of size of the police force and income in explaining burglary rates. Levitt (1997) and Marvell and Moody (1986) argue that increased numbers of police reduce crime. The Bureau of Justice Assistance Annual Crime Victim Survey (1999) reports that residential burglaries tend to concentrate around low-income families, while Buck, Hakim, and Porat (1992) argue that households with higher income are more susceptible to theft. However, when including size of the police force and income as explanatory variables in estimating the net effect of burglar alarms on burglary rates[7], results suggest the existence of multicollinearity. Because of their correlation with ALARM, the inclusion of these variables increases the standard error of ALARM and leads to its statistical insignificance. Intuitively, size of the police force and ALARM are inversely related because of the substitutability

[7] When including these variables, I use data on the total number of sworn officers from the FBI's 2002 "Crime in the United States" and city and county police department websites and per-capita nominal personal income (converted to real using the CPI) from the Regional Economics Information System, Bureau of Economics Analysis.

between private and public protection. The correlation between ALARM and income is due to the fact that wealthier homeowners are more likely to employ burglar alarm services, as suggested by Table 3.1 results. As a result of their correlation with ALARM, I omit both size of the police force and income from my final specification measuring the net effect of burglar alarms on burglary rates. However, their effects are likely to be captured by other variables in the specification with which they are also correlated. Specifically, size of the police force is correlated with the percentage of African American homeowners and income is correlated with nominal median house value. Future research will explore the possibility of eliminating multicollinearity using a larger sample while including size of police force and income as explanatory variables in measuring the net effect of burglar alarms on burglary rates.

Summary statistics for the data used in the measurement of the net effect of burglar alarms on burglary rates are presented in Table 3.2. In order to employ the use of (3), estimation is conducted only for 2002, which means that data on security system services sales from 2002, 1997, and 1992 are used in the construction of ALARM. The final sample consists of data for 219 U.S. counties.

3.2 Results and Discussion

Although an estimate of β from (1) is initially obtained using OLS, it is possible that the employment of burglar alarm services in a given county is endogenous. That is, although burglar alarms likely induce a change in county-level burglary rates, it is also possible that higher burglary rates motivate the use of burglar alarms. This endogeneity makes OLS estimates inconsistent. As a result, I also employ Two-Stage Least Squares (2SLS) analysis

and use the number of security system services establishments by county in 2002 and 1997 as separate instruments for ALARM. The number of security system services establishments is considered a valid instrument because although counties with higher burglary rates may have more security system services establishments, the number of establishments is unlikely to respond contemporaneously to changes in burglaries. County-level data on the number of security system services establishments are obtained from the U.S. Census Bureau, Business and Industry Statistics Sampler, NAICS 56162. Data on the number of security system services establishments are available for the same counties for which original security system services sales data are available. For counties without data on the number of establishments in either 2002 or 1997, I use the number of establishments from the year in which data are available, since the number of establishments in a county is unlikely to change drastically within a 5-year period. Summary statistics for the data used for the 2SLS instruments are also included in Table 3.2.

Table 3.3 presents estimation results. Column A provides OLS results, column B provides 2SLS results using the number of security system services establishments in 2002 and in 1997 as separate instruments, and column C provides 2SLS results using the average number of security system services establishments between the years of 2002 and 1997 as one instrument. As seen from Table 3.3, OLS estimation finds that ALARM is negatively related to burglary rates, but statistically significant only at the 12% level. The 2SLS regressions find that the coefficient on ALARM has the expected negative sign, but is statistically insignificant with a t-statistic less than one. The net effect is also estimated to be larger in the 2SLS regressions. Since the determination of which estimation technique is

consistent depends on whether or not ALARM is endogenous, a Hausman Test is conducted. The Hausman test shows that ALARM is not endogenous. Although this result is surprising, it is consistent with the theory used to predict SALES data, which suggests that violent, rather than property, crime has a significant impact on burglar alarm use. Confidence is therefore placed in OLS estimation of the net effect of burglar alarms on burglary rates. If it is the case that the 2SLS results and finding of the Hausman test are due to weak instruments, rather than the lack of endogeneity, OLS results are still informative in the sense that they only underestimate the true value of β. Since burglary rates are likely to have a positive effect on the use of burglar alarms and I estimate the net effect of burglar alarms on burglary rates to be negative, endogeneity would have the effect of increasing the probability limit of my estimator of β[8].

According to OLS results, a one percentage-point increase in the fraction of homes using burglar alarms leads to roughly a 0.46% decrease in burglary rates[9]. This decrease in burglary rates is quite small, when compared to the finding of Ayres and Levitt (1998) that auto-theft rates decrease by 7% due to a one percentage-point increase in the use of Lojack. To better understand the magnitude of this change, I interpret OLS results in terms of the decrease in the number of burglaries per year due to the use of a burglar alarm by one homeowner. Evaluated at the mean values of BURGLARY and ALARM, the results in

[8] In the presence of endogeneity, the probability limit of my OLS estimate of β would be equal to the sum of the true estimate of β and COV(ALARM,ε)/VAR(ALARM). COV(ALARM,ε)>0 because ε and BURGLARY are positively related, and if BURGLARY were to induce changes in ALARM, their relationship is also likely to be positive. Since VAR(ALARM) is also positive, endogeneity would therefore have the effect of increasing the probability limit of my estimate of β, which I estimate to be negative.

[9] In other words, an increase in the fraction of homes using alarms from 0% to 100% leads to a 46% decrease in burglary rates.

Table 3.3 are consistent with one alarmed home decreasing the number of committed burglaries by 0.45 per year[10]. In other words, it takes approximately three alarmed homes to decrease the number of committed burglaries per year by one. I also calculate a measure of the elasticity of burglary rates with respect to the fraction of homes with burglar alarms for each of the three regressions in Table 3.3. According to Column A, a 1% increase in the fraction of homes[11] installing burglar alarms leads to a 0.06% decrease in burglary rates. Since empirical evidence overwhelmingly shows that burglar alarms deter crime at alarmed homes, the fact that burglary rates respond little to burglar alarms, coupled with the relative statistical significance of ALARM, suggests that the diversion effect may be present.

The statistically significant CONTROL variables in the specification include the percentage of African American homeowners at the 0.01% level, the unemployment rate at the 0.01% level, the percentage of the population aged 25-44 at the 0.02% level, and the dummy variables representing the Northeast and Midwest regions of the U.S. at the 2% and 0.3% levels, respectively. The explanatory power of median age of house and nominal median house value may already be captured by the ALARM variable, as newer and more expensive homes are more likely to install alarms. For those CONTROL variables that are statistically significant, all except the percentage of the population aged 25-44 have the predicted effect. Calculations of elasticities measuring the responsiveness of burglary rates to changes in each significant CONTROL variable reveal that burglary rates respond inelastically to changes in all, except for the 25-44 age group (relative to the omitted age

[10] For cities with more (fewer) housing units, this numerical example overestimates (underestimates) the decrease in the number of burglaries due to the use of a burglar alarm by one homeowner.
[11] Note that a 1% change in the fraction of homes using burglar alarms is different and smaller than a one percentage-point change.

group). Finally, it is important to note that changes in the assumed value of depreciation of burglar alarms do not affect the statistical significance of ALARM in explaining burglary rates. However, the significance level of ALARM decreases in OLS estimation when I assume a larger value for depreciation.

3.3 Joint Estimation of the Diversion Effect and Unobserved Sales Using a Bayesian Estimator

Although the method I use to estimate security system services sales data in section 3.1 successfully increases the sample size for measuring the net effect of burglar alarms on burglary rates, the increase is not large given that the U.S. Census Bureau recognizes over 3,000 counties in the United States. Since data for all other variables in (1) and (4), except SALES, are available for 3,034 counties, the results of section 3.2 leave much to be desired. In this section, I conduct a robustness check of the measure of the net effect of burglar alarms on burglary rates described in section 3.2 using a larger sample of 3,034 U.S. counties. Since SALES are unobserved for the majority of the 3,034 counties, I estimate the net effect using a Bayesian technique that also generates security system services sales data for counties without original data in the years of 2002, 1997, and 1992. The fundamental methodology behind the estimation of security system services sales data is still based on (4), ALARM is still generated from data on security system services sales in 2002, 1997, and 1992 according to (3), and Bayesian estimation of the net effect of burglar alarms on burglary rates for the year of 2002 remains consistent with (1). Observed data for the sample of 3,034 counties are

collected from the same sources described in section 3.1[12].

For simplicity in explaining my Bayesian algorithm, denote X as [INTERCEPT MURDER INCOME UNITS], Z as [INTERCEPT ALARM CONTROL], Θ as [ζ φ θ γ]', Γ as [α β λ]', S as ln(SALES), Y as ln(BURGLARY), and variables with * as representative of the final sample of 3,034 U.S. counties. Define n as equal to all 3,034 counties in the final sample, and T as 3, the number of years for which U.S. Census SALES data are available.

The parameter vector of interest is Γ, which contains the parameter β that measures the net effect of burglar alarms on burglary rates in (1). My primary objective is to jointly estimate security system services sales for counties with missing data and posterior distributions for Γ, based on the observed data. The difficulty in using the joint conditional posterior distribution of unobserved SALES and Γ to estimate unobserved SALES and Γ is that it is not explicitly known. However, I do know the individual conditional distributions of SALES and Γ. Assuming a diffuse Jeffries prior on σ^2_υ, σ^2_υ is distributed as:

$$f(\sigma_\nu^2 \mid S^*, X^*, \Theta) \sim \textit{inverse gamma } ((a + nT/2), (b + ((S^* - X^*\Theta)'(S^* - X^*\Theta)/2))) \quad . \qquad (5)$$

The conditional distribution of unobserved SALES data is:

$$f(S \mid X^*, \Theta, \sigma_\nu^2) \sim \textit{random normal } (X^*\Theta\,,\ \sigma_\upsilon^2) \quad , \qquad (6)$$

and the conditional distribution of Γ is:

$$f(\Gamma \mid Y^*, Z^*, \sigma_\varepsilon^2) \sim \textit{multivariate student-T } ((Z^{*\prime}Z^*)^{-1}(Z^{*\prime}Y^*), (\sigma_\varepsilon^2)(Z^{*\prime}Z^*)^{-1}) \quad . \quad (7)$$

[12] Bayesian estimation is only used to generate SALES data. Data for all other variables in the specification are available for all years from these sources.

Because the individual conditional distributions outlined above are known, I can therefore jointly estimate unobserved SALES and Γ using a Gibbs Sampler, rather than integrating over the joint distribution with respect to SALES*. A Gibbs Sampler is an algorithm that generates a sequence of samples from the joint distribution of two or more random variables. The process produces an instance from each of the unknown variables, conditional on the current values of observed variables. The sequence of samples comprises a Markov Chain, and the stationary distribution of that Markov Chain is the sought-after joint distribution of the unobserved variables, which in this case are SALES and Γ (Gelman et al. 1995).

Logistically, I start the Gibbs Sampler by simulating draws of S* from a random normal distribution with mean $X^*\Theta$ and variance σ^2_υ. Merging these draws with CONTROL*, I then derive the posterior distributions of Γ from a multivariate student-T distribution with mean $(Z^{*\prime}Z^*)^{-1}(Z^{*\prime}Y^*)$, variance $(\sigma^2_\varepsilon)(Z^{*\prime}Z^*)^{-1}$, and degrees of freedom equal to 3,022. The distribution of Γ is assumed to be multivariate student-T, rather than normal, because σ^2_ε is unknown[13]. The specifics of the implementation are described in the algorithm below:

a. To obtain starting values of σ^2_υ and Θ, regress S on X for the sample of counties from section 3.2 for which SALES data are available in the years 2002, 1997, or both.

b. To obtain starting values for S*, draw S for the counties for which SALES data are not originally available from a random normal distribution with mean $X\Theta$ and variance σ^2_υ. Merge the draws with original SALES data.

[13] However, as the number of degrees of freedom increases, a random draw that follows the multivariate student-T distribution approaches the normal distribution (Rowe 2003). With a sample size of 3,034 U.S. counties, this is likely to be the case here. For precision, I rely upon multivariate student-T results.

c. Update Θ using a multivariate normal distribution with mean $(X^{*\prime}X^{*})^{-1}(X^{*\prime}S^{*})$ and variance $(\sigma_{\upsilon}^{2})(X^{*\prime}X^{*})^{-1}$.

d. Update σ^2_{ν} using an inverse gamma distribution with mean (a + nT/2) and variance (b + ((S* - X*Θ)'(S* - X*Θ)/2)).

e. Using the updated σ^2_{ν} and Θ , draw new S for counties without original SALES data from a random normal distribution with mean X*Θ and variance σ_{υ}^{2}. Merge with original SALES data to update S*.

f. Take exponential of S* to obtain SALES* and separate according to year, t.

g. Assuming a value of 0.3 for depreciation, calculate ALARM_STOCK* according to (2).

h. Divide ALARM_STOCK* by UNITS* to obtain ALARM*.

i. Regress Y* on Z* to measure the net effect of burglar alarm on burglary rates, where Z* consists of ALARM* from h. and CONTROL*.

j. Collect σ^2_{ε} from i.

k. Draw Γ from a multivariate student-T distribution with mean $(Z^{*\prime}Z^{*})^{-1}(Z^{*\prime}Y^{*})$ and variance $(\sigma_{\varepsilon}^{2})(Z^{*\prime}Z^{*})^{-1}$.

l. Iterate steps c.-k. many times, using the most recently updated parameters and S*.

The means, standard deviations, and posterior probability intervals for the posterior distributions of Γ based on 2,000 iterations[14] are shown in Table 3.4. Figures 3.1 – 3.12 represent histograms of the posterior distributions for the different elements of Γ based on 2,000 iterations and 500 burns. The histogram of the posterior distribution of the elasticity of BURGLARY with respect to ALARM is shown in Figure 3.13. As expected, the histograms

[14] The first 500 draws are discarded.

reveal both normality, due to the large sample size, and the thicker tails of the multivariate student-T distribution.

As described in section 3.1, the size of the coefficient on ALARM is important in understanding the net effect of burglar alarms on burglary rates. How does the size of the coefficient on ALARM change with a larger sample size? In analyzing the mean of the posterior distribution of the coefficient on ALARM in Table 3.4, it is clear that the size of the estimated net effect actually increases with the larger sample. With the larger sample, for every one percentage-point increase in the fraction of homes using burglar alarms, per-capita burglary rates fall on average by 1.22%. This is consistent with one alarmed homeowner decreasing the number of committed burglaries by two per year. To further understand the magnitude of this relationship, I calculate the elasticity of BURGLARY with respect to ALARM, evaluated at the mean of ALARM. Table 3.4 shows that this elasticity is -0.56, suggesting that a 1% increase in burglar alarm use leads to a 0.56% decrease in burglaries. Although this is larger than the small-sample estimate, burglary rates continue to respond inelastically to burglar alarm use. Additionally, the decrease in burglary rates is still considerably smaller than the decrease in auto-theft rates associated with Lojack.

The statistical significance of ALARM is another way to understand the net effect of burglar alarms on burglary rates. Although discussion on statistical significance is more of a Frequentist, rather than Bayesian, analysis, I compute an implicit t-statistic for ALARM and each of the CONTROL variables in order to be consistent with the discussion on statistical significance in section 3.2. Implicit t-statistics are provided in Table 3.4. Implicit t-statistics are calculated as the ratio of the means to the standard deviations of the posterior

distributions in Table 3.4.

ALARM is statistically significant at the 0.01% level in the large Bayesian sample, which is an improvement over the small sample result in section 3.2. This finding, coupled with the inelastic response of per-capita burglary rates to burglar alarm use in both the small and large samples and previous evidence of deterrence, supports the possible presence of the diversion effect. In terms of the CONTROL variables, all are statistically significant at a level of at least 5%, based on their calculated implicit t-statistics, with the exception of median age of house, the unemployment rate, the percentage of the population aged 25-44, and the dummy variables representing the Northeast and Southern regions of the U.S. The means of the posterior distributions of the coefficients on the statistically significant CONTROL variables all have the expected signs according to previous literature.

3.4 Conclusion

Homeowners employ private precautionary measures to decrease the likelihood that their property will be burgled. When these precautionary measures are observable to criminals, potential burglars likely divert crime to unprotected homes. Both these deterrence and diversion effects arise when burglar alarms are installed. In this chapter, I measure the combination of these two effects by analyzing how burglary rates respond to burglar alarm use. I find that increases in the fraction of households with burglar alarms are associated with only slight decreases in burglary rates. I arrive at this conclusion by overcoming a significant hurdle in data collection, using sales of security system services as a proxy for the fraction of households with burglar alarms, and generating missing data using murder rates.

My finding that burglary rates respond inelastically to burglar alarms for a large sample of U.S. counties, coupled with the evidence that burglar alarms deter criminals, is consistent with the diversion effect muting the effectiveness of observable precautionary measures. The decrease in burglary rates is also much smaller than the decrease in crime rates associated with unobservable private precautionary measures, such as Lojack. Although the size of this diversion effect alone is not discernable from my measure of the net effect of burglar alarms on burglary rates, the findings of this chapter are important to consideration of policy and supports the research devoted to estimating the size of the diversion effect in chapters four and five of this dissertation.

Table 3.1: Parameters Used in Prediction of Sales Data

Variable	Estimate
INTERCEPT	6.13 *0.25*
MURDER, 2002 and 1997: total number of murders	0.34 *0.048*
INCOME, 2002 and 1997: real per-capita personal income	0.00011 *0.000011*
UNITS, 2002 and 1997: total number of housing units	0.00000087 *0.00000016*
No. of Observations	216
R^2	0.58

** Standard errors are in itallics.*

Table 3.2: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
BURGLARY, 2002: per-capita burglary rate (x1000)	0.99	0.54	0.07	3.28
ALARM, 2002: fraction of homes with burglar alarms	0.16	0.12	0.041	1.074
CONTROL, 2002:				
% African American homeowners (of population)	4.76	5.13	0.063	23.62
Median age of house (since built)	28.22	8.51	7.80	54.80
Nominal median house value	153,166.21	74,250.60	55,700.00	546,680.00
Unemployment rate	5.65	1.64	3.00	15.00
% aged 0-17 (of population)	26.10	2.82	14.30	34.80
% aged 18-24 (of population)	9.25	3.21	2.020	32.020
% aged 25-44 (of population)	30.62	3.035	21.92	43.14
Dummy variable - located in Northeast region of U.S.	0.18	0.38	0.00	1.00
Dummy variable - located in Southern region of U.S.	0.35	0.48	0.00	1.00
Dummy variable - located in Midwest region of U.S.	0.21	0.40	0.00	1.00
Instruments:				
No. security system services establishments, 1997	23.63	31.35	3.00	349.00
No. security system services establishments, 2002	24.47	31.77	3.00	344.00
Avg. no. security system services establishments, 1997 and 2002	24.05	31.46	3.00	346.50
No. of Observations	219			

Table 3.3: Regression Results on the Net Effect of Burglar Alarms on Burglary Rates

Variable	A	B	C
INTERCEPT	1.42	1.66	1.66
	0.63	*0.69*	*0.70*
ALARM, 2002: fraction of homes installing alarms	-0.46	-1.65	-1.68
	0.30	*2.081*	*2.086*
CONTROL, 2002:			
% African American homeowners (of population)	0.035	0.035	0.035
	0.0079	*0.0083*	*0.0083*
Median age of house (since built)	-0.0043	-0.0036	-0.0036
	0.0060	*0.0064*	*0.0064*
Nominal median house value	-1.18E-07	-1.14E-07	-1.13E-07
	5.37E-07	*5.69E-07*	*5.70E-07*
Unemployment rate	0.10	0.11	0.11
	0.026	*0.028*	*0.028*
% aged 0-17 (of population)	-0.0096	-0.0073	-0.0072
	0.015	*0.016*	*0.016*
% aged 18-24 (of population)	-0.015	-0.014	-0.014
	0.012	*0.013*	*0.013*
% aged 25-44 (of population)	-0.050	-0.054	-0.054
	0.013	*0.013*	*0.013*
Dummy variable - located in Northeast region of U.S.	-0.32	-0.32	-0.32
	0.14	*0.15*	*0.15*
Dummy variable - located in Southern region of U.S.	-0.21	-0.23	-0.23
	0.12	*0.12*	*0.12*
Dummy variable - located in Midwest region of U.S.	-0.37	-0.38	-0.38
	0.13	*0.13*	*0.13*
Elasticity of BURGLARY with respect to ALARM (evaluated at mean of ALARM)	-0.06	-0.22	-0.23
R^2	0.34	0.32	0.32

** Omitted age group is % aged 44+. Omitted geographical region is Western Region of the U.S. Standard errors are in itallics.*

Table 3.4: Summary Statistics for Parameter Posterior Distributions of Regression Coefficients, Γ

Variable	Mean	Standard Deviation	Implicit t-statistic	Posterior Probability Interavals	
				Lower Bound	***Upper Bound***
INTERCEPT	-2.34	0.59	-3.94	-3.30	-1.33
ALARM, 2002: Fraction of homes installing alarms	-1.23	0.081	-15.21	-1.36	-1.10
CONTROL, 2002:					
% African American homeowners (of population)	0.052	0.0099	5.28	0.036	0.069
Median age of house (since built)	-0.0013	0.0010	-1.30	-0.0030	0.00040
Nominal median house value	2.34E-06	1.10E-06	2.13	5.53E-07	4.20E-06
Unemployment rate	0.035	0.025	1.38	-0.0086	0.077
% aged 0-17 (of population)	0.054	0.014	3.81	0.031	0.058
% aged 18-24 (of population)	0.036	0.014	2.61	0.013	0.058
% aged 25-44 (of population)	-0.0038	0.017	-0.22	-0.031	0.024
Dummy variable - located in Northeast region of U.S.	0.31	0.21	1.49	-0.030	0.65
Dummy variable - located in Southern region of U.S.	0.32	0.17	1.92	0.056	0.60
Dummy variable - located in Midwest region of U.S.	-1.23	0.15	-8.03	-1.49	-0.98
Elasticity of BURGLARY with respect to ALARM (evaluated at mean of ALARM)	-0.56			-0.62	-0.50

** Distributions are based on 2,000 iterations and 500 burns.*

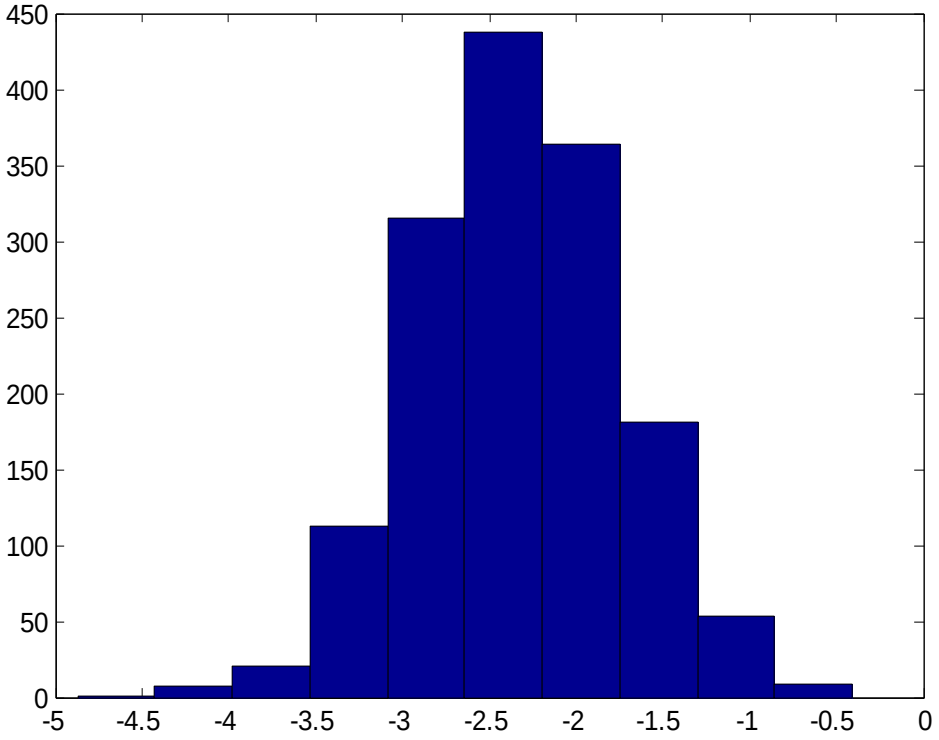

Figure 3.1: Posterior Distribution of Bayesian Parameter Estimates of INTERCEPT Based on 2,000 Iterations and 500 Burns

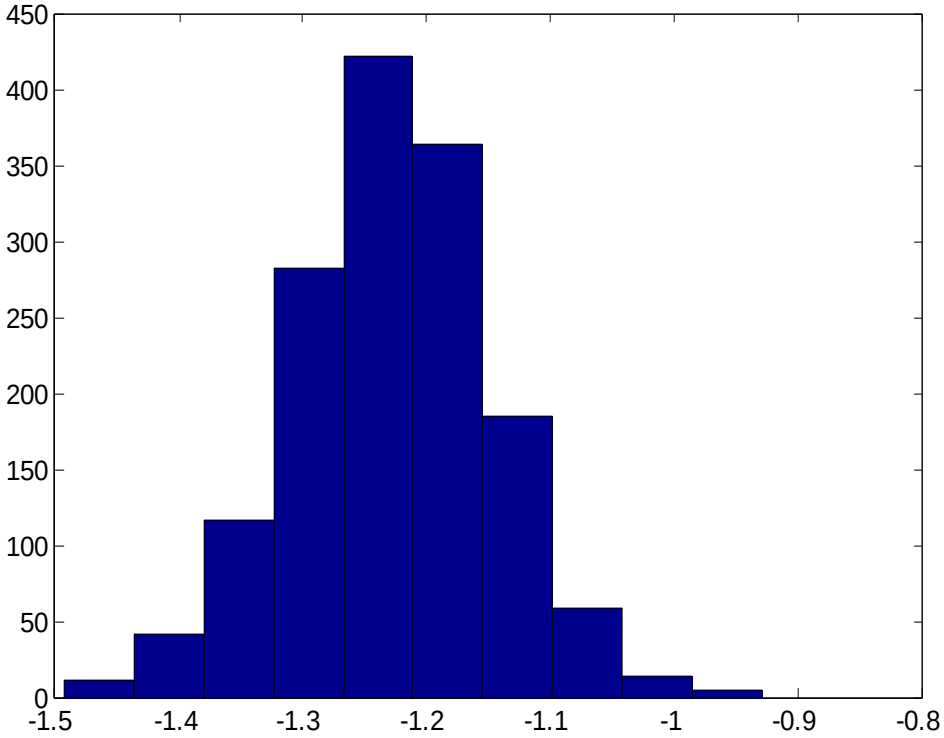

Figure 3.2: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on ALARM Based on 2,000 Iterations and 500 Burns

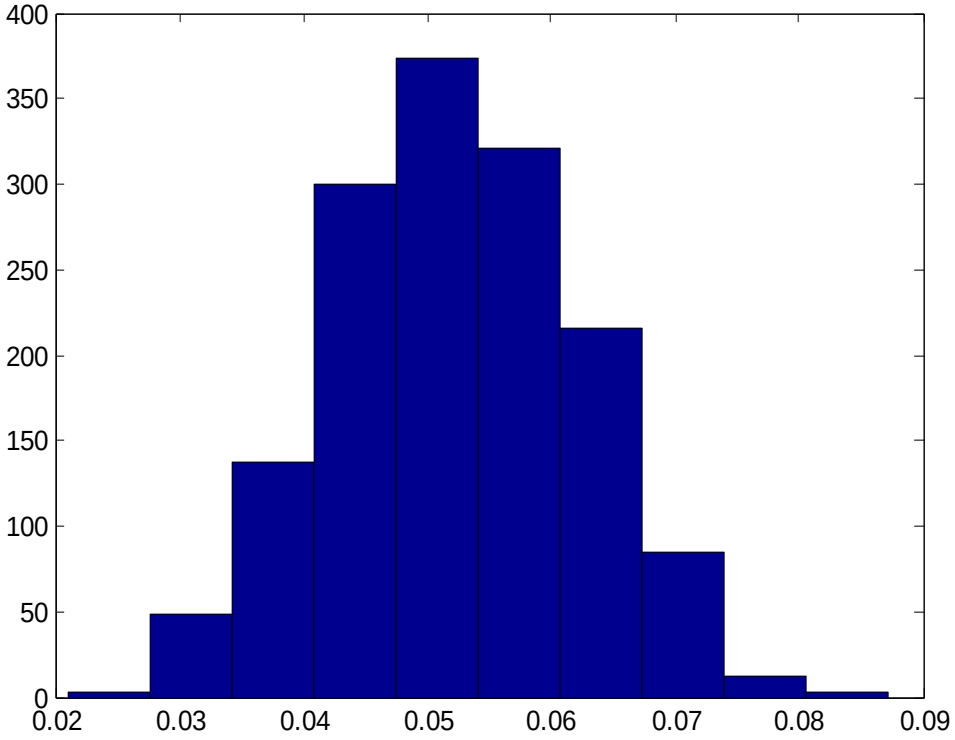

Figure 3.3: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on % African American Homeowners (CONTROL) Based on 2,000 Iterations and 500 Burns

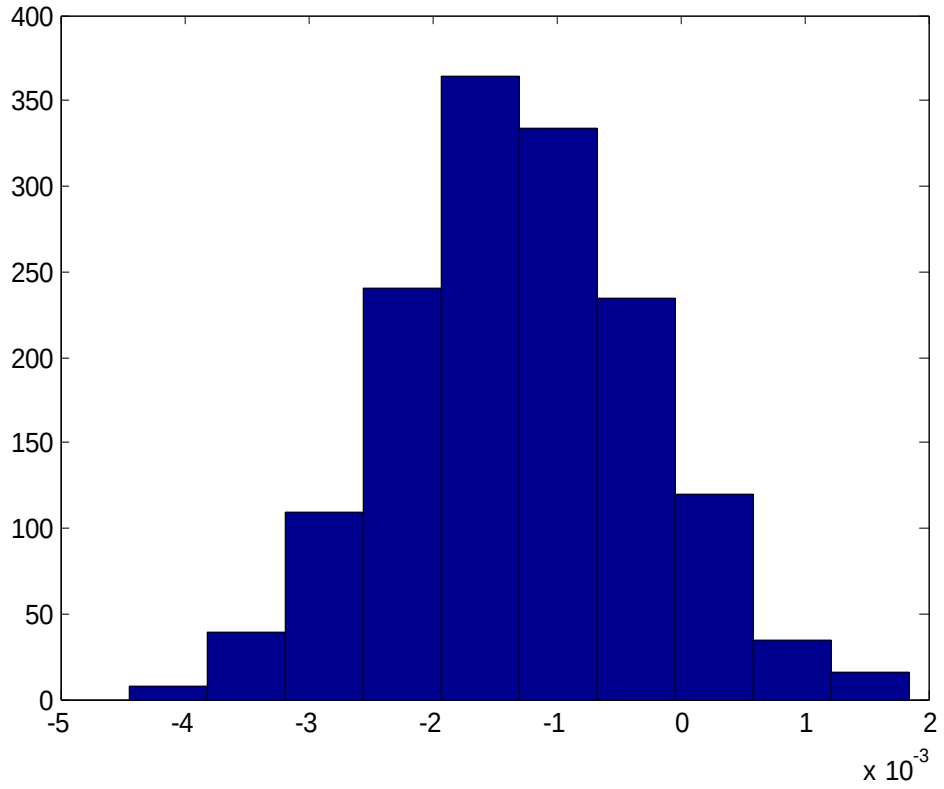

Figure 3.4: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on Median Age of House (CONTROL) Based on 2,000 Iterations and 500 Burns

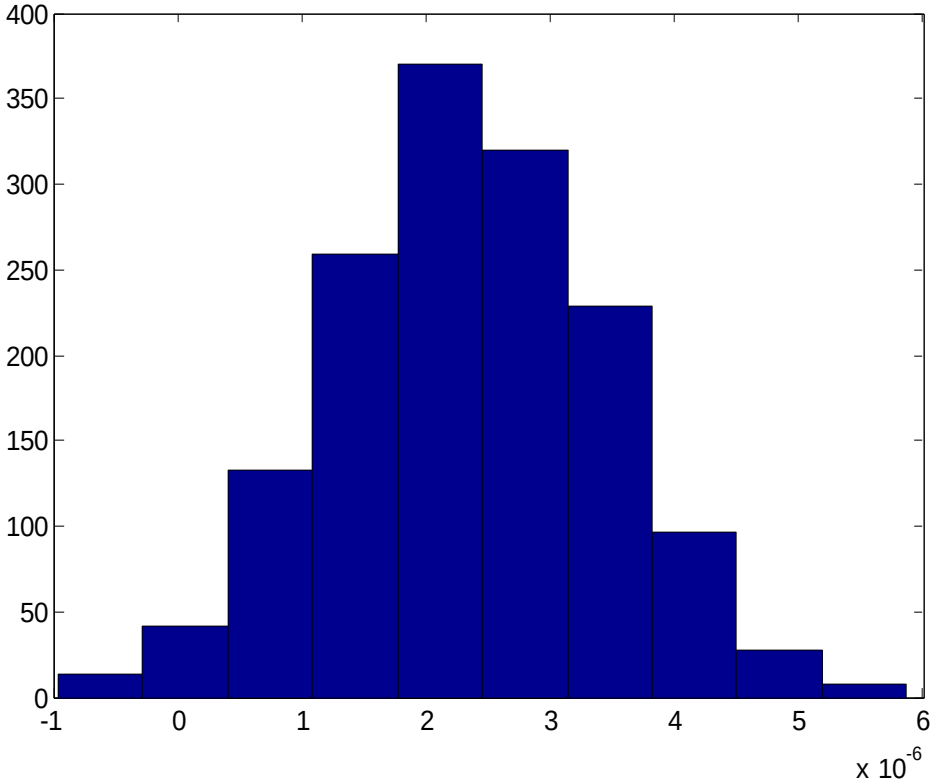

Figure 3.5: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on Nominal Median House Value (CONTROL) Based on 2,000 Iterations and 500 Burns

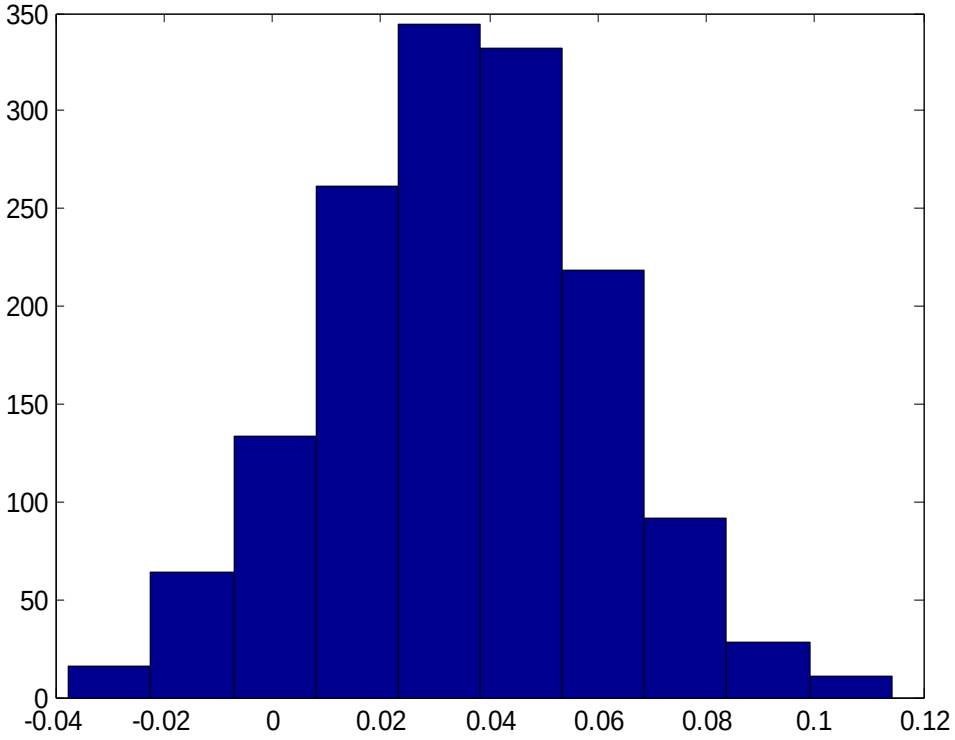

Figure 3.6: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on Unemployment Rate (CONTROL) Based on 2,000 Iterations and 500 Burns

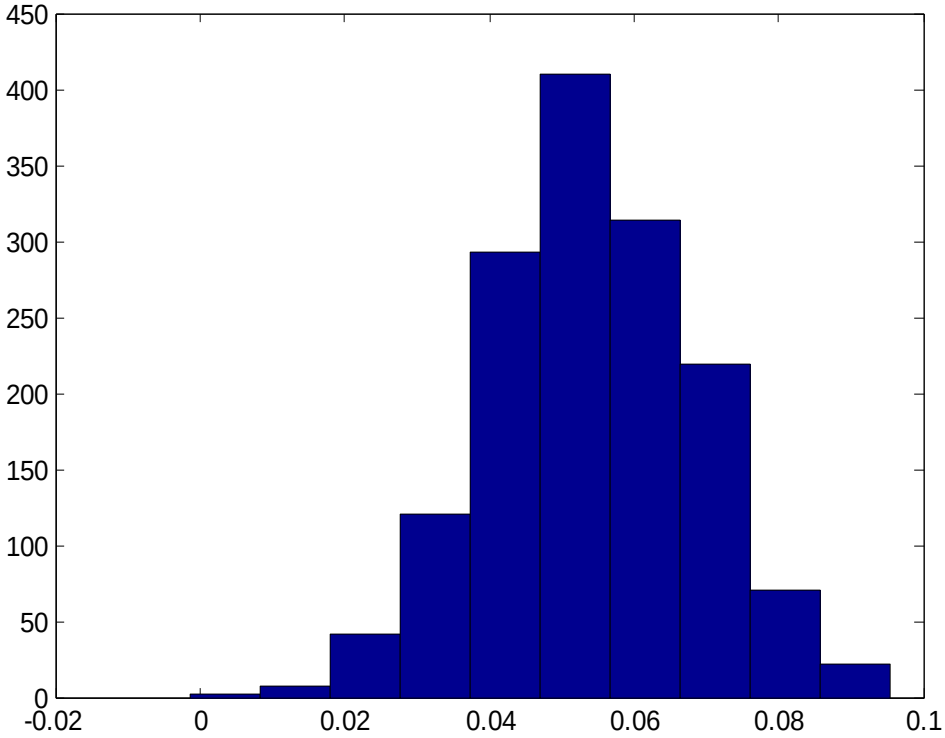

Figure 3.7: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on % Aged 0-17 (CONTROL) Based on 2,000 Iterations and 500 Burns

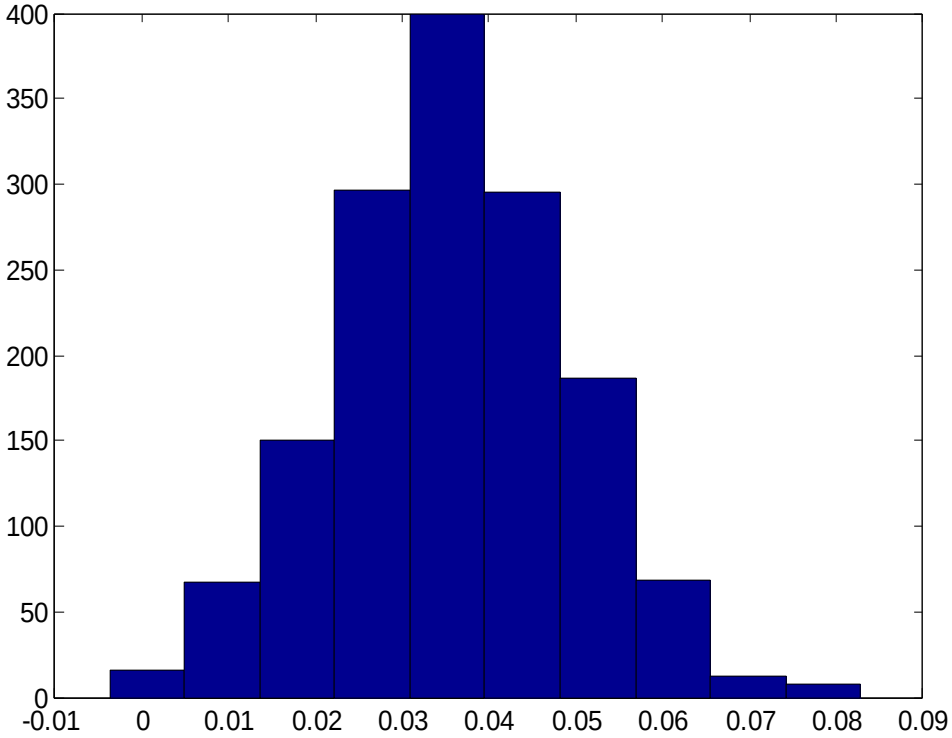

Figure 3.8: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on % Aged 18-24 (CONTROL) Based on 2,000 Iterations and 500 Burns

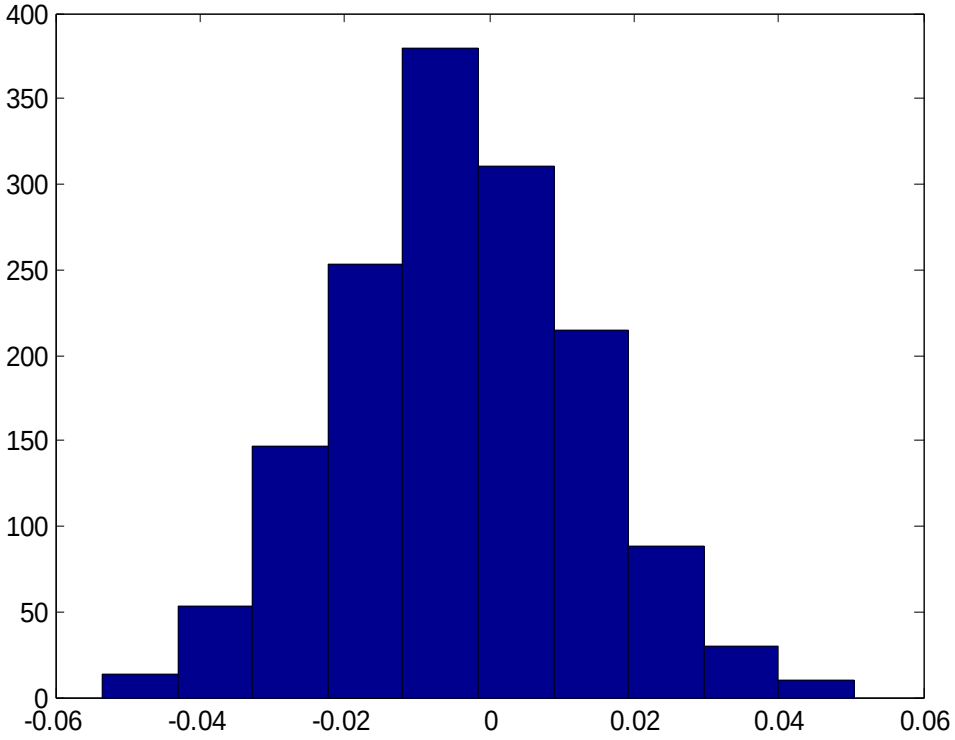

Figure 3.9: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on % Aged 25-44 (CONTROL) Based on 2,000 Iterations and 500 Burns

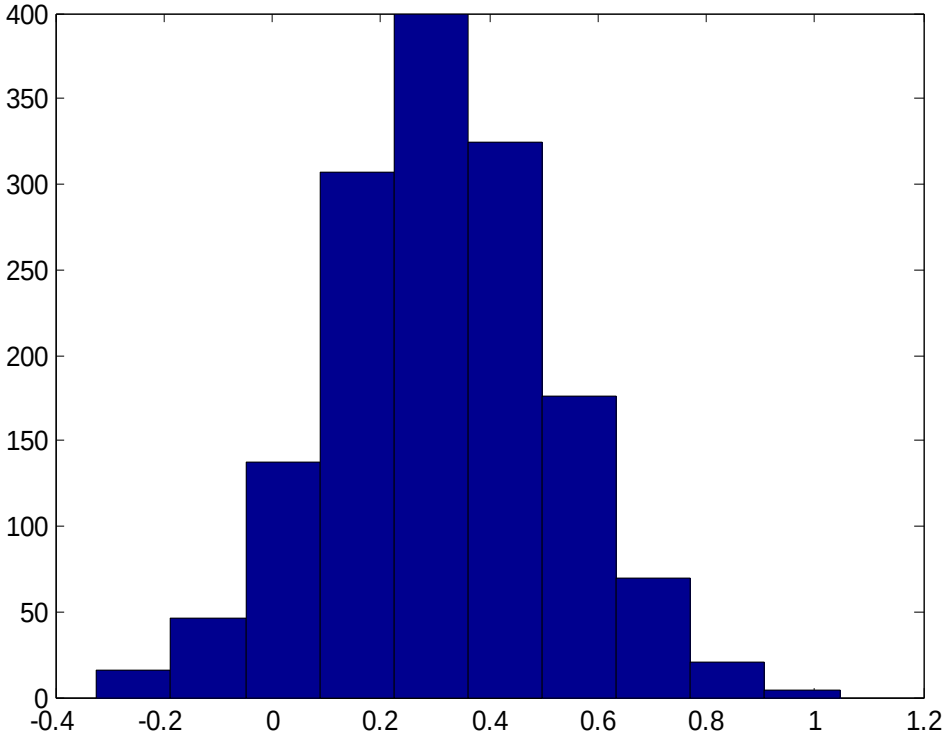

Figure 3.10: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on Northeast Region Dummy Variable (CONTROL) Based on 2,000 Iterations and 500 Burns

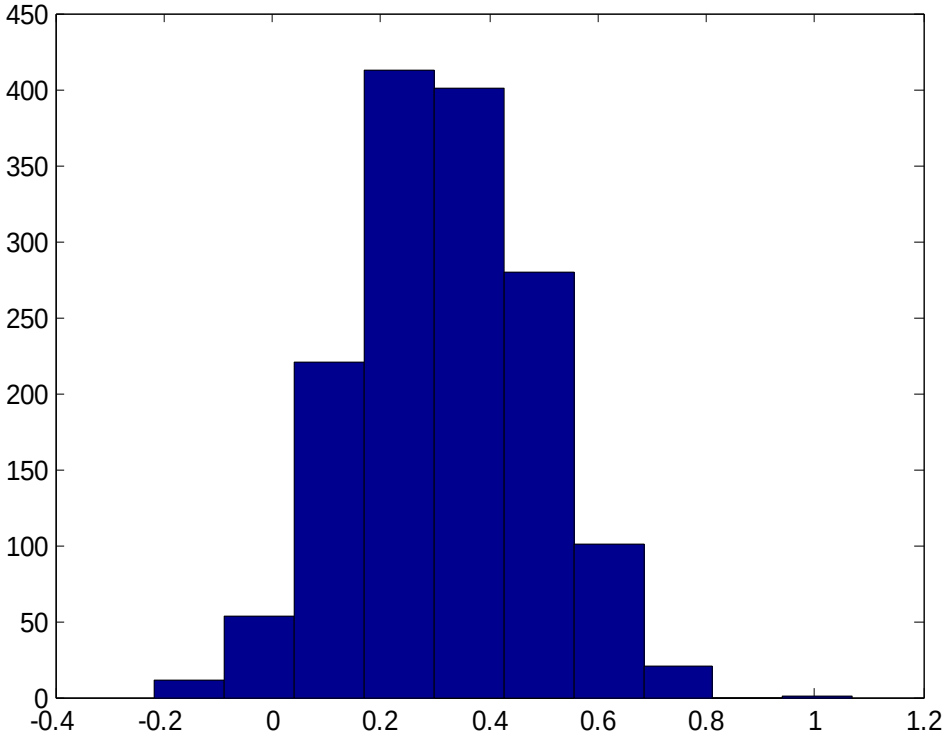

Figure 3.11: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on Southern Region Dummy Variable (CONTROL) Based on 2,000 Iterations and 500 Burns

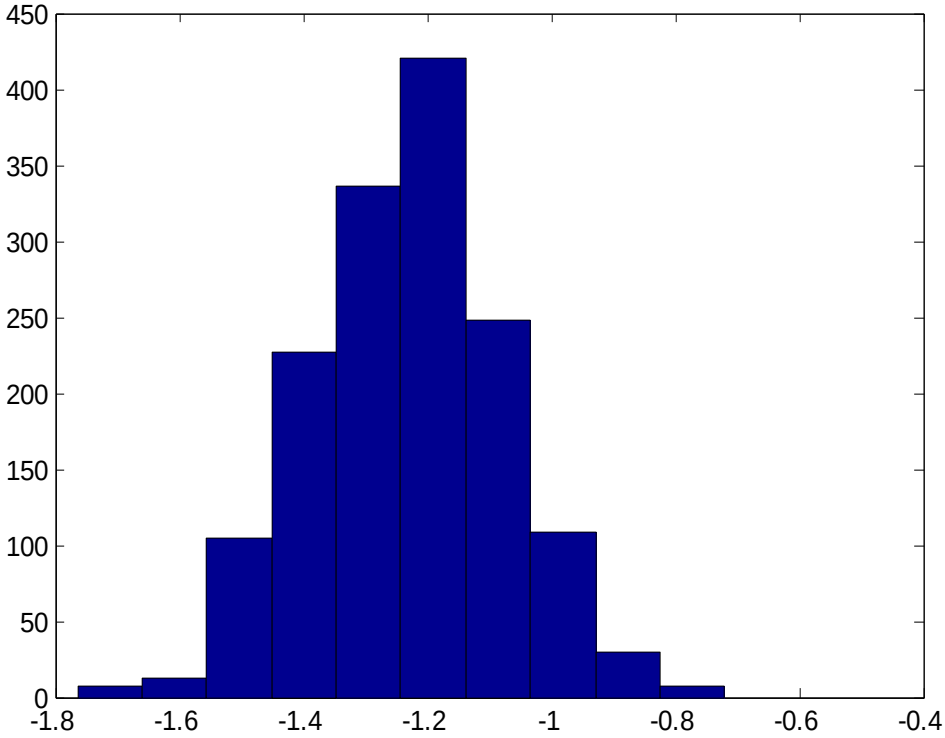

Figure 3.12: Posterior Distribution of Bayesian Parameter Estimates of Coefficient on Midwest Region Dummy Variable (CONTROL) Based on 2,000 Iterations and 500 Burns

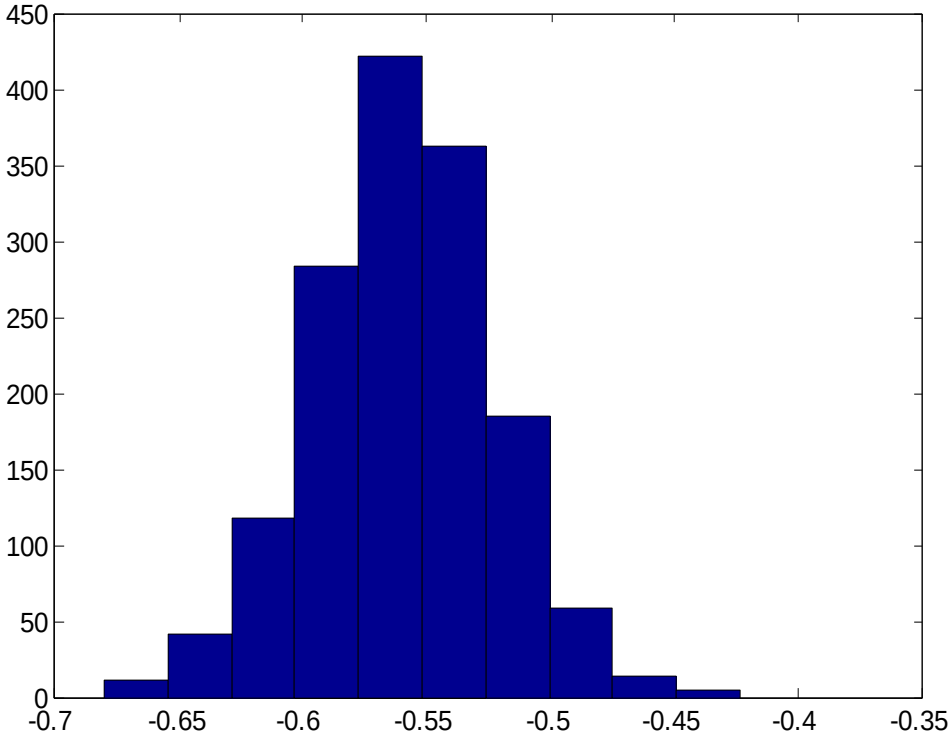

Figure 3.13: Posterior Distribution of Bayesian Estimates of Elasticity of Burglary Rates with respect to ALARM Based on 2,000 Iterations and 500 Burns

CHAPTER 4

USING THE RELATIONSHIP BETWEEN HOMEOWNER'S INSURANCE COMPANY MARKET SHARES AND PROTECTIVE DEVICE DISCOUNTS TO MEASURE THE DIVERSION EFFECT

The finding of a small net effect of burglar alarms on burglary rates in chapter three, along with the considerable evidence of deterrence described in chapter two, suggests that both diversion and deterrence may be present when homeowners employ observable private precaution. However, the methodology of chapter three cannot discern a measure of the diversion effect alone. The diversion effect associated with burglar alarms is notoriously difficult to measure separately from the deterrence effect for two reasons: first, measurement lacks a standardized method, and second, data on burglar alarm use by households are generally unavailable. My purpose in this chapter is to develop a method for measuring the diversion effect associated with burglar alarms using a unique dataset from the homeowner's insurance industry, where insurance companies offer discounts to their customers for installing burglar alarms.

While the welfare of alarmed and non-alarmed homeowners is affected by burglar alarm use due to the deterrence and diversion effects, they are not the only parties affected. Homeowner's insurance companies that provide insurance policies to alarmed and non-alarmed homeowners are also affected. If installing burglar alarms deters crime, companies insuring alarmed households experience a savings when protective devices lower the expected insured loss due to theft. However, if burglar alarms divert crime to non-alarmed homes, homeowner's insurance companies also incur a cost. This cost increases as both the size of the diversion effect and the number of customers not engaging in observable private

precaution increase. From a simple cost/benefit analysis, insurance companies should be willing to offer protective device discounts to their customers if the savings generated by the deterrence effect are greater than the costs generated by diversion. It then follows that insurance companies with more non-alarmed policyholders face larger costs due to diversion, and therefore should offer lower protective device discounts.

4.1 Theoretical Model

The analysis of the diversion effect in this section exploits the relationship between a homeowner's insurance company's market share and the benefit it receives from a protective device discount. I assume rationality on the part of both homeowners and insurance companies. This assumption implies that homeowners derive utility from private protection and the savings generated from protective device discounts, and that insurance companies only offer discounts to customers when a net gain is possible. The market for homeowner's insurance is also assumed to consist of both alarmed and non-alarmed homeowners, with insurance companies offering coverage to both.

Due to the presence of the diversion and deterrence effects, the probabilities of burglary of alarmed and non-alarmed homeowners are affected when the total number of households installing burglar alarms in the market changes. When one homeowner insured by insurance company j, for j=1, ……, N, engages in observable private precaution by installing a burglar alarm, insurance company j enjoys a savings. Let PR_1 be the probability that the alarmed homeowner is burgled, M_1 the average insurance claim of the alarmed homeowner due to burglary, and ΔPR_1 the change in the probability of burglary of the

alarmed homeowner due to the installation of a burglar alarm. The savings to insurance company j is then the total change in the average insurance claim due to burglary that occurs because the alarmed homeowner engages in observable private precaution:

$$\Delta PR_1 M_1 < 0 \quad , \qquad (8)$$

where $\Delta PR_1<0$ and $M_1>0$. ΔPR_1 is a measure of the deterrence effect, as observed private precaution decreases the probability that the alarmed homeowner is burgled.

In addition to insuring the alarmed homeowner, insurance company j insures other homeowners who do not take private precautionary measures. Crime may be diverted to these non-alarmed homeowners when the alarmed homeowner engages in private precaution. This imposes a cost on insurance company j. Let PR_2 represent the probability that non-alarmed homeowners are burgled, M_2 the average insurance claim of non-alarmed homeowners due to burglary, s_j the portion of insurance company j's market share not installing burglar alarms, and ΔPR_2 the change in the probability of burglary of non-alarmed homeowners that occurs as a result of the alarmed homeowner installing a burglar alarm. The cost to insurance company j is then the total change in the average insurance claim of non-alarmed homeowners due to burglary that occurs because the alarmed homeowner engages in observable private precaution:

$$s_j \Delta PR_2 M_2 > 0 \quad , \qquad (9)$$

where $\Delta PR_2>0$, $M_2>0$, and $1\geq s_j \geq 0$. ΔPR_2 is a measure of the diversion effect, as observable private precaution taken by the alarmed homeowner increases the probability that non-alarmed homeowners are burgled. The net savings to insurance company j from the alarmed homeowner engaging in observable private precaution but inducing the diversion effect is:

$$net\ savings = \Delta PR_1 M_1 + s_j \Delta PR_2 M_2 \quad . \qquad (10)$$

Assuming that competition in the homeowner's insurance industry leads to zero-profit equilibrium and the savings of insurance company j generated by the deterrence effect exceeds the cost imposed by the diversion effect, insurance company j passes its net savings off to the alarmed homeowner in the form of a discount, D_j:

$$D_j = net\ savings = \Delta PR_1 M_1 + s_j \Delta PR_2 M_2 \quad , \qquad (11)$$

where D_j is the dollar value of the discount offered by insurance company j to alarmed customers for installing protective devices. Since the discount is a function of ΔPR_2, (11) can be used to estimate the diversion effect. Suppose first that $M=M_1=M_2$, so that the average insurance claim due to burglary is the same for both alarmed and non-alarmed homeowners. In this case, the discount offered by insurance company j to the alarmed homeowner is:

$$D_j = (\Delta PR_1 + s_j \Delta PR_2) M \quad . \qquad (12)$$

D_j is negative if $|\Delta PR_1| > s_j \Delta PR_2$, which suggests that insurance company j offers a discount to the alarmed homeowner if the deterrence effect outweighs the diversion effect. D_j is zero if $|\Delta PR_1| = s_j \Delta PR_2$, or if $|\Delta PR_1| < s_j \Delta PR_2$, implying that insurance company j does not offer a discount to the alarmed homeowner if the costs from diversion are larger than or equal to the benefits of deterrence. Although the discount would be positive if $|\Delta PR_1| < s_j \Delta PR_2$, insurance companies are not observed to tax households for installing burglar alarms.

Dividing both sides of (12) by M and taking the derivative with respect to s_j yields ΔPR_2, the diversion effect generated when the alarmed homeowner engages in private precaution:

$$\partial(D_j/M)/\partial s_j = \Delta PR_2 > 0 \quad , \qquad (13)$$

where $\partial(D_j/M)/\partial s_j$ is the derivative of the dollar value of the protective device discount offered to the alarmed homeowner divided by the average insurance claim of all homeowners due to burglary, with respect to insurance company j's share of the market not installing burglar alarms.

Empirically, however, the average insurance claim due to burglary is not the same among alarmed and non-alarmed homeowners. A survey of homeowners in Tredyffrin Township by Buck et al. in 1993 finds that the average insurance claim, net of deductible and conditional on burglary, is $775 for alarmed homeowners and $1,174 for non-alarmed homeowners (Blackstone and Hakim 1997). These calculations are based on the number of alarmed and non-alarmed homes in Tredyffrin Township and the probability of burglary in each. For the more realistic case where $M_1 < M_2$, the diversion effect becomes:

$$\partial(D_j)/\partial(s_j M_2) = \Delta PR_2 > 0 \quad . \qquad (14)$$

The derivative in (14) reveals that in a regression of D_j on $s_j M_2$, the coefficient on $s_j M_2$ yields an estimate of the diversion effect associated with observable private precautionary measures.

4.2 Empirical Specification and Data Sources

The empirical specification that I use to measure the diversion effect associated with burglar alarms according to (14) is:

$$DISCOUNT_{ij} = \alpha + \delta\, SHARE_{ij} * LOSS + \varepsilon_{ij} \quad , \qquad (15)$$

where i indexes zip code and j represents the homeowner's insurance company. As diversion

is likely to occur over short distances (Bowers and Johnson 2003), the zip-code-level analysis of this chapter is an improvement over the county-level analysis of chapter three.

In (15), DISCOUNT represents the dollar value of the protective device discount offered to the alarmed homeowner by insurance company j and α is the intercept. DISCOUNT is calculated as the product of the base premium charged and protective device discount offered by insurance company j. LOSS is the average insurance claim of non-alarmed homeowners due to burglary, which does not vary among homeowner's insurance companies or zip codes due to data limitations explained later in this section. LOSS is therefore not indexed by i or j in (15). SHARE is the portion of insurance company j's share of insured homeowners without burglar alarms. ε is the error term.

The parameter of interest is δ, which measures the diversion effect associated with burglar alarm use. Unlike in the theoretical model, the diversion effect is expected to be negative in the empirical specification[15]. A negative diversion effect suggests two things: first, insurance companies with larger market shares and therefore more non-alarmed customers offer smaller protective device discounts, and second, the probability of burglary of non-alarmed homeowners increases when the alarmed homeowner engages in private precaution.

When divided by the average insurance claim of the alarmed homeowner due to burglary, α measures the deterrence effect associated with burglar alarm use. The deterrence effect is expected to be positive. Given the results indicating a small net effect of burglar

[15] The diversion effect is positive in section 4.1 because by definition, the dollar value of the discount is negative. In the case of actual data, the discount is positive.

alarms on burglary rates in chapter three, the deterrence effect is also likely to be larger than the diversion effect.

Data on DISCOUNT and SHARE are available at the zip-code level for homeowner's insurance companies operating in the state of Illinois from the Illinois Department of Financial and Professional Regulation, Division of Insurance. I rely on data from Illinois because the state is well-known for successfully deregulating insurance pricing. That is, insurance companies are given a free hand in setting premiums. Illinois insurance pricing has not been governed by insurance rating law since 1971. Studies show that Illinois has more homeowner's insurance companies competing for business than any other state (Whitman 1973).

Although several different types of homeowner's insurance coverage exist, including homeowner dwelling, homeowner contents, condominium, and renter, I rely solely on data relating to HO-3 insurance. HO-3 is the most common type of homeowner's insurance policy and is designed to cover all aspects of the home, structure, and contents. By focusing only on HO-3 insurance policies and omitting the relevance of those policies that protect against the burglary of condominiums, apartments, and other housing structures, I assume that diversion occurs among homes only. For example, I assume that when a burglar alarm deters a burglar from breaking into a home, it does not divert the burglar to a condominium or apartment. Although this assumption is admittedly strong, it is consistent with the literature on the diversion effect discussed in chapter two. This literature noted that diversion is likely to occur between structures that are similar in terms of external characteristics and income (Bowers and Johnson 2003).

Data on homeowner's insurance company base premiums and protective device discounts were extracted from homeowner's insurance company manuals maintained by the Illinois Department of Financial and Professional Regulation, Division of Insurance, in the summer of 2007. Data were collected for 38 homeowner's insurance companies operating in the state of Illinois. The Division of Insurance does not maintain a database of homeowner's insurance company premiums or protective device discounts. Rather, when each company reports its premium and discount information to the state of Illinois, the Division of Insurance files this information in the company's insurance manual. Each time the insurance company makes changes to its premiums and protective device discounts, it must report them to the Division of Insurance. The Division of Insurance then updates the company's insurance manual. When I manually extracted premium and discount data from insurance company manuals in 2007, I only had access to each company's most recently filed data. Historical data were not available, and the Division of Insurance could not estimate how frequently insurance companies update their premiums and discounts.

Homeowner's insurance company premiums are defined as annual base premiums, or the dollar price charged by homeowner's insurance companies for their services before any discounts are applied for such factors as age of house, credit rating, having multiple policies, and protective device use. For the majority of the 38 companies in the sample, premiums are based on $100,000 coverage and a $500 deductible[16]. When assigning a base premium to

[16] I include dummy variables in (15) to identify those companies in the sample that either specified different coverage and/or deductible amounts, or did not specify coverage and/or deductible amounts. The dummy categories included are whether homeowner's insurance companies specify a deductible equal to or greater than $500, whether they specify a deductible less than $500, whether they specify a coverage amount equal to or greater than $100,000, and whether they specify a coverage amount less than $100,000. The categories for not specifying deductible or coverage amounts are excluded.

each zip code in Illinois, homeowner's insurance companies first divide the state into territories. Each company defines these territories differently, but all territories are based on either county and/or zip-code boundaries. Some companies further break each territory into protection classes[17], which are used to set premiums based on the quality of fire protection. Each company assigns one base premium to each territory, or if it uses them, assigns one base premium to each protection class in the territory. In order to obtain data on base premiums at the zip-code level, I match up each zip code in Illinois to a territory for each company without protection classes. For each company with protection classes, I take the unweighted average of base premiums over protection classes[18] in each territory so that each territory has only one associated base premium. I then assign one base premium to each zip code in Illinois for these companies. Since most companies differentiate base premiums by construction type[19], I have separate data for frame and masonry homes.

Protective device discounts are defined as the percentage discount offered for installing a burglar alarm. Discount data were collected for central station reporting burglar alarms, police station connected burglar alarms, and local burglar alarms. Central station reporting burglar alarm systems connect to a central station or responder with a direct phone wire. Police station connected burglar alarms alert a local police station. Local burglar alarms do not include any monitoring, but signal using indoor or outdoor sounders or lights.

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[17] I include a dummy variable in (15) to identify those companies that define protection classes.

[18] Given that protection classes are unrelated to the level of crime or quality of police protection in the community, this is a sound way of assigning one base premium to each territory.

[19] Homeowner's insurance companies likely assign separate premiums to frame and masonry homeowners because frame houses are more susceptible to fire damage. I maintain differences in premiums for the two housing construction types in my dataset simply because that is the way data are presented in the manuals filed at the Illinois Department of Financial and Professional Regulation, Division of Insurance.

Protective device discounts vary only by company, and not by zip code or housing construction type.

Data on total[20] market shares of homeowner's insurance companies by zip code were obtained directly from a database maintained by the Illinois Department of Financial and Professional Regulation, Division of Insurance. Total market shares are based on company-reported data on the total dollar value of HO-3 premiums collected from selling homeowner's insurance policies. I employ market share data from 2006, the most recent year in which data are available. Since not all homeowner's insurance companies operate in all Illinois zip codes, market share data are only available for the zip codes in which the companies operate, or for which the companies report a dollar value of collected premiums equal to zero. Observations for which companies have negative market shares due to premium reversals are excluded from the sample[21], since SHARE is assumed to be positive.

Although SHARE is defined in (15) as insurance company j's share of insured but non-alarmed homes, the market share data from the Illinois Department of Financial and Professional Regulation, Division of Insurance do not distinguish between premiums collected from alarmed and non-alarmed homeowners. I therefore employ total market shares to represent SHARE in (15). On average, this data adjustment does not affect my interpretation of the diversion effect in section 4.3. That is, as long as homeowner's insurance companies have equal shares of both alarmed and non-alarmed customers, ΔPR_2 represents the change in the probability of burglary of non-alarmed homeowners when the

[20] Total market shares include both alarmed and non-alarmed homeowners.
[21] Excluded observations amount to 2.1% of the original sample.

alarmed homeowner installs an alarm. Individually, however, insurance companies are not likely to have equal shares of alarmed and non-alarmed customers. For these companies, measurement of the diversion effect in (15) misrepresents the true diversion effect. Specifically, for an individual homeowner's insurance company with a larger share of non-alarmed customers, (15) underestimates the true diversion effect.

Finally, since data on LOSS are not available at company or zip-code levels, I measure this variable as $1,174, the average loss from burglary to non-alarmed homeowners in the aforementioned Tredyffrin Township study. In calculating the deterrence effect using the intercept in (15), I measure the average insurance claim of the alarmed homeowner as $775, also from the Tredyffrin Township study.

Table 4.1 provides summary statistics for the homeowner's insurance industry, collected from the Illinois Department of Financial and Professional Regulation, Division of Insurance. Data on DISCOUNT are specified according to home construction and burglar alarm types, as analysis is conducted separately for each.

For both types of housing construction, summary statistics reveal that homeowners using central station reporting burglar alarms receive the largest DISCOUNT, while homeowners with local burglar alarms receive the smallest. This is consistent with the evidence in chapter two that central station reporting burglar alarms are the most effective (from a burglar's perspective). As the minimum DISCOUNT is $0.00 for all housing construction and burglar alarm types, it is clear that some homeowner's insurance companies do not offer protective device discounts. Given that DISCOUNT is the product of percentage protective device discounts and base premiums, it is interesting to note the summary statistics

for these variables separately. The average percentage protective device discount offered to alarmed homeowners, which does not vary by housing construction type, is 7.7%, 5.1%, and 2.4% for central station reporting, police station connected, and local burglar alarms, respectively. The average base premium is $726.21 for frame homeowners and $659.64 for masonry homeowners. The higher base premium charged to frame homeowners is the likely explanation for why frame homeowners receive a higher DISCOUNT than masonry homeowners, for all burglar alarm types. The large range in the summary statistics for SHARE indicates that the 38 insurance companies in the final sample vary in size.

4.3 Results and Discussion

The final sample used in estimation consists of zip-code level observations for 38 homeowner's insurance companies operating in a potential of 1,780 zip codes in the state of Illinois. When pooled over all companies, the sample amounts to 23,732 observations. An estimate of δ, which measures the diversion effect associated with burglar alarms, is obtained by estimating (15) via Ordinary Least Squares (OLS) estimation.

Before estimating (15) using the pooled sample, I first determine whether it is necessary to use company-indicator variables. Without company-indicator variables, estimation using the pooled sample of 23,732 observations yields one estimate of the diversion effect for the entire market and assumes that each homeowner's insurance company faces the same diversion effect. The use of company-indicator variables with the pooled sample measures a separate diversion effect for each company and allows for homeowner's insurance companies to face different diversion effects. In order to determine whether

company-indicator variables are suitable for my model, I first estimate (15) using company-indicator variables. I then employ a multiple hypotheses test (F-test) to measure the following for the diversion effect:

$$H_0: \ \delta_1 = \delta_2 = \ldots\ldots = \delta_j \qquad \text{for } j = 1, \ldots, 38 \quad , \qquad (16)$$

and, for completeness, the following for the deterrence effect:

$$H_0: \ \alpha_1 = \alpha_2 = \ldots\ldots = \alpha_j \qquad \text{for } j = 1, \ldots, 38 \quad . \qquad (17)$$

Table 4.2 provides the F-statistics for testing (16) and (17). Based on a critical value of 1.83, results indicate a strong rejection of both hypotheses. Relying on the conclusion that measuring a separate diversion effect for each homeowner's insurance company is suitable for my purposes[22], I then consider the reason why the 38 companies in my sample face different diversion effects. The theoretical model of section 4.2 predicts that companies with different market shares face different diversion effects, but (15) already controls for this prediction. An additional explanation for which I do not account in my theoretical model is that companies may face difficulty in appropriately setting protective device discounts because of the significant costs of measuring the diversion effect. These costs may also vary by company, especially if companies vary in size[23]. For example, a larger company that operates throughout the entire state of Illinois may find it too costly to measure the diversion effect in every zip code or county. For this company, it may be more cost effective to set protective device discounts broadly or according to an average diversion effect across its markets, rather than based on the size of its diversion effect in each zip code or county.

[22] Given that I estimate (15) separately for each company, inclusion of dummy variables regarding protection classes and deductible and coverage amounts is no longer necessary, since variation only occurs between companies for these data.

[23] Companies in this chapter's sample do, in fact, vary in size. See the wide range of SHARE in Table 4.1.

Alternatively, the larger company may incorporate the cost of estimating the diversion effect into the size of its protective device discount, or not offer one at all because the costs of measuring its diversion effect outweigh the benefits of offering a discount. For this type of company, the diversion effect measured by (15) will misrepresent the true effect. A smaller company, on the other hand, may face negligible costs in estimating its diversion effect and thus set its discounts deliberately. For this company, (15) will more precisely measure diversion. It is therefore possible that because not all homeowner's insurance companies will find it worthwhile to accurately measure its diversion effect when setting protective device discounts, the diversion effects that I measure from (15) will vary by company. The same argument applies to estimated deterrence effects.

Another possible explanation is that while my estimation controls for company differences in zip-code market shares, it does not account for the size of relative market shares among nearby zip codes. If diversion, in fact, occurs over short distances, as modeled in this paper and predicted by previous literature, then the size of the diversion effect faced by one company in one zip code heavily relies on the size of that company's market shares in geographically-close zip codes. Suppose insurance company j+1 and j have market shares of approximately the same size in zip code i. When setting their protective device discounts in zip code i, both companies must consider how many of their non-alarmed customers will face diversion in nearby zip code i+1 when their discounts encourage burglar alarm installation in zip code i. If insurance company j's market share in zip code i+1 is smaller than the market share of insurance company j+1, insurance company j will face a smaller diversion effect than insurance company j+1. It is therefore possible that company differences in relative

market shares explain the differences in diversion effects among the 38 homeowner's insurance companies in my sample. The argument here is that zip codes typically underestimate the appropriate size of the market in which diversion occurs. As before, the same argument applies to estimated deterrence effects.

After estimating company-individual diversion and deterrence effects, I analyze the estimates in order to ascertain a general pattern in terms of sign and significance among the 38 homeowner's insurance companies in my sample. Table 4.3 details the percentage of companies in the sample that face a statistically significant and negative diversion effect, as predicted by the theoretical model in section 4.2, for all three types of burglar alarm systems and both frame and masonry homes. More companies face a statistically significant and negative diversion effect when insuring masonry homeowners using central station reporting burglar alarm systems, than when insuring homeowners with any other housing construction or burglar alarm type. For frame homeowners, approximately 63% of the companies in the sample face a negative diversion effect (ignoring significance) when customers use central station reporting burglar alarm systems. This fraction is smaller when frame homeowners use police station connected and local burglar alarm systems. The same pattern is apparent when homeowner's insurance companies insure masonry homeowners.

According to Table 4.3, some homeowner's insurance companies in the sample face a diversion effect equal to zero. This result is misleading because in order for companies not to face a diversion effect, all of their customers must be alarmed, which is highly unlikely. In actuality, this result coincides with those homeowner's insurance companies in the sample that do not offer a protective device discount. As already described in this chapter, there are

several reasons why a company would choose not to offer a protective device discount. As noted in section 4.1, companies may choose not to offer a discount if the costs they face from diversion are greater than or equal to the benefits they experience from deterrence. Other companies may choose not to offer a discount because they face significant costs in measuring the diversion effect, as mentioned in this section. Results in Table 4.3 also indicate that the decision not to offer a protective device discount is a function of the effectiveness of the burglar alarm system employed by homeowners, but not the type of housing construction. Very few companies do not offer a protective device discount for central station reporting burglar alarms, which are considered the most effective at deterring burglaries.

From Table 4.3, I discern the general pattern that, on average, homeowner's insurance companies face a negative, but statistically insignificant, diversion effect. This result is verified by the first two columns of Table 4.4 and Table 4.5. Table 4.4 displays summary statistics for the average diversion effect for the 38 homeowner's insurance companies in my sample, where company-individual diversion effects are averaged using state-wide company market shares as weights. Data on state-wide company market shares are obtained from the Illinois Department of Financial and Professional Regulation, Division of Insurance. Although company-individual diversion effects are insignificant on average, results show that the average diversion effect, when calculated using the market-share weights, is statistically significant at the 5% level for most housing construction and burglar alarm system types. The 95% confidence intervals in Table 4.4 strongly suggest that the average diversion effect is negative and statistically different from zero when companies insure

masonry houses with all burglar alarm types. This result also holds when companies insure frame homeowners that use central station reporting burglar alarms. For frame homeowners using central station reporting burglar alarms, a diversion effect equal to -0.00634 is interpreted as the increase in the probability of burglary of non-alarmed homeowners when the alarmed homeowner installs an alarm. This is consistent with a 37% increase in the probability of burglary of non-alarmed homeowners[24]. For frame homeowners, the percentage increase in the probability of burglary of non-alarmed homeowners is approximately 20% when using police station connected burglar alarms and 11% when using local burglar alarms. For masonry homeowners, the percentage increase in the probability of burglary of non-alarmed homeowners is 48% when using central station reporting burglar alarms, 33% when using police station connected burglar alarms, and 17% when using local burglar alarms. In addition, Table 4.4 shows that the size of the average diversion effect (in absolute value) decreases with the sophistication of the burglar alarm system. If central station reporting burglar alarms are assumed to be the most effective in diverting crime because of their ability to deter, and local burglar alarms are the least effective because of their inability to deter, the difference in the effectiveness of alarms is apparent in Table 4.4.

While the results of Table 4.4 suggest that a negative diversion effect is present with burglar alarm use, the results in Table 4.5 present a different story. Table 4.5 displays summary statistics for the average diversion effect for the 38 homeowner's insurance companies in my sample, where now company-individual diversion effects are averaged

[24] The percentage change in the probability of burglary is based on an initial probability of burglary equal to 1.7% in the state of Illinois, calculated as the ratio of burglaries to households in 2006. This calculation is independent of whether homeowners are alarmed or non-alarmed, as well as housing construction and burglar alarm types.

using an arithmetic mean. When the average diversion effect is calculated in this manner, the average diversion effect is statistically insignificant for all housing construction and burglar alarm types, with the exception of police station connected burglar alarms for both housing construction types. Only for the case of police station connected burglar alarm systems for all housing construction types does there exist strong evidence of a statistically significant and negative average diversion effect. The results of Table 4.5 show the importance of taking into account the state-wide presence of each homeowner's insurance company when looking at the Illinois market as a whole.

I now turn to analysis of company-level deterrence effects, which I estimate for the 38 homeowner's insurance companies in my sample. Table 4.6 reveals that although all homeowner's insurance companies in my sample face a statistically insignificant deterrence effect, the effect is positive for all housing construction and burglar alarm types. Table 4.7 and Table 4.8 present summary statistics on the average deterrence effect, where the average is calculated as a weighted average and as an arithmetic mean in each respective table. Unlike the results on the average diversion effect, results on the sign and statistical significance of the average deterrence effect are the same, no matter how the average effect is calculated. In both cases, company-individual deterrence effects are positive and insignificant, on average, for all housing construction and burglar alarm types. However, the average deterrence effect is positive and statistically significant at the 5% level. The 95% confidence intervals in Table 4.7 and Table 4.8 are strong evidence that the average deterrence effect is positive and statistically different from zero when companies insure both frame and masonry homeowners using all burglar alarm types. Based on Table 4.7, the

average deterrence effects for all housing construction and burglar alarm types are consistent with an enormous decrease in the probability of burglary of alarmed homeowners[25] generally exceeding 100%.

I conclude this section by analyzing the relative sizes of the estimated average diversion and deterrence effects. This analysis is worthwhile because chapter three's measurement of the net effect of burglar alarms on burglary rates shows that if the diversion effect is present, it is likely to be smaller than the deterrence effect. Regardless of how the average diversion and deterrence effects are calculated, results show that the sizes of the average deterrence effects in Table 4.7 and Table 4.8 are larger (in absolute value) than the sizes of the average diversion effects in Table 4.4 and Table 4.5. Deterrence also exceeds diversion in terms of the percentage change in the probability of burglary. These finding are consistent with a small net effect of burglar alarms on burglary rates.

4.4 Conclusion

Due to the lack of methodology and appropriate data, previous literature fails to provide a measure of the separate diversion effect associated with observable private precaution. In this chapter, I overcome this challenge by developing a method for measuring the diversion effect associated with burglar alarm systems using data from the homeowner's insurance industry. The methodology measures the diversion effect using the relationship between homeowner's insurance company market shares and protective device discounts. In

[25] The percentage change in the probability of burglary is again based on an initial probability of burglary equal to 1.7% in Illinois in 2006.

this chapter, I find that while homeowner's insurance companies face individual diversion effects that differ in sign and significance, the average diversion effect facing the entire market is negative and statistically different from zero, suggesting that burglaries are diverted to non-alarmed homes. This finding holds when the average diversion effect is calculated as a weighted average using state-wide company market shares as weights. Additionally, the average deterrence effect facing the market is positive and statistically significant, suggesting that alarms deter burglaries. The average deterrence effect is also estimated to be larger than the average diversion effect. The results of this chapter provide substantial evidence that the presence of the diversion effect cannot be ruled out when homeowners employ observable private precaution. In addition, results are not only consistent with the finding of a small net effect of burglar alarms on burglary rates in chapter three, but also support the analysis of chapter five, which develops yet another method for measuring the diversion effect.

Table 4.1: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Frame Housing				
DISCOUNT: dollar value of discount offered to alarmed homeowners				
Central Station Reporting Burglar Alarm	57.39	37.51	0.00	431.93
Police Station Connected Burglar Alarm	38.48	41.96	0.00	431.93
Local Burglar Alarm	18.40	16.39	0.00	163.85
Masonry Housing				
DISCOUNT: dollar value of discount offered to alarmed homeowners				
Central Station Reporting Burglar Alarm	51.99	33.53	0.00	388.75
Police Station Connected Burglar Alarm	35.07	37.73	0.00	388.75
Local Burglar Alarm	16.70	14.73	0.00	133.90
SHARE: homeowner's insurance company market shares	0.025	0.060	0.00	1.00
Dummy Variables:				
Use of protection classes	0.53	0.50	0.00	1.00
Deductible amount equal to or greater than $500	0.40	0.49	0.00	1.00
Deductible amount less than $500	0.021	0.14	0.00	1.00
Coverage amount equal to or greater than $100,000	0.74	0.44	0.00	1.00
Coverage amount less than $100,000	0.015	0.12	0.00	1.00
No. of Observations	23,732			

Table 4.2: F-Statistics for Multiple Hypotheses Tests

	Central Station Reporting Burglar Alarm	Police Station Connected Burglar Alarm	Local Burglar Alarm
Frame Housing			
H_0: $\delta_1 = \delta_2 = \ldots\ldots = \delta_j$ for j = 1…38	3.54	6.02	4.63
H_0: $\alpha_1 = \alpha_2 = \ldots\ldots = \alpha_j$ for j = 1…38	4.45	3.75	3.06
Masonry Housing			
H_0: $\delta_1 = \delta_2 = \ldots\ldots = \delta_j$ for j = 1…38	3.54	6.10	4.78
H_0: $\alpha_1 = \alpha_2 = \ldots\ldots = \alpha_j$ for j = 1…38	3.91	3.20	2.62

**Results are for 37 numerator degrees of freedom and 23,656 denominator degrees of freedom.*

Table 4.3: Sign and Significance of Individual Company Diversion Effects

	Central Station Reporting Burglar Alarm	Police Station Connected Burglar Alarm	Local Burglar Alarm
Frame Housing			
% of companies for which the diversion effect is significantly positive	7.89%	5.26%	7.89%
% of companies for which the diversion effect is significantly negative	21.05%	10.53%	21.05%
% of companies for which the diversion effect is insignificantly positive	26.32%	15.79%	21.05%
% of companies for which the diversion effect is insignificantly negative	42.11%	42.11%	36.84%
% of companies for which the diversion effect is zero	2.63%	26.32%	13.16%
	100.00%	100.00%	100.00%
Masonry Housing			
% of companies for which the diversion effect is significantly positive	5.26%	2.63%	5.26%
% of companies for which the diversion effect is significantly negative	44.74%	10.53%	18.42%
% of companies for which the diversion effect is insignificantly positive	26.32%	15.79%	21.05%
% of companies for which the diversion effect is insignificantly negative	21.05%	44.74%	42.11%
% of companies for which the diversion effect is zero	2.63%	26.32%	13.16%
	100.00%	100.00%	100.00%

Table 4.4: Average Diversion Effect Calculated as Weighted Average

	Average Diversion Effect	Average T-Statistic	T-Statistic of Average Diversion Effect	Standard Error of Average Diversion Effect	95% Confidence Interval	
Frame Housing					***Lower***	***Upper***
Central Station Reporting Burglar Alarm	-0.0063	-0.57	-2.37	0.0027	-0.012	-0.0011
Police Station Connected Burglar Alarm	-0.0034	-0.25	-1.50	0.0023	-0.0079	0.0011
Local Burglar Alarm	-0.0018	-0.41	-1.89	0.00097	-0.0037	0.000063
Masonry Housing						
Central Station Reporting Burglar Alarm	-0.0082	-0.90	-3.43	0.0024	-0.013	-0.0035
Police Station Connected Burglar Alarm	-0.0056	-0.59	-2.72	0.0021	-0.0096	-0.0016
Local Burglar Alarm	-0.0029	-0.74	-3.35	0.00086	-0.0046	-0.0012

**Average diversion effects and t-statistics are calculated using state-wide company market shares as weights. Results include companies that offer 0% protective device discounts.*

Table 4.5: Average Diversion Effect Calculated as Arithmetic Mean

	Average Diversion Effect	Average T-Statistic	T-Statistic of Average Diversion Effect	Standard Error of Average Diversion Effect	95% Confidence Interval	
Frame Housing					***Lower***	***Upper***
Central Station Reporting Burglar Alarm	-0.0055	-0.67	-0.36	0.015	-0.035	0.024
Police Station Connected Burglar Alarm	-0.033	-0.81	-2.58	0.013	-0.059	-0.0080
Local Burglar Alarm	-0.0053	-0.65	-0.97	0.0055	-0.016	0.0054
Masonry Housing						
Central Station Reporting Burglar Alarm	-0.0092	-0.69	-0.67	0.014	-0.036	0.018
Police Station Connected Burglar Alarm	-0.030	-0.84	-2.60	0.012	-0.053	-0.0075
Local Burglar Alarm	-0.0057	-0.67	-1.17	0.0049	-0.015	0.0039

**Average diversion effects and average t-statistics are calculated as arithmetic means. Results include companies that offer 0% protective device discounts.*

Table 4.6: Sign and Significance of Individual Company Deterrence Effects

	Central Station Reporting Burglar Alarm	Police Station Connected Burglar Alarm	Local Burglar Alarm
Frame Housing			
% of companies for which the deterrence effect is significantly positive	0.00%	0.00%	0.00%
% of companies for which the deterrence effect is significantly negative	0.00%	0.00%	0.00%
% of companies for which the deterrence effect is insignificantly positive	100.00%	100.00%	100.00%
% of companies for which the deterrence effect is insignificantly negative	0.00%	0.00%	0.00%
	100.00%	100.00%	100.00%
Masonry Housing			
% of companies for which the deterrence effect is significantly positive	0.00%	0.00%	0.00%
% of companies for which the deterrence effect is significantly negative	0.00%	0.00%	0.00%
% of companies for which the deterrence effect is insignificantly positive	100.00%	100.00%	100.00%
% of companies for which the deterrence effect is insignificantly negative	0.00%	0.00%	0.00%
	100.00%	100.00%	100.00%

Table 4.7: Average Deterrence Effect Calculated as Weighted Average

	Average Deterrence Effect	Average T-Statistic	T-Statistic of Average Deterrence Effect	Standard Error of Average Deterrence Effect	95% Confidence Interval	
Frame Housing					***Lower***	***Upper***
Central Station Reporting Burglar Alarm	0.10	0.16	10.25	0.0098	0.081	0.12
Police Station Connected Burglar Alarm	0.088	0.14	10.54	0.0084	0.072	0.10
Local Burglar Alarm	0.044	0.15	12.60	0.0035	0.038	0.051
Masonry Housing						
Central Station Reporting Burglar Alarm	0.090	0.16	10.24	0.0088	0.072	0.11
Police Station Connected Burglar Alarm	0.079	0.14	10.50	0.0075	0.064	0.093
Local Burglar Alarm	0.040	0.15	12.38	0.0032	0.033	0.046

**Average deterrence effects and t-statistics are caluclated using state-wide company market shares as weights. Results include companies that offer 0% protective device discounts.*

Table 4.8: Average Deterrence Effect Calculated as Arithmetic Mean

	Average Deterrence Effect	Average T-Statistic	T-Statistic of Average Deterrence Effect	Standard Error of Average Deterrence Effect	95% Confidence Interval	
Frame Housing					***Lower***	***Upper***
Central Station Reporting Burglar Alarm	0.074	0.16	15.54	0.0047	0.064	0.083
Police Station Connected Burglar Alarm	0.048	0.17	11.85	0.0041	0.040	0.056
Local Burglar Alarm	0.023	0.16	13.59	0.0017	0.020	0.027
Masonry Housing						
Central Station Reporting Burglar Alarm	0.067	0.16	15.67	0.0043	0.058	0.075
Police Station Connected Burglar Alarm	0.044	0.17	12.10	0.0036	0.037	0.051
Local Burglar Alarm	0.021	0.16	13.86	0.0015	0.018	0.024

**Average deterrence effects and average t-statistics are calculated as arithmetic means. Results include companies that offer 0% protective device discounts.*

CHAPTER 5

ESTIMATING THE DIVERSION EFFECT USING THE PROBABILITY OF BURGLARY OF NON-ALARMED HOMEOWNERS

In one of the most influential papers of the empirical Industrial Organization literature, Berry, Levinsohn, and Pakes (1995) present a procedure for estimating supply and demand parameters in an oligopolistic, differentiated product setting. The authors use only widely-available, product-level, aggregate data, rather than data at the consumer level, to analyze equilibrium in the U.S. automobile industry. Their general approach is to posit a distribution of consumer preferences over products, and then to explicitly aggregate these preferences into a market-level demand system in order to generate equilibrium prices and quantities.

My purpose in this chapter is to present another method for measuring the diversion effect associated with observable private precaution that is separate from the deterrence effect. This method, which is loosely based on the work of Berry, Levinsohn, and Pakes, involves a structural model of equilibrium in an oligopolistic setting. I then test this method empirically using the homeowner's insurance data introduced in chapter four. The benefit of using an approach similar to that of Berry, Levinsohn, and Pakes to measure the diversion effect is that it does not require data on individual homeowners, and actually estimates the alarmed and non-alarmed portions of the market. Although anecdotal evidence of the percentage of homeowners who install burglar alarms is generally available, actual data are rarely observed. Oligopolistic competition may also be a more reasonable assumption for the homeowner's insurance industry in the state of Illinois, compared to the perfectly

competitive setting of chapter four. Although Illinois has been described as a "competition state," more than half of the state's homeowner's insurance industry consists of just five large companies[26].

Previous literature suggests that protective device discounts are only effective in encouraging alarm installation if alarmed homeowners are aware of them and take them into account when purchasing an alarm system (Blackstone and Hakim 1997). The empirical methodology of this section assumes that homeowners derive utility from private precaution and the savings generated from protective device discounts. Insurance companies are also assumed to only offer protective device discounts to their customers when a net gain is possible. That is, homeowner's insurance companies offer protective device discounts when it is cost-effective in the sense that the amount sacrificed by offering discounts is less than the savings on claims from burglaries prevented by burglar alarms.

5.1: The Demand Side

In this section, I use mean utility levels of both alarmed and non-alarmed homeowners to define demand-side parameters. I then use these parameters to calculate market shares, which are a function of the decision of homeowners to purchase insurance and install burglar alarms.

On the demand side of the market, homeowners gain utility from both installing burglar alarms and purchasing insurance from a specific homeowner's insurance company. Homeowners install the type of alarm and purchase homeowner's insurance from the

[26] This finding is based on state-wide market shares calculated according to the value of premiums collected by homeowner's insurance companies.

company that yields the highest utility. Define N as the number of homeowner's insurance companies operating in the market. The utility specification for homeowners insuring with insurance company j and installing burglar alarms is:

$$U^1_j = X_j \gamma + \zeta - \eta\, p^1_j + \varepsilon^1_j, \text{ for } j = 1, \ldots\ldots, N \quad . \qquad (18)$$

X_j is a vector of product (insurance company) characteristics, including a constant, ζ represents the net benefit of installing burglar alarms and is assumed to be positive and constant among alarmed homeowners, p^1_j is the price charged by insurance company j, which is discounted because homeowners install burglar alarms, and ε^1_j is a disturbance term that is identically and independently distributed with extreme value distribution over homeowners and insurance company j. γ and η are the marginal utility of product characteristics and price, respectively. Note that unlike Berry, Levinsohn, and Pakes, γ and η are assumed to be the same for all homeowners.

Homeowners decide not to install burglar alarms and insure with homeowner's insurance company j if doing so yields the highest utility. The utility specification for homeowners insuring with insurance company j but not installing burglar alarms is:

$$U^2_j = X_j \gamma - \eta\, p^2_j + \varepsilon^2_j, \text{ for } j = 1, \ldots\ldots, N \quad . \qquad (19)$$

In (19), X_j, γ and η are defined as before. p^2_j is the price charged by insurance company j, which is not discounted because homeowners do not install burglar alarms, and ε^2_j is a disturbance term that is identically and independently distributed over homeowners and insurance company j. Note that since non-alarmed homeowners do not receive a protective device discount, $p^2_j > p^1_j$, unless the homeowner's insurance company chooses not to offer a discount to customers installing burglar alarms.

Albeit a small portion, not all of the market purchases homeowner's insurance. Define the "outside good" as the option not to purchase homeowner's insurance. What distinguishes the "outside good" from the option that homeowners have to purchase insurance is that the price of the "outside good" is not set in response to the price of the "inside good." The "inside good" is the option to purchase homeowner's insurance. The utility specification for homeowners not purchasing homeowner's insurance but installing burglar alarms is:

$$U^1_0 = \zeta + \varepsilon^1_0 \quad . \quad (20)$$

The utility specification for homeowners not purchasing insurance or installing burglar alarms is:

$$U^2_0 = \varepsilon^2_0 \quad . \quad (21)$$

For use in defining market shares, denote the mean utility level of homeowners insuring with company j and installing burglar alarms as:

$$\delta^1_j = X_j \gamma + \zeta - \eta\, p^1_j \text{ , for } j = 1, \ldots, N \quad , \quad (22)$$

the mean utility level of homeowners insuring with company j and not installing burglar alarms as:

$$\delta^2_j = X_j \gamma - \eta\, p^2_j \text{ , for } j = 1, \ldots, N \quad , \quad (23)$$

the mean utility level of homeowners not purchasing homeowner's insurance but installing burglar alarms as:

$$\delta^1_0 = \zeta \quad , \quad (24)$$

and the mean utility level of homeowners not purchasing homeowner's insurance or

installing burglar alarms as:

$$\delta^2_0 = 0 \quad . \quad (25)$$

Now consider the following definitions of market shares, for j = 1, …, N:

s^1_j = fraction of the market insuring with insurance company j and installing burglar alarms,

s^2_j = fraction of the market insuring with insurance company j and not installing burglar alarms[27] *,*

and for j=0:

s^1_0 = fraction of the market not purchasing homeowner's insurance but installing burglar alarms,

s^2_0 = fraction of the market not purchasing homeowner's insurance or installing burglar alarms.

Since insurance company j's customers are either alarmed or non-alarmed, the total market share of insurance company j is defined as:

$$s^m_j = s^1_j + s^2_j \quad . \quad (26)$$

The total share of the market installing burglar alarms is:

$$s^1 = \sum_{j=0}^{N} s^1_j \ , \quad (27)$$

and the total share of the market not installing burglar alarms is:

$$s^2 = \sum_{j=0}^{N} s^2_j \quad . \quad (28)$$

Since ε^1_j and ε^2_j are identically and independently distributed with extreme value distribution and drawn from the same density, only the mean utility levels, δ^1_j and δ^2_j, differentiate homeowner's insurance companies (Berry 1994). As a result, all properties of

[27] Note that this variable is denoted as s_j in chapter four.

market demand, including market shares, are determined solely by δ^1_j and δ^2_j. Assuming that homeowners purchase insurance from just one company and employ the combination of homeowner's insurance and burglar alarm installation that generates the highest utility, market shares defined in terms of mean utility levels are:

$$s^1_j = exp(\delta^1_j) / (\sum_{j=0}^{N} exp(\delta^1_j) + \sum_{j=0}^{N} exp(\delta^2_j)), for\ j = 1, \ldots, N \qquad (29)$$

and

$$s^2_j = exp(\delta^2_j) / (\sum_{j=0}^{N} exp(\delta^1_j) + \sum_{j=0}^{N} exp(\delta^2_j)), for\ j = 1, \ldots\ldots, N\ . \qquad (30)$$

For the fraction of the market not purchasing homeowner's insurance or installing burglar alarms, for which mean utility is zero, the market share is:

$$s^2_0 = 1 / (\sum_{j=0}^{N} exp(\delta^1_j) + \sum_{j=0}^{N} exp(\delta^2_j))\ . \qquad (31)$$

Given that alarmed and non-alarmed portions of market shares are defined in terms of mean utility and are functions of γ, ζ, and η, it is now possible to generate estimates of demand-side parameters. If data were readily available on s^1_j and s^2_j, non-linear least squares analysis could be used to obtain estimates of γ, ζ, and η directly from (29) and (30). However, as described in chapter four, s^1_j and s^2_j are not observable. I therefore estimate γ, ζ, and η using data on total market shares, s^m_j, and, in turn, use those estimates to compute s^1_j and s^2_j.

Recall that s^m_j is defined by (26). Given that s^1_j and s^2_j are also defined by (29) and

(30), s^m_j for j = 1, ……, N is:

$$s^m_j = (exp(\delta^1_j) + exp(\delta^2_j)) / (\sum_{j=0}^{N} exp(\delta^1_j) + \sum_{j=0}^{N} exp(\delta^2_j)) \quad . \qquad (32)$$

Dividing (32) by s^m_0, which is a function of the market share of the "outside good," and assuming s^m_j/s^m_0 is observed with error:

$$(s^m_j/s^m_0) = (exp(\delta^1_j) + exp(\delta^2_j))/ (exp(\delta^1_0) + exp(\delta^2_0))$$

$$= (exp(X_j \gamma + \zeta - \eta\, p^1_j) + exp(X_j \gamma - \eta\, p^2_j))/ (exp(\zeta) + 1) \quad , \qquad (33)$$

I estimate γ, ζ, and η using non-linear least squares estimation[28]:

$$min \sum_{j=1}^{N} [(s^m_j/s^m_0) - ((exp(X_j \gamma + \zeta - \eta\, p^1_j) + exp(X_j \gamma - \eta\, p^2_j))/ (exp(\zeta) + 1))]^2 \quad , \qquad (34)$$

where X_j, p^1_j, p^2_j, s^m_j, and s^m_0 are observed in the data. Substituting estimates of γ, ζ, and η into (29) and (30), I calculate s^1_j and s^2_j. Based on (27) and (28), s^1 and s^2 are also computed.

5.2: The Supply Side

In this section, I assume that homeowner's insurance companies maximize profit with respect to the prices and protective device discounts they offer. Since these companies incur a cost when crime is diverted to their non-alarmed customers, then when they maximize profit, they must consider how the probability of burglary of their customers changes with the fraction of the total market installing burglar alarms. I therefore define the profit of homeowner's insurance companies as a function of the probability of burglary, which, in

[28] Endogeniety of price was addressed by Berry, Levinsohn, and Pakes (1995) in their analysis of the automobile industry because consumer utility was a function of unobserved product characteristics, which were correlated with the product's price. Here, ζ is uncorrelated with insurance policy prices, so endogeneity is not considered.

turn, is a function of the fraction of the market installing burglar alarms, s^1. I estimate supply-side parameters from homeowner's insurance companies' first order conditions using Generalized Method of Moments (GMM) estimation, and use them to compute the probability of burglary of both alarmed and non-alarmed homeowners when some homeowners install burglar alarms.

On the supply side of the market, the N homeowner's insurance companies operating in the market are assumed to be price setters, competing in a Bertrand fashion. Each company generates revenue by selling homeowner's insurance policies at different prices, offering a protective device discount to homeowners installing burglar alarms. Homeowner's insurance companies incur a marginal cost of production, as well as an additional cost when their customers are burgled. The expected cost of burglary depends on the probability of burglary and the value of the property stolen. Define the profit of homeowner's insurance company j as:

$$\Pi_j = (p^1_j - c^1_j)s^1_j + (p^2_j - c^2_j)s^2_j - PR^1M^1s^1_j - PR^2M^2s^2_j \quad . \qquad (35)$$

p^1_j, s^1_j, p^2_j, and s^2_j are defined as before. c^1_j is the marginal cost of production that homeowner's insurance company j incurs when insuring alarmed homeowners, c^2_j is the marginal cost of production that homeowner's insurance company j incurs when insuring non-alarmed homeowners, M^1 is the average insurance claim of alarmed homeowners due to burglary, and M^2 is the average insurance claim of non-alarmed homeowners due to burglary. PR^1 is the probability of burglary of alarmed homeowners when some homeowners in the market install burglar alarms, specified as:

$$PR^1 = (exp(\alpha_0 + \alpha\, s^1(p))) / (1 + exp(\alpha_0 + \alpha\, s^1(p))) \quad . \qquad (36)$$

To incorporate the presence of the diversion effect, PR^1 is a function of the total share of the market installing burglar alarms, s^1. s^1 is a function of all prices, p, since firms compete on price. Since the deterrence effect is defined as the decrease in the probability of burglary of alarmed homeowners when they install burglar alarms, α is assumed to be negative.

In a similar fashion, PR^2 is the probability of burglary of non-alarmed homeowners when some homeowners in the market install burglar alarms, specified as:

$$PR^2 = (exp(\beta_0 + \beta\, s^1(p))) / (1 + exp(\beta_0 + \beta\, s^1(p))) \quad . \qquad (37)$$

Since the diversion effect is associated with an increase in the probability of burglary of non-alarmed homeowners when burglar alarm use increases, β is assumed to be positive.

Maximizing (35) with respect to both p^1_j and p^2_j and assuming p^1_j and p^2_j are observed with error, homeowner's insurance company j's first order conditions are:

$$p^1_j = \{(1/\eta)/(1-s^1_j)\} + \{((p^2_j - c^2_j)s^2_j)/(1-s^1_j)\} + \{(M^1PR^1[(1-s^1_j) + (1-PR^1)\alpha\,(1-s^1)s^1_j])/(1-s^1_j)\} - \{(M^2PR^2[s^2_j - s^2_j(1-PR^2)\beta\,(1-s^1)])/(1-s^1_j)\} + c^1_j \qquad (38)$$

and

$$p^2_j = \{(1/\eta)/(1-s^2_j)\} + \{((p^1_j - c^1_j)s^1_j)/(1-s^2_j)\} + \{(M^2PR^2[(1-s^2_j) - s^2_j(1-PR^2)\beta\, s^1])/(1-s^2_j)\} - \{(M^1PR^1[s^1_j + s^1_j(1-PR^1)\alpha\, s^1])/(1-s^2_j)\} + c^2_j \quad . \qquad (39)$$

The derivations of (38) and (39) are detailed in the appendix. Since data on marginal cost are unavailable, I assume c^1_j is specified as:

$$c^1_j = X_j\,\theta + e^1_j \quad , \qquad (40)$$

where X_j is the same vector of eight homeowner's insurance company characteristics

(including a constant) used in demand-side estimation in section 5.1. c^2_j is specified as:

$$c^2_j = X_j \theta + e^2_j \quad . \qquad (41)$$

Substituting the demand-side estimate of η, computations of s^1_j, s^1, s^2_j, and s^2, c^1_j and c^2_j from (40) and (41), PR^1 and PR^2 from (36) and (37), and data on p^1_j, p^2_j, M^1, and M^2 into (38) and (39), I obtain supply-side estimates of θ, α_0, α, β_0, and β using GMM analysis. Given that θ consists of eight elements, at least 12 moment conditions are required for GMM estimation. With two first order conditions given by (38) and (39) and eight exogenous variables in X_j, I easily meet this requirement with 16 moment conditions. The 16 moment conditions are defined by:

$$E(X_j' e_j) = 0 \quad , \qquad (42)$$

where the first eight elements of $X_j' e_j$ are $X_j' e^1_j$ and the last eight elements of $X_j' e_j$ are $X_j' e^2_j$.

Define L as the total number of observations in the sample. The objective function I use in GMM estimation is:

$$\{(\frac{1}{L})X_j' e_j\}' I \{(\frac{1}{L})X_j' e_j\} \quad , \qquad (43)$$

where I is an identity matrix that serves as the weighting matrix.

Substituting supply-side estimates of θ, α_0, α, β_0, and β into (36) and (37), I compute PR^1 and PR^2, the probabilities of burglary of alarmed and non-alarmed homeowners, respectively, when some homeowners install burglar alarms.

5.3: Calculating the Diversion Effect

Sections 5.1 and 5.2 describe the first stages of measuring the diversion effect associated with observable private precaution by computing the probability of burglary of non-alarmed homeowners when some homeowners make the decision to install burglar alarms. The final stage compares this calculation to the probability of burglary of non-alarmed homeowners when homeowners collectively decide not to install burglar alarms, which I compute in this section. The difference in these probabilities measures the change in the probability of burglary of non-alarmed homeowners due to an increase in burglar alarm use, or the diversion effect.

Consider the case if all homeowners are non-alarmed. Using similar notation as the first scenario when some homeowners install burglar alarms, I now redefine the probabilities of burglary described in section 5.2.

The probability of burglary of non-alarmed homeowners is no longer a function of s^1, given that the homogeneous decision of all homeowners not to install burglar alarms eliminates the diversion effect. Since $s^1=0$, the probability of burglary of non-alarmed homeowners who are also non-alarmed in sections 5.1 and 5.2 is:

$$PR^N = (exp(\beta_0)) / (1 + exp(\beta_0)) \quad . \qquad (44)$$

The probability of burglary of non-alarmed homeowners who are alarmed in sections 5.1 and 5.2 is:

$$PR^A = (exp(\alpha_0)) / (1 + exp(\alpha_0)) \quad . \qquad (45)$$

As the method of Berry, Levinsohn, and Pakes is structural in nature, I use the estimates of β_0 and α_0, generated from GMM estimation of (38) and (39), to calculate PR^N, as

defined by (44), and PR^A, defined by (45). The diversion effect is estimated as the difference between the probability of burglary of non-alarmed homeowners when some homeowners install burglar alarms, PR^2, and the probability of burglary of those same homeowners when all homes are non-alarmed, PR^N:

$$DIV = PR^2 - PR^N \quad . \qquad (46)$$

The diversion effect, DIV, is expected to be positive. A positive diversion effect suggests that the probability of burglary of non-alarmed homeowners increases with the use of observable protective devices by surrounding homeowners.

The deterrence effect is estimated as the difference between the probability of burglary of alarmed homeowners when some homeowners install burglar alarms, PR^1, and the probability of burglary of those same homeowners when all homes are non-alarmed, PR^A:

$$DET = PR^1 - PR^A \quad . \qquad (47)$$

The deterrence effect, DET, is expected to be negative. A negative deterrence effect suggests that the probability of burglary of alarmed homeowners decreases with the use of observable protective devices.

5.4: Data Sources

To empirically investigate the method for measuring the diversion effect described in sections 5.1-5.3, I use the data from the Illinois Department of Financial and Professional Regulation, Division of Insurance employed in chapter four. I define the market at the zip-code level in order to capture diversion within short distances.

On both the demand and supply sides of the market, the price charged by

homeowner's insurance company j to alarmed homeowners, p^1_j, is defined as insurance company j's base premium, discounted by the protective device discount. Because homeowner's insurance companies offer different premiums to frame and masonry homeowners, as well as different protective device discounts depending on the burglar alarm type, p^1_j varies by homeowner's insurance company, zip code, type of housing construction, and protective device discount. The price charged to non-alarmed homeowners, p^2_j, is defined as insurance company j's base premium before any discounts are applied. Since p^2_j is not associated with any protective device discount, p^2_j varies only by homeowner's insurance company, zip code, and type of housing construction. I measure the diversion effect separately for each type of burglar alarm and housing construction, as in chapter four.

The market share of homeowner's insurance company j, s^m_j, is defined as the total market, or zip code, share of homeowner's insurance company j. I obtain data on s^m_j from the Illinois Department of Financial and Professional Regulation, Division of Insurance, which provided the total dollar value of homeowner's insurance premiums collected by homeowner's insurance company j in each zip code. Data on s^m_0, the share of the market not purchasing homeowner's insurance, are not available from the Illinois Department of Financial and Professional Regulation, Division of Insurance. Because data on s^m_0 are not available but required for estimation of the diversion effect, I proxy s^m_0 using data from the 2000 U.S. Census on the number of occupied housing units in Illinois and the average premium charged by the 38 homeowner's insurance companies in my sample. This proxy also affects the way s^m_j is represented in the data. First, I sum the actual total value of premiums collected by each homeowner's insurance company in each zip code in order to

obtain the actual total value of premiums collected by all homeowner's insurance companies in each zip code. I then calculate the theoretical total value of premiums collected by all homeowner's insurance companies if all frame homeowners purchased insurance by multiplying the average frame premium of the 38 homeowner's insurance companies in my sample by the total number of housing units in each zip code. I do the same for masonry homeowners. Data on the total number of housing units by zip code are collected from the 2000 U.S. Census[29]. I then calculate the total value of premiums lost in each zip code from homeowners not purchasing homeowner's insurance by subtracting the actual total value of premiums collected from the theoretical total value of premiums collected if all homeowners purchased insurance. I do this separately for each housing construction type. After omitting from the sample those observations for which this difference is negative, I calculate s^m_j for all j by dividing the actual total value of premiums collected by homeowner's insurance company j in each zip code by the theoretical total value of premiums collected by all homeowner's insurance companies if all homeowners purchased insurance in each zip code. Finally, I calculate s^m_0 by dividing the value of premiums lost from homeowners not purchasing homeowner's insurance in each zip code by the theoretical total value of premiums collected by homeowner's insurance companies if all homeowners purchased insurance in each zip code.

Based on these calculations, s^m_j and s^m_0 both vary by housing construction type. s^m_j and s^m_0 also sum to one in each zip code. Due to the fact that data on s^m_0 are not observable and proxied using the aforementioned technique, s^m_0 represents not only the share of the

[29] Those zip codes for which this information is not available are omitted from the sample.

market not purchasing homeowner's insurance, but also the share of the market insuring with a homeowner's insurance company not represented in the sample[30].

Data on homeowner's insurance company characteristics, which are used to define both the utility of homeowners and the marginal cost of homeowner's insurance companies, are denoted by the vector X_j. These data are available from the information that I manually extracted from each homeowner's insurance company's manual on file at the Illinois Department of Financial and Professional Regulation, Division of Insurance. The vector X_j includes dummy variables for the following characteristics: if the homeowner's insurance company sets its premiums according to protection class, bases its polices on a coverage amount less than $100,000 or does not specify an amount, bases its policies on a deductible amount less than $500 or does not specify an amount, offers a multi-policy discount to customers purchasing more than one insurance policy, and is domiciled in the state of Illinois. It is important to note that data for these characteristics are based solely on the information I obtained from the filed manuals at the Illinois Department of Financial and Professional Regulation, Division of Insurance. If information on a given homeowner's insurance company was missing from these manuals, I did not have access to it. As a result, when companies are presented as not specifying deductible or coverage amounts, it may actually mean that the company specifies this information elsewhere.

Finally, I use the statistics on the average loss from burglary from the Tredyffrin Township study mentioned in chapter four as data for M^1 and M^2, the average insurance

[30] The sample includes 38 homeowner's insurance companies for which data were available at the time of data collection in the summer of 2007.

claims of alarmed and non-alarmed homeowners, respectively, due to burglary. As before, these statistics do not vary by homeowner's insurance company or zip code, due to data limitations.

5.5: Results and Discussion

The final dataset used in measurement of the diversion effect associated with burglar alarm use consists of a pooled sample of 17,949 observations at the zip-code level for 38 homeowner's insurance companies operating in the state of Illinois at the time of data collection in the summer of 2007. Table 5.1 presents summary statistics for data related to frame housing that I use for initial, demand-side estimation. Table 5.2 presents the same summary statistics for data related to masonry housing. For both types of housing structures, it is immediately clear that s^m_0, the variable representing the fraction of the market not purchasing homeowner's insurance, is quite large. This is an unusual finding, as it is not realistic for 85% of the market, on average, not to purchase homeowner's insurance. This is especially true because most mortgages require that homeowners purchase insurance. However, recall that data are not available on the fraction of the market not purchasing homeowner's insurance. Because of the way I estimated s^m_0, as described in section 5.4, s^m_0 not only represents non-insured homeowners, but also those homeowners who insure with companies that do not appear in my sample. Given that the 38 homeowner's insurance companies in the sample make up approximately 30% of the state-wide market, the finding of a large s^m_0 in Table 5.1 and Table 5.2 is understandable.

For both types of housing construction, summary statistics additionally reveal that the

average homeowner's insurance company in the sample offers the largest discount for central station reporting burglar alarms. Non-alarmed customers pay the highest prices for their insurance policies[31]. In comparing the two housing construction types, frame homeowners pay higher prices for homeowner's insurance than masonry homeowners.

Recall that data on the dummy variables used as homeowner's insurance company characteristics were limited, so that companies in my sample not offering standard deductible or coverage amounts may actually be misrepresented. As a result, little interpretation comes from the summary statistics for these variables or from their role in measurement of the diversion effect. However, it is interesting to note that more than half of the homeowner's insurance companies in the sample set their premiums using protection classes and offer a multi-policy discount.

Table 5.3 includes demand-side parameter estimates obtained using non-linear least squares estimation of (34). Demand-side estimation is conducted separately for frame and masonry housing, as well as for central station reporting burglar alarms, police station connected burglar alarms, and local burglar alarms. For all housing construction and burglar alarm types, the dummy variables that are statistically significant at the 5% level include if the homeowner's insurance company sets its premiums according to protection classes, does not specify deductible and coverage amounts, offers multi-policy discounts, and is domiciled in the state of Illinois. The exception to this finding is that the dummy variable representing if the homeowner's insurance company does not specify a coverage amount is not statistically significant for masonry homeowners using police station connected and local

[31] Assuming all other factors constant.

burglar alarms. Referring to statistically significant variables only, results show that homeowners prefer to insure with companies that do not use protection classes when setting their premiums, do not specify coverage amounts but do specify deductible amounts, offer multi-policy discounts, and are domiciled in Illinois.

Although the net benefit of installing burglar alarms and price are not statistically significant for any housing construction or burglar alarm types, they bear the expected signs. That is, for all housing construction and burglar alarm types, the net benefit of installing burglar alarms is positive, and ceteris paribus, higher protective device discounts increase the utility of homeowners. Additionally, results show that for frame homeowners, local burglar alarms yield the highest net benefit. Since this type of burglar alarm is considered to be less sophisticated, the finding of a high net benefit may be due to the fact that the price of a local burglar alarm and its associated operating costs are lower, relative to other types of alarms. For masonry homeowners, police station connected burglar alarms yield the highest net benefit. Among housing construction types, frame homeowners tend to receive a higher net benefit from installing burglar alarms than masonry homeowners.

Table 5.4 displays summary statistics for market-share estimates. Market shares are calculated using the demand-side parameter estimates displayed in Table 5.3. Note that all market shares are scaled by 1,000 because of the small sizes of s^2_j and s^2. Mean values of market shares are calculated using an unweighted average over all zip codes and homeowner's insurance companies. Although the purpose of calculating these market shares is to complete supply-side estimation and measure the diversion effect associated with burglar alarm use, their calculations are interesting independently because they offer insight

into generally unavailable data on how many homeowners install burglar alarms. Unfortunately, several anomalies are apparent in these summary statistics. Table 5.4 shows that virtually 100% of the market installs burglar alarms. This is certainly unrealistic, as demonstrated by the finding of chapter three that roughly 16% of the county-level market installs burglar alarms. Additionally, according to Hakim and Blackstone, alarm ownership ranges from 11% to 15% of all homes and business (1997). The finding of a large s^1 poses a significant challenge to measuring the diversion effect using the method of this chapter. Although the diversion effect theoretically increases as more homeowners install burglar alarms, estimation is unlikely to find the presence of a diversion effect if the non-alarmed portion of the market to which crime could be diverted is virtually non-existent.

Results from demand-side estimation provide insight as to why the fraction of the market installing burglar alarms is estimated to be so large. By specifying the net benefit of burglar alarm installation to be positive and constant among homeowners in (18), demand-side estimation fails to take into account the several reasons why individuals may decide not to install burglar alarms. In fact, it assumes that all homeowners have a positive net benefit of installing burglar alarms and therefore predicts that all homeowners will install. Without taking homeowner characteristics into account, my measure of the diversion effect in this chapter assumes that all homeowners are alike and that any differences in market shares arise solely from differences in insurance products in different markets. Homeowner characteristics to consider include those related to the likelihood of burglary. Previous literature shows that certain qualities of both homes and homeowners increase the probability of burglary, such as the race and income of homeowners and the age and value of homes. A

homeowner may decide not to install a burglar alarm if any of these factors decrease their probability of burglary, or if the direct costs of burglar alarm installation are large enough to outweigh the benefits received from deterrence. Including those characteristics that may affect a homeowner's decision to install a burglar alarm in demand-side estimation may help reduce the estimate of s^1. Section 5.8 of this chapter proposes future research that will attempt to resolve the difficulty in measuring the fraction of the market installing burglar alarms.

Keeping the identified anomalies in estimated market shares in mind, Table 5.5 displays supply-side parameter estimates for frame and masonry homeowners using all three types of burglar alarms. Note that GMM estimation does not converge[32] for the majority of housing construction and burglar alarm types, as identified in Table 5.5, and GMM estimation fails for frame homeowners using local burglar alarms. Despite these problems, estimates of α and β, which are key parameters in estimating the deterrence and diversion effects, respectively, yield anticipated signs. The estimate of α is negative for all housing construction and burglar alarms types, which is consistent with the presence of the deterrence effect decreasing the probability of burglary of alarmed homeowners when they install burglar alarms. For all housing and burglar alarm types, the estimate of β is positive and consistent with the diversion effect increasing the probability of burglary of non-alarmed homeowners when other homeowners install burglar alarms. The key parameters are statistically insignificant, except for frame homeowners using central station reporting burglar alarms and masonry homeowners using local burglar alarms. For frame homeowners

[32] GMM optimization likely fails because the objective function is highly non-linear.

using central station reporting burglar alarms, the marginal cost parameters found to be statistically significant at the 5% level include those associated with dummy variables for if the homeowner's insurance company does not specify coverage and deductible amounts. Results show that homeowner's insurance companies that do not specify deductible and coverage amounts have lower marginal costs of production than companies that do specify these amounts. For frame homeowners using police station connected burglar alarms, the statistically significant marginal cost parameters include the dummy variables for if the homeowner's insurance company sets its premiums according to protection classes, bases its policies on a deductible amount less than $500, and does not specify deductible and coverage amounts. Results show that homeowner's insurance companies that use protection classes in their pricing structures face higher marginal costs, and that companies that base their policies on a deductible amount less than $500, and do not specify deductible and coverage amounts face lower marginal costs. Finally, for masonry homeowners using a local burglar alarm system, all marginal cost parameters are found to be statistically significant at the 5% level, except the dummy variable for if the homeowner's insurance company sets it premiums according to protection classes. Results show that homeowner's insurance companies that base their policies on a deductible amount less than $500, base their policies on a coverage amount less than $100,000, and do not specify deductible or coverage amounts have lower marginal costs. Companies face higher marginal costs if they offer multi-policy discounts and are domiciled in the state of Illinois. Housing construction and burglar alarm types not mentioned have statistically insignificant marginal cost parameters.

Table 5.6 includes results on the mean probabilities of burglary for both alarmed and

non-alarmed homeowners. Mean probabilities are determined using an unweighted average over all zip codes and homeowner's insurance companies. PR^1 and PR^2 represent the probabilities of burglary when some homeowners install burglar alarms, and PR^A and PR^N represent the probabilities of burglary when all homeowners are non-alarmed. Because of the lack of homeowner characteristics in the model, these statistics represent the probabilities of burglary under the assumption that all homeowners are exactly the same, except for their decision to install burglar alarms. As a result, the fact that PR^A exceeds PR^N suggests that even before homeowners decide to install burglar alarms, the homeowners that eventually become alarmed face a higher likelihood of burglary than those homeowners who remain non-alarmed. It is then no surprise that after some homeowners install burglar alarms, those who decide to install burglar alarms still face a higher probability of burglary. The fact that alarmed homeowners face a higher probability of burglary than non-alarmed homeowners suggests that alarmed homeowners decide to install burglar alarms because they have more valuable assets to protect. As mentioned in chapter three, homeowners with higher income may be more likely to install burglar alarms. Furthermore, it is possible that the presence of a burglar alarm alone makes the alarmed homeowner more susceptible to burglary because it provides a signal to burglars of the valuable assets inside the home. It is interesting to note that the probability of burglary, regardless of whether the home is alarmed, is generally larger for frame homeowners.

Finally, Table 5.7 illustrates the estimated mean diversion effect for all housing construction and burglar alarm types. Again, the mean is calculated as the unweighted average over all zip codes and homeowner's insurance companies in the sample. Table 5.8

presents estimated mean deterrence effects. Both mean effects have the anticipated signs for all housing construction and burglar alarm types. That is, the diversion effect is found to be positive, which indicates that the probability of burglary of non-alarmed homeowners increases when homeowners around them install burglar alarms. A diversion effect equal to 0.040 for frame homeowners using central station reporting burglar alarms is interpreted as meaning that the probability of burglary of non-alarmed homeowners increases by 0.040 when other homeowners install burglar alarms. Converted to a percentage change for comparison purposes, a diversion effect equal to 0.040 coincides with an increase in the probability of burglary equal to approximately 6%. This calculation is based on the mean probability of burglary of non-alarmed homeowners when all homeowners are non-alarmed, which is equal to 0.63 in Table 5.6. For masonry homeowners, the estimated diversion effect is consistent with an 11% increase in the probability of burglary. For police station connected burglar alarms, the diversion effect is associated with an increase in the probability of burglary equal to 12% for frame homeowners and 11% for masonry homeowners. For masonry homeowners using local burglar alarms, the diversion effect causes the probability of burglary of non-alarmed homeowners to increase by 9%. Averaging over all housing construction and burglar alarm types, the diversion effect increases the probability of burglary of non-alarmed homeowners by roughly 10%. Across all burglary alarm types, police station connected burglar alarms cause the largest amount of diversion. This is surprising because police station connected burglar alarms are not considered to be the most sophisticated. However, they have the advantage of connecting directly to a police station, rather than a central station that eventually contacts the police. As expected, local

burglar alarms are associated with the least amount of diversion.

The deterrence effect is negative for all types of housing construction and burglar alarms. This finding is consistent with the probability of burglary decreasing for alarmed homeowners when they install burglar alarms. Results suggest that central station reporting burglar alarms decrease the probability of burglary of alarmed frame homeowners by approximately 5% and alarmed masonry homeowners by 10%. Police station connected burglar alarms decrease the probability of alarmed frame homeowners by approximately 5% and alarmed masonry homeowners by 9%. Alarmed masonry homeowners using local burglar alarms experience roughly a 1% decrease in their probability of burglary. Averaging over all housing construction and burglar alarm types, the deterrence effect decreases the probability of burglary of alarmed homeowners by 6%. The results of Table 5.8 show that central station reporting burglar alarms and police station connected burglar alarms are comparable in their ability to deter criminals for all housing construction types, with central station reporting burglar alarms being slightly more effective for masonry homeowners. Not surprisingly, local burglar alarms deter the least.

It is also interesting to compare the deterrence and diversion effects for each housing construction and burglar alarm type. For both frame and masonry homeowners using central station reporting burglar alarms, the absolute size of the deterrence effect in Table 5.8 outweighs the size of the diversion effect in Table 5.7. However, when comparing the percentage change in the probability of burglary, the diversion effect causes a percentage increase in the probability of burglary of non-alarmed homeowners that is larger than the percentage decrease in the probability of burglary of alarmed homeowners caused by the

deterrence effect[33]. For police station connected burglar alarms, the estimated diversion effect is larger than the absolute value of the deterrence effect for frame homeowners, but smaller than the absolute value of the deterrence effect for masonry homeowners. Again, when comparing the percentage change in the probability of burglary, the diversion effect causes a percentage increase in the probability of burglary of non-alarmed homeowners that is larger than the percentage decrease in the probability of burglary of alarmed homeowners caused by the deterrence effect for both housing construction types. Finally, for masonry homeowners using local burglar alarms, the diversion effect outweighs the deterrence effect in both absolute size and percentage change in the probability of burglary. On average, burglar alarms divert more crime than they deter, in terms of the percentage change in the probability of burglary. However, given that estimation generates so few non-alarmed homes in this exercise, the total amount of crime is still likely to decrease even though the diversion effect outweighs the deterrence effect.

5.6: Robustness Check on s^m_j/s^m_0

While the results discussed in section 5.5 provide substantial evidence of the presence of the diversion effect with all housing construction and burglar alarm types, several anomalies are duly noted. These anomalies include unrealistically large estimates of s^1 and s^m_0, as well as difficulty in successfully completing GMM estimation for some housing construction and burglar alarm types. In the next two sections, I perform a robustness check on this chapter's method for measuring the diversion effect associated with burglar alarms by

[33] It is possible that this result is an artifact of a higher initial probability of burglary of alarmed homeowners, PR^A.

correcting for the abnormally large values of s^1 and s^m_0 and then exploring how these corrections affect measurement of the diversion effect. I present results for frame and masonry homeowners using central station reporting burglar alarms only, but the results are easily transferable to the other burglar alarm types. In this section, I focus on how a reduction in s^m_0 changes estimation of the diversion effect. I refer to the results discussed in section 5.5 as "original results."

As described in section 5.5, s^m_0 is estimated to be entirely too large in original results because only 30% of the homeowner's insurance industry is represented in the sample. In order to reduce s^m_0, I scale the left-hand side of (33) and conduct non-linear least squares estimation using (34). By scaling, I not only increase the ratio of s^m_j to s^m_0, but also reduce the estimated s^1. Because scaling s^m_j/s^m_0 influences estimates of s^1, it is also likely to affect estimates of the diversion effect. To determine by how much to scale the left-hand side of (33), I establish the following criteria:

1. Maintain predicted signs on the key parameters of η and ζ in demand-side estimation,
2. Decrease the estimated s^1 , and
3. Establish convergence in supply-side GMM estimation.

Based on these criteria, I employ a scale of 23,000 for frame housing and 12,000 for masonry housing. Table 5.9 presents results from demand-side estimation for frame and masonry homeowners using central station reporting burglar alarms, where now s^m_j/s^m_0 is scaled. Compared to original results, the signs and statistical significance of demand-side parameters have not changed for both frame and masonry housing (except for the intercept), as expected. Although statistically insignificant, the net benefit of installing a central station

reporting burglar alarm is found to be higher for masonry homeowners than for frame homeowners.

The impact of scaling the ratio of s^m_j to s^m_0 is certainly seen in Table 5.10, which presents summary statistics for market shares. For both frame and masonry housing, the share of the market installing burglar alarms, s^1, decreases from approximately 100% of the market in original results to approximately 52% for frame homeowners and 65% for masonry homeowners. While these estimates are still too large according to previous research, they provide a more realistic estimate of s^1. All other market shares increase as a result of the scaling.

Table 5.11 displays the supply-side parameters obtained after scaling the ratio of s^m_j to s^m_0. Compared to original results, α and β retain their anticipated signs for both frame and masonry homeowners. That is, α is still negative and likely to be consistent with a negative deterrence effect, and β is positive. Given that β is still found to be positive, a positive diversion effect is also likely. In terms of the marginal cost parameters, now only the dummy variable representing if the homeowner's insurance company does not specify a deductible amount is statistically significant. Results show that homeowner's insurance companies that do not specify a deductible amount face lower marginal costs than those companies that do specify an amount.

As seen in Table 5.12, the mean probabilities of burglary for frame homeowners increase when I scale the ratio of s^m_j to s^m_0, compared to original results for frame homeowners using central station reporting burglar alarms. As in the original results for the case when all homes are non-alarmed, the probability of burglary of homeowners that

become alarmed, PR^A, is larger than the probability of burglary of homeowners that remain non-alarmed, PR^N. The mean probabilities of burglary of masonry homeowners stay approximately the same, compared to original results. The exception to this finding is that PR^N is significantly smaller than original results. This probability of burglary decreases from 0.57 to 0.07. As with original results, all mean probabilities of burglary are higher for frame homeowners than for masonry homeowners.

As predicted, the measured mean diversion effect is positive for both frame and masonry homeowners when I scale s^m_j/s^m_0, as shown in Table 5.13. A diversion effect equal to 0.032 for frame homeowners is consistent with an increase in the probability of burglary of non-alarmed homeowners equal to 5%. The diversion effect for masonry homeowners is consistent with an increase in the probability of burglary equal to approximately 800%. This result is unrealistic, but clearly due to the fact that PR^N is so small for masonry homeowners.

Table 5.14 shows that the mean deterrence effect for both frame and masonry homeowners using central station reporting burglar alarms is negative when I scale s^m_j/s^m_0. For alarmed frame homeowners, their probability of burglary decreases by 3% when they install burglar alarms. The probability of burglary of alarmed masonry homeowners decreases by 10%. For frame homeowners, the mean diversion and deterrence effects are approximately the same size in absolute value. However, when comparing the percentage change in the probability of burglary, diversion causes the probability of burglary of non-alarmed homeowners to increase more than deterrence causes the probability of burglary of alarmed homeowners to decrease. As for masonry homeowners, the diversion effect clearly outweighs the deterrence effect in both absolute size and percentage change in the probability

of burglary. Since the estimate of the fraction of alarmed homeowners is still unrealistically large, the results of this section are likely to be consistent with a decrease in the total level of crime, as in section 5.5.

Compared to the original results described in section 5.5, measurement of the diversion effect for frame homeowners does not appear to be affected by scaling the ratio of s^m_j to s^m_0. Although estimates of s^1 are smaller, the percentage change in the probability of burglary of frame homeowners using central station reporting burglar alarms is still approximately 5-6%. The measured deterrence effect for both frame and masonry homeowners also appears to be unaffected by scaling s^m_j/s^m_0. As a result, the robustness check of this section shows that while the method presented in this chapter for measuring the diversion effect may not be precise in estimating s^1 or s^m_0, it provides solid estimates of the diversion effect that are robust to changes in s^m_0. Estimation is also robust to decreases in s^1 that are caused by changes in s^m_0. The exception to this finding is that the diversion effect associated with masonry homeowners using central station reporting burglar alarms increases from an 11% change in the probability of burglary of non-alarmed homeowners to an unrealistic 800% change, when the ratio of s^m_j to s^m_0 is scaled.

5.7: Robustness Check on s^1

In this section, I focus on how a direct reduction in s^1 to the published estimate of approximately 15% affects this chapter's method for measuring the diversion effect associated with burglar alarms. Although the diversion effect is assumed to increase with the fraction of the market installing burglar alarms, the finding of a large s^1 is problematic

because without any non-alarmed homeowners in the market, there is unlikely to be a presence of the diversion effect. In order to reduce s^1, I first assume the results of Table 5.3 and then scale the market shares displayed in Table 5.4 so that s^1 has a mean of approximately 0.15. In turn, s^2 is scaled to a mean of 0.85. s^1_j and s^2_j are scaled in the same manner as s^1 and s^2, respectively. As in section 5.6, analysis is conducted only for frame and masonry homeowners using central station reporting burglar alarms. I compare the results of this section to the original results of section 5.5 only.

Table 5.15 displays supply-side parameters for frame and masonry homeowners using central station reporting burglar alarms. By scaling s^1 directly, the key parameters used in measuring deterrence and diversion, α and β, remain statistically insignificant. However, β bears the incorrect sign, according to theory, for both housing construction types. Since α is still estimated to be negative, the deterrence effect is likely to be associated with a decrease in the probability of burglary of alarmed homeowners. However, since β is positive, scaling s^1 is likely to be associated with a negative diversion effect. This suggests that scaling s^1 to a more realistic size may not only decrease the size of the diversion effect, but also cause a decrease in the probability of burglary of non-alarmed homeowners. In reality, this may only be the case if the fraction of the market installing alarms becomes so large that burglars are deterred from the entire market, including non-alarmed homes. For frame homeowners, the statistically significant marginal cost parameters at the 5% level include dummy variables for if the homeowner's insurance company does not specify deductible or coverage amounts and is domiciled in the state of Illinois. Marginal cost is lower for companies that fail to establish coverage and deductible amounts, but higher for companies that make the state of Illinois

their domicile. For masonry homeowners, the only statistically significant marginal cost parameter at the 5% level is the dummy variable for if the homeowner's insurance company does not specify a deductible amount. For these companies, marginal cost is lower.

Table 5.16 shows that compared to original results, calculations of the mean probabilities of burglary when some homeowners install burglar alarms increase for frame housing, but stay approximately the same for masonry housing, when s^1 is reduced. For the probabilities of burglary when all homes are non-alarmed, PR^N increases for both frame and masonry homeowners. This suggests that homeowners that remain non-alarmed are more susceptible to burglary when s^1 is scaled downward, compared to the case when s^1 is virtually 100%. PR^A for both types of housing construction remain fairly close to one. The mean probabilities of burglary are higher for frame homeowners than for masonry homeowners.

Table 5.17 reveals that, compared to original results, the diversion effect is negative for both housing construction types. The finding of a negative diversion effect is expected, given that β is found to be negative in supply-side estimation. A diversion effect equal to -0.13 for frame housing suggests that the probability of burglary of non-alarmed homeowners decreases by approximately 16% when other homeowners install burglar alarms. The diversion effect for masonry homeowners is consistent with a 12% decrease in the probability of burglary of non-alarmed homeowners. Compared to original results, this suggests that when s^1 decreases, the diversion effect also decreases.

As for the deterrence effect, Table 5.18 shows that the deterrence effect is negative for both housing construction types using central station reporting burglar alarms when s^1 is scaled downward. For frame homeowners, the deterrence effect is associated with a 0.02%

decrease in the probability of burglary of alarmed frame homeowners and a 2% decrease in the probability of burglary of alarmed masonry homeowners. Combining the deterrence and diversion effects when s^1 is scaled downward suggests an overall decrease in the probability of burglary for all homeowners using central station reporting burglar alarms. In fact, diversion is found to decrease the probability of burglary of non-alarmed homeowners by more than deterrence decreases the probability of burglary of alarmed homeowners.

Compared to the original results described in section 5.5, measurement of the diversion effect for both frame and masonry homeowners is definitely affected by direct changes in s^1. That is, scaling s^1 to a more realistic estimate not only fails to provide evidence of a diversion effect, but also shows that the installation of burglar alarms by some homeowners decreases the probability of burglary of all homeowners in the market, including those that are non-alarmed. As for the deterrence effect, a decrease in the fraction of the market installing burglar alarms is associated with a smaller deterrence effect. Overall, the original results described in section 5.5 are not robust to direct changes in s^1. If s^1 is to be scaled downward, the most effective way to do so is to scale s^m_j/s^m_0 before conducting non-linear least squares estimation, as in section 5.6.

5.8: Future Research

It is admittedly difficult to be confident in the results discussed in section 5.5 because of the aforementioned anomalies in estimation, including large estimates of s^1 and s^m_0 and weak GMM analysis. Although the results of section 5.5 still provide reasonable measurements of the diversion effect, the true contribution of the findings of this chapter is

the methodology for measuring the diversion effect. The results of section 5.5 not only show that the diversion effect can be measured, but they also identify the problems with the methodology outlined in sections 5.1 – 5.3. Additionally, these results suggest that precision in measuring the diversion effect can be obtained if these problems are addressed. In this section, I outline the steps that I would take in future research in order to address these fundamental problems.

The fact that demand-side estimation fails to take into account the factors that influence a homeowner's decision to install a burglar alarm is the likely explanation as to why s^1 is estimated to be so large in original results. At first glance, an obvious resolution would be to simply add homeowner characteristics to (18), such as home value, age of home, and homeowner income. However, by simply adding homeowner characteristics to the utility specification of both alarmed and non-alarmed homeowners, I still fail to take into account the likelihood that homeowners have different preferences regarding homeowner's insurance and burglar alarms. That is, I still assume that consumers differ only in their decisions regarding homeowner's insurance companies and therefore estimate one set of demand-side parameters for the entire market. In reality, consumers differ in their tastes and preferences, and therefore are likely to have a different set of demand-side parameters to explain these differences. I verified that simply adding homeowner characteristics to (18) is not sufficient to take into account the different tastes and preferences of homeowners by adding zip-code level data on the percentage of African American homeowners, real per-capita homeowner income, age of home, and median house value to demand-side estimation. I chose these variables due to their importance in determining burglary rates in chapter three.

However, I immediately ran into difficulties in demand-side estimation when key parameters, ζ and η, turned out to be statistically significant and of the incorrect signs.

As a result, a solution that introduces homeowner variation in tastes and preferences into the methodology of this chapter is to use random, or individual, coefficients in (18) that are drawn from a posited distribution that is a function of the aforementioned homeowner characteristics at the zip-code level. In this sense, my methodology would be less simplified than described in sections 5.1-5.3, but more like the original work of Berry, Levinsohn, and Pakes (1995). Random coefficients allow for the decision of homeowners to employ observable private precaution to be a function of the different ways in which they value homeowner's insurance and burglar alarms. In order to account for homeowner variation using random coefficients, (18) becomes the utility specification for homeowner i insuring with homeowner's insurance company j and installing a burglar alarm:

$$U^1_{ij} = X_j \gamma_i + \zeta_i - \eta_i p^1_j + \varepsilon^1_{ij}, \; for\; j = 1, \ldots\ldots, N \quad , \qquad (48)$$

where now demand-side parameters vary by homeowner.

In terms of improving the empirical application of the methodology of this chapter, the most obvious improvement would be the measurement of s^m_0. As shown in the robustness check of section 5.6, scaling s^m_j/s^m_0 also improves the estimate of s^1. In addition to having to proxy for s^m_0, the reason why s^m_0 is found to be so large in original results is because the estimate includes the 70% of the homeowner's insurance industry not included in my sample. As a result, I can improve measurement of s^m_0 by obtaining data on more homeowner's insurance companies operating in the state of Illinois. If possible, I could also reduce s^m_0 by obtaining accurate data on how many homeowners choose not to purchase

insurance. As these data are likely difficult to obtain, I could simulate data on s^m_0, in a manner similar to the way data on security system services sales are simulated in chapter three. A final improvement would be to refine the GMM estimation routine in section 5.2 in order to ensure convergence.

5.9: Conclusion

In the spirit of the methodology outlined in chapter four, this chapter provides another technique for measuring the diversion effect associated with burglar alarm use and empirically examines the technique using data from the homeowner's insurance industry in Illinois. This method is different than the one presented in chapter four because it measures the diversion effect in an oligopolistic, rather than perfectly competitive, setting. Based on the work of Berry, Levinsohn, and Pakes, this method additionally allows for estimation of the diversion effect without data on the number of homeowners installing burglar alarms. This feature is a breakthrough in the current literature because of the difficulty in obtaining such data. Several anomalies are admittedly apparent in the empirical application of this chapter's technique. But despite these anomalies, the primary contribution of this chapter is the presentation of a unique methodology for measuring the diversion effect. This chapter demonstrates that the diversion effect associated with burglar alarms can be measured, identifies the fundamental problems with the methodology, and proposes resolutions to these problems for future research. Even with the anomalies present in the empirical application, results of this chapter suggest that the diversion effect exists when homeowners install burglar alarms. The diversion effect is likely to be small, but still nearly as large as the

deterrence effect, or even larger, for some housing construction and burglar alarm types.

Table 5.1: Summary Statistics for Frame Housing

Variable	Mean	Standard Deviation	Minimum	Maximum
s^m_j: total market share of homeowner's insurance company j	0.0061	0.015	0.0000	0.37
s^m_0: total share of market not purchasing homeowner's insurance	0.85	0.088	0.14	1.00
p^1_j: price charged by homeowner's insurance company j to alarmed homeowners				
Central Station Reporting Burglar Alarm	673.78	323.67	95.00	3,887.33
Police Station Connected Burglar Alarm	692.42	328.036	95.00	3,887.33
Local Burglar Alarm	713.18	343.55	100.00	4,189.67
p^2_j: price charged by homeowner's insurance company j to non-alarmed homeowners	731.62	355.22	100.00	4319.25
X_j: characteristics of homeowner's insurance company j				
Structures rates according to protection classes	0.53	0.50	0.00	1.00
Bases policies on deductible less than $500	0.02	0.15	0.00	1.00
Does not specify deductible on which policies are based	0.55	0.50	0.00	1.00
Bases its policies on coverage amount less than $100,000	0.019	0.14	0.00	1.00
Does not specify coverage amount on which policies are based	0.25	0.43	0.00	1.00
Offers multi-policy discount	0.71	0.45	0.00	1.00
IL is the state of domicile	0.15	0.36	0.00	1.00
No. of Observations	17,949			

Table 5.2: Summary Statistics for Masonry Housing

Variable	Mean	Standard Deviation	Minimum	Maximum
s^m_j: total market share of homeowner's insurance company j	0.0067	0.016	0.00	0.41
s^m_0: total share of market not purchasing homeowner's insurance	0.84	0.096	0.061	1.00
p^1_j: price charged by homeowner's insurance company j to alarmed homeowners				
Central Station Reporting Burglar Alarm	612.95	288.15	95.00	3,498.75
Police Station Connected Burglar Alarm	629.64	291.49	95.00	3,498.75
Local Burglar Alarm	648.64	305.79	100.00	3,770.88
p^2_j: price charged by homeowners's insurance company j to non-alarmed homeowners	665.44	316.30	100.00	3887.20
X_j: characteristics of homeowner's insurance company j				
Structures rates according to protection classes	0.53	0.50	0.00	1.00
Bases policies on deductible less than $500	0.024	0.15	0.00	1.00
Does not specify deductible on which policies are based	0.55	0.50	0.00	1.00
Bases its policies on coverage amount less than $100,000	0.019	0.14	0.00	1.00
Does not specify coverage amount on which policies are based	0.25	0.43	0.00	1.00
Offers multi-policy discount	0.71	0.45	0.00	1.00
IL is the state of domicile	0.15	0.36	0.00	1.00
No. of Observations	17,949			

Table 5.3: Demand-Side Parameters

		Central Station Reporting Burglar Alarm					
		Frame Housing			Masonry Housing		
Parameter	Variable	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Constant		-9.22	0.46	-20.22	-8.99	0.79	-11.39
γ_1	Structures rates according to protection classes	-0.59	0.12	-5.055	-0.54	0.21	-2.54
γ_2	Bases policies on deductible less than $500	0.94	0.92	1.026	0.92	1.68	0.55
γ_3	Does not specify deductible on which policies are based	2.41	0.25	9.65	2.42	0.45	5.36
γ_4	Bases its policies on coverage amount less than $100,000	0.16	1.18	0.14	0.46	1.68	0.27
γ_5	Does not specify coverage on which policies are based	-0.50	0.11	-4.51	-0.47	0.21	-2.29
γ_6	Offers multi-policy discount	2.49	0.37	6.69	2.43	0.63	3.87
γ_7	IL is the state of domicile	1.93	0.10	18.74	1.95	0.18	10.69
ζ	Net benefit from installing alarms	7.53	20,219.56	0.00040	6.84	13,261.89	0.0005
η	Price of homeowner's insurance	0.00020	0.00020	0.85	0.00030	0.00040	0.65

Table 5.3: (Continued)

		Police Station Connected Burglar Alarm					
		Frame Housing			Masonry Housing		
Parameter	Variable	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Constant		-9.25	0.51	-18.14	-8.98	0.88	-10.24
γ_1	Structures rates according to protection classes	-0.60	0.12	-5.090	-0.55	0.22	-2.52
γ_2	Bases policies on deductible less than $500	0.94	0.93	1.014	0.95	1.63	0.58
γ_3	Does not specify deductible on which policies are based	2.43	0.25	9.60	2.41	0.45	5.42
γ_4	Bases its policies on coverage amount less than $100,000	0.16	1.19	0.14	0.45	1.67	0.27
γ_5	Does not specify coverage on which policies are based	-0.53	0.16	-3.33	-0.48	0.29	-1.65
γ_6	Offers multi-policy discount	2.53	0.39	6.48	2.43	0.64	3.79
γ_7	IL is the state of domicile	1.93	0.11	17.18	1.95	0.20	9.74
ζ	Net benefit from installing alarms	10.94	460,016.47	0.00	9.37	133,621.77	0.00010
η	Price of homeowner's insurance	0.00020	0.00020	1.14	0.00030	0.00040	0.82

Table 5.3: (Continued)

		Local Burglar Alarm					
		Frame Housing			Masonry Housing		
Parameter	Variable	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Constant		-9.06	0.50	-18.14	-8.79	0.87	-10.12
γ_1	Structures rates according to protection classes	-0.60	0.13	-4.51	-0.55	0.24	-2.25
γ_2	Bases policies on deductible less than $500	0.92	0.90	1.027	0.85	1.66	0.51
γ_3	Does not specify deductible on which policies are based	2.36	0.24	9.71	2.34	0.42	5.51
γ_4	Bases its policies on coverage amount less than $100,000	0.10	1.20	0.080	0.36	1.71	0.21
γ_5	Does not specify coverage on which policies are based	-0.52	0.19	-2.73	-0.47	0.34	-1.39
γ_6	Offers multi-policy discount	2.39	0.33	7.16	2.31	0.55	4.18
γ_7	IL is the state of domicile	1.93	0.14	13.53	1.95	0.26	7.61
ζ	Net benefit from installing alarm	11.07	1,809,230.92	0.00	8.42	181,268.80	0.00
η	Price of homeowner's insurance	0.00020	0.00030	0.71	0.00030	0.00050	0.50

Table 5.4: Summary Statistics for Market Shares (x1,000)

	Central Station Reporting Burglar Alarm			
Frame Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	6.00	10.30	0.039	42.80
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.0032	0.0054	0.000020	0.023
s^1: share of the market installing burglar alarms	999.50	0.00015	999.50	999.50
s^2: share of the market not installing burglar alarms	0.53	0.00015	0.53	0.54
Masonry Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	7.00	12.20	0.045	52.10
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.0074	0.013	0.000046	0.055
s^1: share of the market installing burglar alarms	998.90	0.00044	998.90	998.90
s^2: share of the market not installing burglar alarms	1.10	0.00044	1.10	1.10

Table 5.4: (Continued)

	Police Station Connected Burglar Alarm			
Frame Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	6.017	10.35	0.036	42.89
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.00011	0.00018	0.00000063	0.00075
s^1: share of the market installing burglar alarms	999.98	0.0000045	999.98	999.98
s^2: share of the market not installing burglar alarms	0.018	0.0000045	0.018	0.018
Masonry Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	7.02	12.22	0.045	52.18
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.00059	0.0010	0.0000037	0.0044
s^1: share of the market installing burglar alarms	999.92	0.000031	999.91	999.92
s^2: share of the market not installing burglar alarms	0.085	0.000031	0.085	0.085

Table 5.4: (Continued)

	Local Burglar Alarm			
Frame Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	6.05	10.32	0.044	42.85
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.000093	0.00016	0.00000068	0.00066
s^1: share of the market installing burglar alarms	999.98	0.0000018	999.98	999.98
s^2: share of the market not installing burglar alarms	0.015	0.0000018	0.015	0.016
Masonry Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	7.071	12.17	0.055	52.026
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.0015	0.0027	0.000012	0.011
s^1: share of the market installing burglar alarms	999.78	0.000037	999.78	999.78
s^2: share of the market not installing burglar alarms	0.22	0.000037	0.22	0.22

Table 5.5: Supply-Side Parameters

	Central Station Reporting Burglar Alarm					
	Frame Housing			Masonry Housing*		
Parameter	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Marignal cost parameters:						
θ_1	37.41	174.44	0.21	-10.05	26.64	-0.38
θ_2	38.25	36.33	1.05	11.49	387.23	0.03
θ_3	-364.12	216.44	-1.68	-95.75	199.71	-0.48
θ_4	-145.79	44.63	-3.27	-110.68	114.41	-0.97
θ_5	-420.51	204.91	-2.05	-77.47	417.79	-0.19
θ_6	-197.22	3.35	-58.83	-137.17	381.46	-0.36
θ_7	10.42	45.07	0.23	-1.57	75.16	-0.02
θ_8	108.90	131.21	0.83	123.95	88.39	1.40
Deterrence effect parameters:						
α_0	42.54	159.56	0.27	14.50	9.69	1.50
α	-39.55	10.85	-3.64	-12.30	185.86	-0.07
Diversion effect parameters:						
β_0	0.53	330.66	0.0016	0.29	550.50	0.0005
β	0.18	331.16	0.0005	0.26	549.18	0.0005

** GMM estimation does not converge.*
*** GMM estimation fails.*

Table 5.5: (Continued)

	Police Station Connected Burglar Alarm					
	Frame Housing*			Masonry Housing*		
Parameter	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Marignal cost parameters:						
θ_1	77.38	647.96	0.12	-10.43	94.18	-0.11
θ_2	34.032	13.058	2.61	22.25	256.72	0.087
θ_3	-241.23	75.23	-3.21	-50.39	949.98	-0.053
θ_4	-138.55	41.46	-3.34	-100.39	544.018	-0.18
θ_5	-227.86	274.64	-0.83	-31.18	1,342.23	-0.023
θ_6	-209.18	61.35	-3.41	-127.21	367.29	-0.35
θ_7	-20.31	91.92	-0.22	-13.27	67.45	-0.20
θ_8	91.69	158.10	0.58	125.60	868.98	0.14
Deterrence effect parameters:						
α_0	90.38	95.080	0.95	11.047	107.67	0.10
α	-87.39	390.43	-0.22	-8.73	689.26	-0.013
Diversion effect parameters:						
β_0	0.31	182.98	0.0017	0.27	238.53	0.0011
β	0.29	182.94	0.0016	0.27	238.20	0.0011

** GMM estimation does not converge.*
*** GMM estimation fails.*

Table 5.5: (Continued)

	Local Burglar Alarm					
	Frame Housing**			Masonry Housing*		
Parameter	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Marignal cost parameters:						
θ_1	-	-	-	-24.31	5.96	-4.077
θ_2	-	-	-	-1.13	1.23	-0.92
θ_3	-	-	-	-329.60	10.065	-32.75
θ_4	-	-	-	-139.48	0.15	-924.70
θ_5	-	-	-	-374.71	8.25	-45.42
θ_6	-	-	-	-154.41	0.15	-1,030.58
θ_7	-	-	-	25.069	0.32	78.79
θ_8	-	-	-	113.13	1.66	68.043
Deterrence effect parameters:						
α_0	-	-	-	119.49	1.40	85.57
α	-	-	-	-114.70	1.76	-65.29
Diversion effect parameters:						
β_0	-	-	-	0.44	83.72	0.0053
β	-	-	-	0.24	83.70	0.0029

** GMM estimation does not converge.*
*** GMM estimation fails.*

Table 5.6: Mean Probabilities of Burglary

	Central Station Reporting Burglar Alarm	Police Station Connected Burglar Alarm	Local Burglar Alarm
Frame Housing			
When some homes are alarmed:			
PR^1: probability of burglary in alarmed homes	0.95	0.95	-
PR^2: probability of burglary in non-alarmed homes	0.67	0.64	-
When all homes are non-alarmed:			
PR^A: probability of burglary in homes that become alarmed	1.00	1.00	-
PR^N: probability of burglary in homes that remain non-alarmed	0.63	0.58	-
Masonry Housing			
When some homes are alarmed:			
PR^1: probability of burglary in alarmed homes	0.90	0.91	0.99
PR^2: probability of burglary in non-alarmed homes	0.63	0.63	0.66
When all homes are non-alarmed:			
PR^A: probability of burglary in homes that become alarmed	1.00	1.00	1.00
PR^N: probability of burglary in homes that remain non-alarmed	0.57	0.57	0.61

Table 5.7: Mean Diversion Effect

	Central Station Reporting Burglar Alarm	Police Station Connected Burglar Alarm	Local Burglar Alarm
Frame Housing	0.040	0.069	-
Masonry Housing	0.062	0.064	0.056

Table 5.8: Mean Deterrence Effect

	Central Station Reporting Burglar Alarm	Police Station Connected Burglar Alarm	Local Burglar Alarm
Frame Housing	-0.047	-0.048	-
Masonry Housing	-0.098	-0.089	-0.0081

Table 5.9: Demand-Side Parameters Scaling s^m_j/s^m_0

		Central Station Reporting Burglar Alarm					
		Frame Housing			Masonry Housing		
Parameter	Variable	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Constant		0.91	0.44	2.075	0.40	0.79	0.50
γ_1	Structures rates according to protection classes	-0.60	0.12	-5.089	-0.54	0.21	-2.53
γ_2	Bases policies on deductible less than $500	0.94	0.89	1.064	0.93	1.66	0.56
γ_3	Does not specify deductible on which policies are based	2.37	0.24	9.88	2.41	0.45	5.39
γ_4	Bases its policies on coverage amount less than $100,000	0.11	1.19	0.092	0.46	1.66	0.28
γ_5	Does not specify coverage amount on which policies are based	-0.51	0.11	-4.58	-0.47	0.21	-2.28
γ_6	Offers multi-policy discount	2.45	0.36	6.86	2.44	0.63	3.86
γ_7	IL is the state of domicile	1.93	0.10	18.76	1.95	0.18	10.69
ζ	Net benefit from installing alarms	0.059	47.46	0.0012	0.58	64.87	0.009
η	Price of homeowner's insurance	0.00020	0.00020	0.80	0.00030	0.00040	0.63

Table 5.10: Summary Statistics for Market Shares Scaling s^m_j/s^m_0

	Central Station Reporting Burglar Alarm			
Frame Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	0.024	0.043	0.00014	0.52
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.022	0.040	0.00013	0.48
s^1: share of the market installing burglar alarms	0.52	0.00051	0.52	0.52
s^2: share of the market not installing burglar alarms	0.48	0.00051	0.48	0.48
Masonry Housing	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
s^1_j: share of the market purchasing homeowner's insurance from company j and installing burglar alarms	0.029	0.054	0.00017	0.65
s^2_j: share of the market purchasing homeowner's insurance from company j and not installing burglar alarms	0.016	0.030	0.000092	0.35
s^1: share of the market installing burglar alarms	0.65	0.00063	0.64	0.65
s^2: share of the market not installing burglar alarms	0.35	0.00063	0.35	0.36

Table 5.11: Supply-Side Parameters Scaling s^m_j/s^m_0

	Central Station Reporting Burglar Alarm					
	Frame Housing			Masonry Housing		
Parameter	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Marignal cost parameters:						
θ_1	-0.20	9.85	-0.021	-1.41	8.15	-0.17
θ_2	46.066	229.37	0.20	11.86	153.77	0.077
θ_3	-376.086	928.27	-0.41	-321.52	670.34	-0.48
θ_4	-140.23	10.43	-13.45	-130.66	2.60	-50.22
θ_5	-382.32	833.93	-0.46	-341.99	568.094	-0.60
θ_6	-190.98	144.45	-1.32	-141.82	94.15	-1.51
θ_7	10.46	47.77	0.22	19.92	34.40	0.58
θ_8	113.39	98.68	1.15	112.84	70.33	1.60
Deterrence effect parameters:						
α_0	10.56	84.28	0.13	10.34	42.30	0.24
α	-13.75	71.067	-0.19	-12.61	12.44	-1.014
Diversion effect parameters:						
β_0	0.62	24.62	0.025	-2.58	361.99	-0.007
β	0.28	19.19	0.014	4.86	262.38	0.019

Table 5.12: Mean Probabilities of Burglary Scaling s^m_j/s^m_0

	Central Station Reporting Burglar Alarm
Frame Housing	
When some homes are alarmed:	
PR^1: probability of burglary in alarmed homes	0.97
PR^2: probability of burglary in non-alarmed homes	0.68
When all homes are non-alarmed:	
PR^A: probability of burglary in homes that become alarmed	1.00
PR^N: probability of burglary in homes that remain non-alarmed	0.65
Masonry Housing	
When some homes are alarmed:	
PR^1: probability of burglary in alarmed homes	0.90
PR^2: probability of burglary in non-alarmed homes	0.63
When all homes are non-alarmed:	
PR^A: probability of burglary in homes that become alarmed	1.00
PR^N: probability of burglary in homes that remain non-alarmed	0.070

Table 5.13: Mean Diversion Effect Scaling s^m_j/s^m_0

	Central Station Reporting Burglar Alarm
Frame Housing	0.032
Masonry Housing	0.56

Table 5:14: Mean Deterrence Effect Scaling s^m_j/s^m_0

	Central Station Reporting Burglar Alarm
Frame Housing	-0.031
Masonry Housing	-0.10

Table 5.15: Supply-Side Parameters Scaling s[1]

	Central Station Reporting Burglar Alarm					
	Frame Housing			Masonry Housing		
Parameter	Estimate	Standard Error	T-Statistic	Estimate	Standard Error	T-Statistic
Marignal cost parameters:						
θ_1	-2.32	75.0028	-0.031	-0.75	1.050	-0.72
θ_2	43.47	79.34	0.55	10.31	181.32	0.057
θ_3	-374.99	484.036	-0.77	-320.45	814.59	-0.39
θ_4	-136.053	32.52	-4.18	-127.83	2.80	-45.62
θ_5	-385.51	425.70	-0.91	-343.91	684.00	-0.50
θ_6	-192.52	59.29	-3.25	-142.59	112.29	-1.27
θ_7	14.16	71.98	0.20	22.29	39.45	0.57
θ_8	127.26	61.49	2.070	122.37	84.60	1.45
Deterrence effect parameters:						
α_0	5.00	528.96	0.0094	2.40	21.074	0.11
α	-2.16	79.61	-0.027	-1.35	1.75	-0.77
Diversion effect parameters:						
β_0	1.55	325.73	0.0047	0.96	172.20	0.0056
β	-4.73	126.89	-0.037	-2.71	26.060	-0.10

Table 5.16: Mean Probabilities of Burglary Scaling s[1]

	Central Station Reporting Burglar Alarm
Frame Housing	
When some homes are alarmed:	
PR^1: probability of burglary in alarmed homes	0.99
PR^2: probability of burglary in non-alarmed homes	0.70
When all homes are non-alarmed:	
PR^A: probability of burglary in homes that become alarmed	0.99
PR^N: probability of burglary in homes that remain non-alarmed	0.82
Masonry Housing	
When some homes are alarmed:	
PR^1: probability of burglary in alarmed homes	0.90
PR^2: probability of burglary in non-alarmed homes	0.63
When all homes are non-alarmed:	
PR^A: probability of burglary in homes that become alarmed	0.92
PR^N: probability of burglary in homes that remain non-alarmed	0.72

Table 5.17: Mean Diversion Effect Scaling s[1]

	Central Station Reporting Burglar Alarm
Frame Housing	-0.13
Masonry Housing	-0.088

Table 5.18: Mean Deterrence Effect Scaling s[1]

	Central Station Reporting Burglar Alarm
Frame Housing	-0.0025
Masonry Housing	-0.017

CHATPER 6

CONCLUSION

Burglar alarms are an observable form of private precaution because they are generally visible in the form of a sign or sticker on a window or mailbox to a burglar contemplating the entry of a protected home. These visible signs or stickers that warn the burglar of protected properties allow burglar alarms to serve two functions. First, observable private precautionary measures deter burglars from alarmed homes, therefore exhibiting the deterrence effect. Secondly, such measures also make unprotected homeowners a more likely target for burglars, increasing their probability of burglary. As a result, burglar alarms and other observable private precautionary measures are also associated with the diversion effect.

Previous literature champions burglar alarms as "the single most effective precaution one can take" (Buck and Hakim 1997), suggesting that burglar alarms deter crime. Very little emphasis, however, is placed on the diversion effect associated with burglar alarms. Few efforts have been made to measure the deterrence and diversion effects separately. Some may argue these efforts are lacking because of the unavailability of data on burglar alarm use by homeowners. Others simply do not believe diversion exists.

This dissertation tackles the challenge of assessing the existence and magnitude of crime diversion with burglar alarms. I first provide justification for seeking an estimate of the diversion effect by looking at how overall burglary rates are influenced by burglar alarm use. Assuming that burglar alarms deter crime, I conclude in chapter three that the small response of burglary rates to burglar alarm use suggests the presence of the diversion effect

muting the deterrence of burglar alarms. Since I do not have access to data on the number of homeowners using burglar alarms, I proxy alarm adoption using Bayesian estimation and data on security system services sales. In chapters four and five, I develop two different but robust methods for measuring the diversion and deterrence effects separately. I also test these methods empirically using a dataset from the homeowner's insurance industry in Illinois. The first method relies on the relationship between homeowner's insurance company market shares and the protective device discounts they offer. Assuming a perfectly competitive setting, the diversion effect is measured by regressing the dollar value of the discounts offered to homeowners who install burglar alarms on the product of homeowner's insurance company market shares and the average insured loss due to burglary. The intuition behind this approach is that homeowner's insurance companies with larger shares of the market, and therefore larger costs due to diversion, offer smaller protective device discounts. The second method is based on the work of Berry, Levinsohn, and Pakes (1995) in the field of Industrial Organization. Unlike chapter four, this method models the homeowner's insurance industry as an oligopoly. Here, I define the diversion effect as the difference between the probability of burglary of non-alarmed homeowners when all homes are non-alarmed, and the probability of burglary of non-alarmed homeowners when some homeowners have alarms. Not surprisingly, the empirical applications of both methods support the already-established evidence that burglar alarms deter. However, they also suggest that a diversion effect exists and they yield estimates of it for different housing construction and burglar alarm types. Although empirical estimates of the diversion effect will improve with more developed data collection and model specification, especially in

chapter five, the primary contribution of my work is that it justifies interest in the diversion effect and shows that the diversion effect can be measured.

Given that this dissertation supports the presence of the diversion effect with observable private precaution and provides different ways of measuring it, several questions remain as to what to do with its findings. Some of these questions focus on the homeowner's insurance industry, and include: If alarms are effective at deterring intruders and it is in the interest of insurers to encourage alarm installation (Gaffney and Hakim 1994), then why don't homeowner's insurance companies promote burglar alarms? Could it be due to the high costs that they face from diversion? If some insurance companies obtain a net gain from offering protective device discounts, then why are only 2% of all homeowners aware of the discounts offered by their insurance companies (Gaffney and Hakim 1994)? Others questions involve the alarm industry: What, if any, efforts are alarm companies making to negate the crime diversion caused by their product? Is it possible to make burglar alarms unobservable in order to eliminate the diversion effect? Could alarm adoption actually increase if non-alarmed homeowners were informed of diversion by the burglar alarm industry?

Other implications that arise with the understanding of a possible division effect involve policy. The diversion effect will likely be present as long as a community is heterogeneous in its decision to install burglar alarms. Community leaders that are concerned about the level of crime may therefore consider the effects of widespread burglar alarm adoption. For example, a community leader, or even a unified group such as a homeowner's association or community crime watch, may consider how a policy that

requires all homeowners to install burglar alarms affects the likelihood of burglary or even community-wide crime rates.

Since public and private precautionary measures are substitutes, public enforcement officers should also consider how the presence of the diversion effect influences their decision to change their level of enforcement, as in the size of the police force. Given the affirmative belief in the deterrence effect, public officials may be tempted to provide incentives to homeowners to employ private protection in order to decrease crime while still lowering the costs of public protection. However, if the size of the diversion effect increases with the fraction of the market installing burglar alarms, public enforcement officers may not see a large decrease in burglary rates with an increase in burglar alarm use. The failure to take the diversion effect into account when deciding to substitute private for public enforcement could be a perilous error.

Finally, this research poses one lingering question to its readers: Should YOU get a burglar alarm? There are clearly several factors that affect a homeowner's likelihood of burglary, regardless of the presence of a burglar alarm. However, ceteris paribus, burglar alarms are found to both deter burglars and make a target of non-alarmed homeowners. Homeowners should therefore carefully consider both the benefits of private protection and the costs of failing to protect. They may even want to consider "faking" observable private precaution with a sign in their front yard until burglars become the wiser. How about that for alarming behavior?

REFERENCES

Ayres, Ian and Steven D. Levitt. "Measuring Positive Externalities from Unobservable Victim Precaution: An Empirical Analysis of Lojack." *The Quarterly Journal of Economics* 113 (1998): 43-77.

Becker, Gary. "Crime and Punishment – An Economic Approach." *Journal of Political Economy* 76 (1968): 169-217.

Ben-Shahar, Omri and Alon Harel. "Blaming the Victim: Optimal Incentives for Private Precautions against Crime." *Journal of Law, Economics and Organization* 11 (1995): 434-455.

Benzion, Uri, Simon Hakim, Uriel Spiegel, and J. Weinblatt. "Crime Prevention Policies and Externalities: A Theoretical Analysis." *Public Finance/Finances Publiques* 38 (1983): 111-131.

Berry, Steven T. "Estimating Discrete-Choice Models of Product Differentiation." *RAND Journal of Economics* 25 (1994): 242-262.

Berry, Steven, James Levinsohn and Ariel Pakes. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (1995): 841-890.

Blackstone, E. and Simon Hakim. *Securing Home and Business : A Guide To The Electronic Security Industry.* Boston: Butterworth-Heinemann (1997).

Blackstone, E., Simon Hakim and U. Spiegel. *The Schizophrenian Good: The Case of Police Response to Alarms.* Unpublished paper (2000).

Blumstein, Alfred, Jacqueline Cohen, Jeffrey Roth and Christy Roth. *Criminal Careers and "Career Criminals."* Washington, D.C. National Academy of Sciences (1986).

Bowers, Kate J. and Shane D. Johnson. "Measuring the Geographical Displacement and Diffusion of Benefit Effects of Crime Prevention Activity." *Journal of Quantitative Criminology* 19 (2003): 275-301.

Buck, Andrew J. and Simon Hakim. "Burglar Alarms: What Do We Know About Them?" *Security Journal* 1 (1990): 101-108.

Buck, Andrew J. and Simon Hakim. "Proof that Alarms Really Work." *Security Distributing and Marketing* (1992): 78-79.

Buck, Andrew J, Simon Hakim and Mary Ann Gaffney. "Are Discounts on Homeowner's Premiums for Burglar and Fire Alarms Cost Effective for Insurers?" *The Society of Chartered Property and Casualty Underwriters* 46 (2003): 107-111.

Buck, Andrew J., Simon Hakim and M. Moshe Porat. "Suburban Burglaries, Alarms, and Loss Exposures: Lessons for the Insurance Industry." *The Society of Chartered Property and Casualty Underwriters* (1992): 98-107.

Buck, Andrew J, Simon Hakim and George Rengert. "Burglar Alarms and the Choice Behavior of Burglars: A Suburban Phenomenon." *Journal of Criminal Justice* 21 (1993): 497- 507.

Bureau of Labor Statistics, U.S. Department of Labor. Consumer Price Index, U.S. City Average (1982-84=100) and Unemployment Rates. Retrieved September 2007 by Kristen E. Collett-Schmitt. http://www.bls.gov/lau/home.htm

Chiricos, Theodore. "Rates of Crime and Unemployment: An Analysis of Aggregate Research Evidence." *Social Problems* 34: (1987): 187-211.

Clarke, R.V.G., J.M. Hough, P. Mayhew, and A. Sturman. "Crime As Opportunity." *Home Office Research Study No. 34* (1976).

Clotfelter, Charles. "Private Security and the Public Safety." *Journal of Urban Economics* 5 (1978): 388-402.

County and City Data Books. Retrieved September 2007 from the University of Virginia, Geospatial and Statistical Data Center: http://fisher.lib.virginia.edu/collections/stats/ccdb/.

Cromwell, Paul, J. Olson, and D. Avary. "Breaking and Entering: An Ethnographic Analysis of Burglary." *Crime, Law, and Social Change* 29 (1998): 341-346.

D'Arcy, S. "Insurance Price Deregulation: The Illinois Experience." *Deregualting Property-Liability Insurance*. American Enterprise Institute-Brookings Institution Joint Center for Regulatory Studies (2002): 248-284.

de Meza, David and J.R. Gould. "The Social Efficiency of Private Decisions to Enforce Property Rights." *Journal of Political Economy* 100 (1992): 561-580.

Department of Justice, Federal Bureau of Investigation. http://www.fbi.gov/homepage.htm.

Department of Justice, Federal Bureau of Investigation. "Crime in the United States 1997 – Law Enforcement Personnel." http://www.fbi.gov/ucr/97cius.htm.

Department of Justice, Federal Bureau of Investigation. "Crime in the United States 2002 – Law Enforcement Personnel." http://www.fbi.gov/ucr/02cius.htm.

Department of Justice, Federal Bureau of Investigation. "Crime in the United States 2004 – Burglary." http://www.fbi.gov/ucr/cius_04/offenses_reported/property_crime/burglary.html.

Di Tella, Rafael, Sebastian Galiani and Ernesto Schargrodsky. "Crime Victimization and Income Distribution." *Inter-American Development Bank*. Working Paper (2002).

Dimitz, S. and C.F. Huff. "The Figgue Report, Part VI: The Business of Crime – The Criminal Perspective." Richmond, VA: Figgie International.

Dingle,Derek. "Theft-Proof Your Home." *Money Magazine* (August 1991).

"Former Thief Cites Electronic Security as Deterrent to Crime." *Security Sales* (June 1994).

Freeman, Richard. "Why Do So Many Young American Men Commit Crimes and What Might We Do About It?" *Journal of Economics Perspectives* 10 (1996): 25-42**.**

Hakim, Simon. "Are Insurance Discounts Effective?" *Security Distributing and Marketing Economic Viewpoint* (1996): 87.

Hakim, Simon and Mary Ann Gaffney. "Insurance and Alarm Installation." *Locksmith Ledger* (1994).

Hakim, Simon and Mary Ann Gaffney. "Residential Burglary Patterns." *Locksmith Ledger* (1995).

Hakim, Simon and George G. Rengert. "Crime Spillover." Sage Research Progress Series in Criminology, Vol. 23. Beverly Hills: Sage Publications, Inc. (1981).

Hakim, Simon, George F. Rengert and Yochanan Schachmurove. "Burglar and Fire Alarms: Costs and Benefits to the Locality." *Security Journal* 6 (1995): 197-204.

Hui-wen, Koo and I.P.L. Png. "Private Security: Deterrent or Diversion?" *International Review of Law and Economics* 14 (1994): 87-101.

Landsburg, Steven E. "Property Is Theft." (August 1997) www.slate.com.

LeBeau, James L. and Karen L. Vincent "Mapping It Out: Repeat-Address Burglar Alarms and Burglaries*." Southern Illinois University at Carbondale, Center for the Study of Crime, Delinquency and Corrections* (1998).

Levitt, Steven. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime." *American Economic Review* 97 (1997): 270-290.

Lott, John and John Whitley. "Measurement Error in County-Level UCR Data." *Journal of Quantitative Criminology* 19 (2003): 185-198.

MacKenzie, D.W. "Is Crime Prevention Wasteful? Should It Be Taxed?" *The Mises Institute* (2005).

Marvell, Thomas and Carlisle Moody. "Police Levels, Crime Rates, and Specification Problems*." Criminology* 34 (1996): 609-646.

North Carolina Burglar and Fire Alarm Association. http://www.ncbfaa.net/.

North Carolina State Bureau of Investigation. http://www.ncsbi.gov/.

Rasmusen, Eric. "The BLP Method of Demand Curve Estimation in Industrial Organization." Indiana University, Kelley School of Business, Department of Business Economics and Public Policy Working Paper 2006-04.

Regional Economics Information System, Bureau of Economics Analysis, US Department of Commerce: http://www.bea.gov/regional/reis/CA1-3fn.cfm.

Rengert, George, and John Wasilchick. "Space, Time and Crime: Ethnographic Insights into Residential Burglary." *Final report submitted to U.S. Department of Justice, National Institute of Justice,* 1994, Grant 88-IG-CX-0013, Washington, DC.

Rowe, Daniel. "Multivariate Bayesian Statistics: Models for Source Separation and Signal Unmixing." Chapman and Hall/CRC (2003).

Shavell, Steven. "Individual Precautions To Prevent Theft: Private Versus Socially Optimal Behavior." *International Review of Law and Economics* 11 (1991): 123-132.

Sherman, Lawrence. "The Police" in Crime, in J.Q. Wilson and J. Petersilia, eds. (San Francisco Institute for Contemporary Studies, 1995).

U.S. Census Bureau; 1990 Summary Tape File 1 (STF 1) - 100-Percent Data. Retrieved on September 2007 by Kristen E. Collett-Schmitt using American FactFinder: http://factfinder.census.gov.

U.S. Census Bureau; 1990 Summary Tape File 3 (STF 3) - Sample Data. Retrieved on September 2007 by Kristen E. Collett-Schmitt using American FactFinder: http://factfinder.census.gov.

U.S. Census Bureau; Census 2000 Summary File 1 (SF 1) 100-Percent Data. Retrieved on September 2007 by Kristen E. Collett-Schmitt using American FactFinder: http://factfinder.census.gov.

U.S. Census Bureau; Census 2000 Summary File 3 (SF 3) - Sample Data. Retrieved on September 2007 by Kristen E. Collett-Schmitt using American FactFinder: http://factfinder.census.gov.

U.S. Census Bureau; Economic Census 1992, CD-Rom Report Series Disc 1i.

U.S. Census Bureau; Economic Census 1997. Retrieved on September 2007 by Kristen E. Collett-Schmitt using American FactFinder: http://factfinder.census.gov.

U.S. Census Bureau; Economic Census 2002. Retrieved on September 2007 by Kristen E. Collett-Schmitt using American FactFinder: http://factfinder.census.gov.

Uniform Crime Reports County Data. Retrieved on September 2007 by Kristen E. Collett-Schmitt from the University of Virginia, Geospatial and Statistical Data Center: http://fisher.lib.virginia.edu/collections/stats/crime/.

United States Census Bureau Industry Statistics Sampler. NAICS 56162: Security Systems Services: www.census.gov/econ/census02/data/industry/E561621.HTM.

Whitehurst, S.A. "Protecting residential America." Security Distributing and Marketing (March 1983): 36-42.

Whitehurst, S.A. "Protecting residential America part II." *Security Distributing and Marketing* (February 1984a): 345-358.

Whitman, Andrew F. and C. Arthur Williams. "Open Competition Rating Laws and Price Competition." *The Journal of Risk and Insurance* 40 (1973): 483-496.

Wright, Richard T. and Scott H. Decker. *Burglars on the Job*. Boston: Northeastern University Press (1994).

Wright, R. and R.H Logie. "How young house burglars choose targets: the influence of situational clues on decision making." Unpublished manuscript, Department of Administration of Justice, University of Missouri, St. Louis, MO.

Zellner, Arnold. *An Introduction to Bayesian Inference in Econometrics*. John Wiley & Sons (1971).

APPENDIX

Derivation of First Order Conditions in 5.2

The first derivative of (35) with respect to p^1_j is:

$$(\partial \Pi_j/\partial p^1_j) = (p^1_j - c^1_j)(\partial s^1_j/p^1_j) + s^1_j + (p^2_j - c^2_j)(\partial s^2_j/\partial p^1_j) - M^1[PR^1(\partial s^1_j/p^1_j) + s^1_j(\partial PR^1/\partial p^1_j)]$$

$$- M^2[PR^2(\partial s^2_j/p^1_j) + s^2_j(\partial PR^2/\partial p^1_j)] = 0 \quad , \quad (49)$$

where

$$\partial s^1_j/\partial p^1_j = -\eta\,(1-s^1_j)s^1_j < 0 \quad , \quad (50)$$

$$\partial s^2_j/\partial p^1_j = s^2 j s^1_j\,\eta > 0 \quad , \quad (51)$$

$$\partial PR^1/\partial p^1_j = (1-PR^1)\alpha\, PR^1(\partial s^1/\partial p^1_j) > 0 \;\; since\ \alpha < 0\,, \quad (52)$$

$$\partial PR^2/\partial p^1_j = (1-PR^2)\beta\, PR^2(\partial s^1/\partial p^1_j) < 0 \quad , \quad (53)$$

and

$$\partial s^1/\partial p^1_j = -(1-s^1)\eta\, s^1_j < 0 \;. \quad (54)$$

The intuition of the model is revealed in (50)-(54). Given that the sign of (50) is negative, then as the protective device discount offered by homeowner's insurance company j becomes smaller, fewer homeowners insuring with company j install alarms. This decreases s^1_j. The portion of insurance company j's market share not installing burglar alarms likewise increases, as seen by the positive sign of (51). A negative sign for (53) reveals the diversion effect. As the protective discount offered by homeowner's insurance company j decreases and fewer homes install burglar alarms, the diversion effect is smaller for the entire market. Recall that the diversion effect is assumed to become larger as the fraction of the market installing burglar alarms increases.

Substituting (50)-(54) into (49) yields the first order condition described by (38).

The first derivative of (35) with respect to p^2_j is:

$$(\partial \Pi_j/\partial p^2_j) = (p^1_j - c^1_j)(\partial s^1_j/p^2_j) + s^2_j + (p^2_j - c^2_j)(\partial s^2_j/\partial p^2_j) - M^1[PR^1(\partial s^1_j/p^2_j) + s^1_j(\partial PR^1/\partial p^2_j)]$$

$$- M^2[PR^2(\partial s^2_j/p^2_j) + s^2_j(\partial PR^2/\partial p^2_j)] = 0 \ , \qquad (55)$$

where

$$\partial s^1_j/\partial p^2_j = \eta\, s^1_j s^2_j > 0 \ , \quad (56)$$

$$\partial s^2_j/\partial p^2_j = -\eta\,(1-s^2_j)s^2_j < 0 \quad , \quad (57)$$

$$\partial PR^1/\partial p^2_j = (1-PR^1)\alpha\, PR^1(\partial s^1/\partial p^2_j) < 0 \ \ since\ \alpha < 0 \quad , \quad (58)$$

$$\partial PR^2/\partial p^2_j = (1-PR^2)\beta\, PR^2(\partial s^1/\partial p^2_j) \quad > 0 \ , \quad (59)$$

and

$$\partial s^1/\partial p^2_j = s^1 s^2_j\, \eta > 0 \ . \quad (60)$$

Again, the signs of (56)-(60) provide intuition for this model. (57) reveals that as the protective device discount offered by homeowner's insurance company j decreases and fewer people install burglar alarms, the portion of homeowner's insurance company j's market share not installing burglar alarms increases. The diversion effect is seen through (59). A positive sign for (59) means that as more homeowners are induced to install burglar alarms in order to benefit from the protective device discount offered by homeowner's insurance company j, the probability of burglary of non-alarmed homeowners increases.

Substituting (56)-(60) into (55) yields the first order condition described by (39).