Linking Origins with Destinations for DWI Motor Vehicle Crashes: An Application of Crime Travel Demand Modeling[1]

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Key Words

Offender travel
Journey to crime
Geographic profiling
Metropolitan crime
Methodology

Abstract

Using a crime travel demand model, analysis was conducted of 862 Driving While Intoxicated (DWI) motor vehicle crash trips that occurred in Baltimore County, Maryland between 1999 and 2001. Aside from population, factors associated with the origin location of the drivers were a high percentage of non-Hispanic White persons, a rural environment, and a greater number of bars and liquor stores while factors associated with the crash locations were commercial land uses and a greater number of bars. Two types of interventions were examined. First, DWI citations in any one year did not reduce the number of crashes in the next year. Second, it was estimated that a 7.5% reduction in DWI crashes could be obtained by targeting 3% of the origin zones and 6% of the destination zones with anti-DWI efforts. The crime travel demand model is useful for modeling interventions as well as alternative scenarios.

This article describes the use of the *CrimeStat III* crime travel demand module to model motor vehicle crashes involving drunk drivers in Baltimore County, Maryland between 1999 and 2001. Drunk driving is a serious problem that affects the safety of motorists on the highway and places a substantial burden on police departments. Drivers under the influence of alcohol or drug (DWI) are much more likely to become involved in motor vehicle crashes due to impaired physical abilities and contribute disproportionately to the fatalities and injuries occurring on the roadways. The National Highway Traffic Safety Administration documented that 15,826 persons were killed in alcohol-impaired driving crashes in 2006, the latest year for which national data are available. This represented 37 percent of the 42,532 motor vehicle fatalities in that year (NHTSA, 2008). While the alcohol fatality rate has decreased over the last thirty years, it still represents a major problem.[2] Nationally, in 2006 there were almost as many fatalities from drunk driving as from homicides, and two years earlier there were more (NHTSA, 2008; FBI, 2006).

Travel Behavior of DWI Offenders

Drunk driving is considered a severe crime in all States. Almost all States have laws that define levels of alcohol-impaired driving. The unit of analysis is Blood Alcohol Content (BAC) defined in terms of grams of alcohol per 100 grams of blood. In most States, a BAC of 0.08 is grounds for being convicted of Driving While Intoxicated (DWI) whereas any BAC level above 0.00 is grounds for convicting a minor of DWI (IIHS, 2008a). All States distinguish between DWI and Driving Under the Influence (DUI); the latter is appropriate for minors and for adult drivers who are arrested for not having adequate control over their vehicles.

There is a very large literature on alcohol use by drivers and, in particular, in relation to crashes. Understanding the travel behavior of persons involved in DWI crashes is another matter, however. There is some information about the geographical location of drunk driving crashes. According to the National

[2] In 1982, the alcohol-related fatality rate (alcohol deaths per 100 million vehicle miles traveled) was 1.64. By 2001, this rate had dropped to 0.63. NHTSA, 2002.

Highway Traffic Safety Administration, fatality rates from drunk driving are much higher in the rural than in urban areas. For example, in 2001 61% of DWI fatalities occurred in the rural areas (NHTSA, 2001). Yet, the NHTSA report concluded that this was primarily due to poorer driving conditions in the rural areas, rather than differential drinking behavior.

There have been several studies that have examined the location of DWI crashes (DWI Resource Center, 2008; Levine, 2007a; Levine, Kim and Nitz, 1995). There are definite hot spots where DWI crashes occur, often at locations that tax the ability of an impaired driver to handle the road conditions (e.g., curves, entrance or exit ramps to freeways). However, there have been few studies that have examined where drunk drivers come from or the travel link between where they live and where they become involved in crashes. In the few studies that exist, there appears to be some concentration in where DWI offenders reside. For example, Wieczorek and Naumov (2002) examined the residence location of 15,500 DWI offenders in Eire County, PA, and found that there were definite clusters where concentrations of offenders lived.

It is also known that drunk driving is a highly repetitive behavior (IIHS, 2008b; Cleary, 2003; Rauch et al, 2002; NHTSA, 1995). According to the Insurance Institute for Highway Safety, drivers convicted of DUI/DWI are 1.8 times as likely to be involved in a fatal crash within three years than drivers with no prior DWI conviction and are four times more likely to be involved in a fatal crash in which drivers have BAC levels of 0.10 or higher (IIHS, 2008b). According to *Mothers Against Drunk Driving*, about one-third of all drivers arrested or convicted of drunk driving are repeat offenders and are 40% more likely to be involved in fatal crashes than those without prior convictions (MADD, 2008).

What hasn't been studied is the relationship of the residential location to the crash location. The crime travel demand model is an appropriate tool for studying this relationship given that it can model both the residence (origin) location as well as the crash (destination) location. Further, it has been created to model so-called 'rare events', those that are a small proportion of the total occurring and that are highly skewed in time and in location. If data are available on the residence location of DWI offenders, then it becomes possible to model the trip from the residence location to the crash location.

Over the last ten years, researchers have developed a variety of statistical tools for examining the travel behavior of offenders (Rossmo, 2000; Canter et al, 2000, Snook 2004; Levine, 2004, Ch. 10). The increasing use of Geographic Information Systems (GIS) and the development of crime mapping applications have encouraged an examination of the spatial dimension of crimes. Much of this analysis has, however, been static, looking at spatial relationships while ignoring the temporal aspects that affect them. Without understanding the links between where offenders live and where they go after the crime, it becomes difficult to intervene to reduce that behavior. What is needed is a more dynamic framework that links space and time together in a meaningful way.

Travel Demand Modeling

Crime travel demand theory is a framework for modeling crime travel over a jurisdiction or even a metropolitan area. It is an application of travel demand theory, widely used in transportation planning (Shiften et al, 2003; Culp, 2002; Betlyon and Culp, 2001; Ortuzar and Willumsen, 2001; Hensher and Button, 2002; Recker, 2000; Pas, 1996; Ben-Akiva and Lerman, 1985). Travel demand modeling has developed over the last 50 years as a framework for modeling travel over metropolitan areas. The logic is to build the model with known data and then use it as a basis for analyzing scenarios in making transportation decisions by estimating the effects of changes in the transportation network on likely travel behavior.

Over the last 50 years, the Federal Highway Administration (FHWA) has funded the development of the methodology in order to provide a basis for approving Federal funds that will be used to build new roads or expand existing ones. Virtually all large metropolitan areas in the United States utilize travel demand modeling as a basis for transportation infrastructure decisions (USDOT, 2003: 23CFR450).

Crime Travel Demand Modeling

Crime travel demand modeling is an adaptation of travel demand modeling to crime analysis. The first use of it appeared in version 3 of the *CrimeStat* software (Levine, 2004, ch. 11-16), though its antecedents go back to the early 1980s (see, for example, Rengert, 1981; LeBeau, 1987). In the *CrimeStat* version, the theory behind the model was explained and examples were provided for several jurisdictions; Baltimore County, Chicago and Las Vegas (Levine, 2004; Block and Helms, 2004). Software for the model is included in the latest version of CrimeStat and can be downloaded at:

http://www.icpsr.umich.edu/crimestat

There are two major stages in building the model. First, there is a *data collection* stage that involves collecting information on crimes by both the residence location of the offender (called an ‘origin’ in the framework) and the actual crime location (called a 'destination'). The incidents are allocated to zones, separately by origins and by destinations. Demographic, socio-economic, and land use data are obtained for predicting the number of crimes that originate or end in these zones along with data appropriate for analyzing interventions.

Second, there is the modeling stage, which is divided into four steps. The first modeling step is *trip generation* in which separate predictive models for crime origins and for crime destinations are developed. In *CrimeStat III*, these models are constructed using a regression framework, either as Ordinary Least Squares (OLS) or log-linear (Poisson) forms. If the dependent variable is highly skewed, then a Poisson model is more appropriate (Cameron and Trivedi, 1998; Levine, 2004, chapter 13).

The second modeling step is *trip distribution* in which the number of trips that go from each origin zone to each destination zone is estimated using a spatial interaction model. The model is calibrated using the predicted origins and destinations from the trip generation stage along with a model of the cost of travel (called ‘impedance’). The predicted distribution is compared with the actual trip distribution and the impedance function adjusted until there is a good fit (Ortuzar and Willumsen, 2001).

The third modeling step is *mode split*. This involves separating the number of predicted trips from each origin zone to each destination zone into distinct travel modes, such as driving, walking, bus, train or bicycle. The split is modeled using a multinomial logit model to estimate the utility of using a particular mode relative to the utility of using all modes (Domencich and McFadden, 1975; Ben-Akiva and Lerman, 1985; Train, 2003).

The fourth, and final, modeling step is *network assignment*. This involves assigning the predicted trips (by travel mode) to specific routes. For driving, walking, or bicycle modes, a street network can be used while for transit modes (bus and rail), specific transit networks are needed. The network assignment is done on the basis of an impedance calculation for each segment in the network. This allows travel time or, even, travel cost to be used for the assignment, rather than distance, allowing for a more realistic representation of the likely travel routes used by offenders.

Once calibrated, the model can then be used for testing policy and policing scenarios. For example, alternative routes can be explored by altering the impedance along network segments or shifts in the destination locations or, even, the origin locations can be modeled as a consequence of an intervention (e.g., increased target hardening around high crime locations; *weed and seed* programs in neighborhoods with concentrations of offenders). Levine (2007b) provides an example of probable bank robbery escape routes using the model.

Travel Behavior of DWI Crashes

This framework can be applied to the analysis of drunk driving. Baltimore County is a suburban county that surrounds the City of Baltimore on three sides. There were approximately 787,000 persons living in the County within a metropolitan area of 2.6 million in 2006 (U.S. Census Bureau, 2006). The problem of DWI is a serious one in Baltimore County, Maryland and throughout the State of Maryland. Crashes from impaired driving have been rising in Baltimore County at about 3.8% a year, from 1,170 in 1999 to 1,348 in 2003. While the alcohol fatality rate has increased nationally from 16,572 to 17,013 from 1999 to 2003 (or by less than one percent per year), in the State of Maryland deaths from drunk driving increased an average of 7% per year from 1999 to 2003. By 2004, the percentage of alcohol-related traffic fatalities (45%) was the highest reported in Maryland since 1990. Alcohol-related fatalities have since declined in Maryland. In 2006, 36% of all traffic fatalities were related to alcohol (Alcohol Alert, 2007). Further, there is evidence that Blood Alcohol Content for female drivers in Baltimore County remains considerably higher than for male drivers.[3]

The Baltimore County Police Department (BCPD) has maintained a vigilant effort to combat the problem. Between 1999 and 2003, the number of citations for DWI increased from 2,104 to 5,557. Nevertheless, the problem persists. DWI imposes a burden on the police themselves (DWI arrests constitute about 4% of the total arrests for the County) as well as a continual risk to other drivers on the road. The costs from drunk driving crashes are considerable, both in terms of human suffering as well as in actual monetary costs.

Data Sources

Data on DWI crashes in Baltimore County between 1999 and 2001 was obtained from Maryland's Criminal Justice Information System (CJIS). A total of 862 DWI crashes were identified in which both the crash location and the offending driver's residence was known. These were used to model DWI crashes from the residence location to the crash location. Figure 1 shows the distribution of the crashes while figure 2 shows the distribution of the residences of the drunk drivers involved in the crashes.

/Insert Figure 1 here/

/Insert Figure 2 here/

A couple of caveats should be stated. First, the 862 crash records are only about 25% of the total number of DWI crashes over the period as the residence address or crash location of the others were not

[3] Alcohol Influence Summary Report, 1992-2004, Traffic Resource Management, Baltimore County Police Department Analysis Unit. 2005).

known. Many address locations could not be geocoded due to data entry errors, missing address information, use of address abbreviations, or an overall lack of address naming standards. Thus, this sample may or may not represent the geographical components of a DWI crash.

Second, in the model we assumed that the ‘trip’ went from the residence to the crash location, an assumption that is not necessarily correct. However, if these ‘trips’ are considered as links between a residence location and a crash location, then the modeling is consistent. Essentially, we’re looking at origin-destination links in DWI crashes and possible routes that are taken.

The zonal framework used was Traffic Analysis Zones (TAZ). These are typically super-sets of census geography but are designed to ensure that each zone has approximately the same number of trips. They were put together by the Baltimore Metropolitan Council (BMC), the Metropolitan Planning Organization for the greater Baltimore region. TAZ boundaries were used because of the availability of estimates on employment along with population. Whereas the Census only provides information on the residential population, the BMC will continually produce estimates of employment for each zone.

For the location of the crashes, only the 325 TAZs in Baltimore County were used. However, for the origin location of the crashes, the 532 TAZs in both Baltimore County and the City of Baltimore were used since about 10% of the crashes were associated with drunk drivers who lived in the City of Baltimore. An additional 11% of the drunk drivers lived in other jurisdictions; these were not analyzed because they were dispersed over a number of jurisdictions. The crashes were allocated to TAZs by both the crash location (destinations) and the residence location of the DWI driver (origins).

In addition, a collection of socio-economic and land use variables was collected in order to provide predictors of the number of crimes originating in each origin zone or the number of crimes ending in each destination zone. The final list of variables that was included for each TAZ were:

Population	The 2000 population
Percent White	The percent of the population who were non-Hispanic White in 2000

Rural	Whether the zone falls outside a Baltimore County designated rural line
Commercial acreage	The acreage associated with commercial properties
Number of liquor stores	The number of licensed liquor stores[4]
Number of bars	The number of licensed bars
Beltway passes through zone	A dummy variable indicating the Baltimore Beltway (I-695) passed through the zone
Area of zone	The area of the zone in square miles. This was a control variable to adjust for different sized zones

Trip Generation

The first modeling stage is trip generation. In this stage, separate models are produced for the number of-DUI/DWI crash trips originating in each origins zone (origins) and the number of DUI/DWI crash trips occurring in each destination zone (destinations). The type of model used was a regression model. In most cases, crash data are very skewed with a few zones accounting for the bulk of the events. Consequently, an Ordinary Least Squares (OLS) regression is not appropriate since it assumes a normally distributed dependent variable (Cameron and Trivedi, 1998). A log-linear (Poisson) is more appropriate with skewed data. However, the Poisson distribution assumes that the variance equals the mean, which will not be true if the data are extremely skewed. Consequently, there are alternative models that can be used including a Poisson regression with an over-dispersion correction as well as a Negative Binomial model (Cameron and Trivedi, 1998; Lord, 2006).

For the origin model, we used the log-linear (Poisson) form with the over-dispersion correction (see Levine, 2004, Ch. 13 for details). However, for the destination model, we used an OLS regression model because the distribution of crashes by zone was almost normally distributed.

[4] Data on liquor stores and bars were obtained from the Baltimore County Liquor Board.

Origin model

Table 1 presents the results of the best regression model fitting the number of DWI crashes that originated from each of the 532 TAZs in Baltimore County and the City of Baltimore.

/Insert Table 1 here/

The six variables are reasonably independent as seen from the Tolerance variable.[5] There is some overlap between the rural variable and the area of the zone; this would be expected as TAZs are typically larger in the more rural parts of the region. Testing of R-squares in a non-linear function is not as straightforward as in an OLS model (Miaou, 1996). However, the likelihood ratio, the AIC criterion and the deviance r-square criterion suggest that the predictor variables are capturing a substantial amount of the variance associated with number of DWI drivers living in each zone. The largest predictive effect is due to population, as would be expected. TAZs that have larger populations have more persons living in them who become involved in drunk driving crashes. The second strongest predictor was the percentage of the population that were non-Hispanic White. In Baltimore County, zones with a higher percentage of their population being White were more likely to have drivers involved in a DWI crash. The third variable was being in the Baltimore County-designated rural area, again as might be expected. As pointed out in the introduction, rural areas have higher DWI crash rates than urban areas primarily because of more difficult driving conditions.

After these variables, however, the number of bars and the number of liquor stores are significantly correlated with more drunk driving crash origins. That is, people who live in zones that have more liquor stores and bars are more likely to become involved in a DWI crash. The probability is very small, of course, but the likelihood is consistent. It almost suggests that a 'culture of alcohol' is

[5] Tolerance is degree to which an independent variable is predicted by the other independent variables in the equation. In this case, it measures $1 - R^2$ predicted by an OLS regression.

operating. In this case, 'cause and effect' cannot be easily distinguished. Whether persons who get involved in DWI crashes are attracted to the zones because of the bars and liquor stores or, conversely, whether people who live in the zones are encouraged to drink cannot be determined from this type of model. It is generally well known that crashes will occur near bars. However, our data demonstrate that persons who become involved in DWI crashes (and, presumably, DWI citations prior to becoming involved in a crash) have been living in an environment with many retail alcohol outlets.

The final variable is the area of the zone, which is used as a control because of the different zone sizes. In short, persons who become involved in DWI crashes live in larger zones that are predominantly White, tend to be more rural, and tend to have more liquor stores and bar outlets.

Destination model

Table 2 presents the results of the best regression model fitting the number of DWI crashes that ended in each of the 325 TAZs in Baltimore County. As mentioned above, in this case, an OLS model was used since the dependent variable was more normally distributed. The five independent variables are quite independent though the overall prediction is not very strong, though significant (R^2 of 0.25). The strongest predictor is the number of bars in the zones. Crashes tend to occur in zones with lots of bars. Of course, we don't know whether the drivers were actually drinking in those bars, but the association has been made before (NHTSA, 1995; Lugo, 2008).[6] The second strongest variable is population, as might be expected. This is followed by the commercial acreage and a dummy variable measuring whether the Baltimore Beltway passed through the zone. The area of the zone is not significant, but is left in the equation as a control variable.

In summary, DWI crashes tend to occur in zones with more bars that are in commercial areas and that tend to be located adjacent to the Baltimore Beltway. These zones have older housing stock, transitioning economic status, and transient populations. Many of the zones contain socially and

[6] Lugo (2008) examined the relation between alcohol outlet density and crime and pointed out that the relationship only appears to hold for bars that promote overconsumption.

economically distressed communities that have been targeted for intensive revitalization, high quality development, and government increased services.

The final step in the trip generation model is to balance the number of predicted origins with the number of predicted destinations. This is necessary because a trip has to have both an origin and a destination. In this case, the predicted DWI origins were adjusted to match the DWI crash locations since the crash database is more accurate than the origin database.

/Insert Table 2 here/

Trip Distribution

The second modeling step distributes the predicted origins and destinations to actual trip links. For each origin zone, a prediction is made of the trips to destinations where DWI crashes will occur. The usual way of making this prediction is through a spatial interaction model (Ortuzar and Willumsen, 2001; equation 1):

$$T_{ij} = \alpha P_i^{\lambda} \beta A_j^{\rho} I_{ij} + e_{ij} \qquad (1)$$

where T_{ij} is the predicted number of trips from zone "i" to zone "j", P_i is the predicted number of DWI crash trips that will originate in zone "i", A_j is the predicted number of DWI crashes that will occur in zone "j", I_{ij} is the ease of travel from zone "i" to zone "j" and is typically a function of the cost of travel, and e_{ij} is the error in prediction. The ease of travel term, I_{ij}, is historically called an *impedance* function, referring to the difficulty of travel from "i" to "j".[7]

Observed

There are actually two trip distribution outputs, the empirical (observed) distribution and the modeled (predicted) distribution. Figure 3 displays a map of the major trip links that were observed from

[7] In the original 'gravity' conception of this interaction, it was placed in the denominator of the function. In equation (1), it is placed in the numerator and is, therefore, a proxy for the *utility* of travel from "i" to "j".

the 862 crashes. The map shows both inter-zonal links (as lines) and intra-zonal links (as circles), both scaled proportionally to the number of crashes. The trip links (lines from the driver's residence – origin, to the DWI crash location – destinations) is a complicated pattern. However, there is a fairly high density of trips that end in locations on the southeastern part of the county, whether they are inter-zonal or intra-zonal trips. In particular, zones bordering the Chesapeake Bay show a high frequency of trip crash locations. Many of these trips are of fairly short distance though some involve longer distances.

/Insert Figure 3 here/

Predicted

A best fitting predicted trip distribution model was created using the variables in equation (1) above. Because of the number of possible trip links is very large (325 x 532 = 172,900 links), the model was fitted to the trip length distribution to replicate the number of trips by length. This is standard practice in travel modeling (Ortuzar and Willumsen, 2001). Figure 4 shows the fit between the modeled (predicted) trip length distribution and the actual (observed) trip length distribution. The congruence between these curves is good and has a Coincidence Ratio of 0.90.[8]

Figure 5 shows the predicted and observed inter-zonal DWI crash trips while figure 6 shows the predicted and observed intra-zonal DWI crash trips. Comparing these, it is apparent that the model was good at fitting trips that ended on the eastern part of the county, particularly the southeast. But, it was not very good at fitting trip links in the central and western parts of the county. Further, the model is better at predicting inter-zonal trips than intra-zonal ones, a result that has been found before (Levine, 2004, ch. 14).

[8]The Coincidence Ratio is an indicator of congruence varying from 0 to 1 (Levine, 2004, chapter 14).

/Insert Figure 4 here/

/Insert Figure 5 here/

/Insert Figure 6 here/

Mode Split

In the usual crime travel demand model, the third stage involves splitting the trip links by specific travel modes (e.g., walking, bike, driving, bus, train). However, in this study, the mode split is not relevant for this analysis since all DWI crash trips are by driving.

Network Assignment

The fourth, and last, modeling step is network assignment whereby the trips (by origin-destination link and mode) are assigned to a network. In the case of DWI trips that end in crashes, the network is the road system. As mentioned above, a modeling network was obtained from the Baltimore Metropolitan Council that estimated travel times along particular road segments. This allows a more realistic representation of the route take since most transportation models assume that drivers will attempt to minimize travel time, rather than distance *per se* (Ortuzar and Willumsen, 2001; Wachs, Taylor, Levine & Ong, 1993). In CrimeStat III, the assignment is done using the A* shortest path algorithm, which is a one-to-many path algorithm (Nilsson, 1980; Stout, 2000; Rabin 2000a, 2000b; Sedgewick, 2002).

Figure 7 shows the modeled trip volumes of assumed DWI trips ending in crashes on the major road network. The thickness of the lines is proportional to the number of assigned trips. As seen, the bulk of the predicted trips occurred on the eastern part of the county and, in particular on the freeways – the Baltimore Beltway (I695) and the part of I95 that is within the county. This would be expected given the higher speeds possible and the generally heavier travel use on the freeways.

While this is a modeled network assignment, not one actually measured, nevertheless it points to an obvious enforcement strategy of patrolling the entry and exit ramps on the eastern part of I695 and at the junctions with I95 and several major arterials (Harford Rd and Belair Rd). One of the advantages of the network assignment type of model is that it provides information for which police can develop enforcement strategies. Baltimore County Police Department are currently enforcing DWI along the routes modeled here.

/Insert Figure 7 here/

Examining Possible Interventions to Reduce Crashes

Once the model has been calibrated using the four-step process (in this case, three steps since mode split was not run), it can then be used to test alternative strategies. This, in fact, is the major reason for developing the model in the first case. While the model is only a skeleton resemblance to the actual behavior of offenders, it can serve as a framework to ask questions about interventions and policy alternatives.

In this study, we examine three potential interventions to reduce drunk driving crashes:

1) DWI enforcement
2) Interventions in the residence zones with a concentrated number of drivers who get involved in drunk driving crashes; and
3) Interventions in the zones where there are many DWI crashes.

Effect of Citations on DWI Crashes

The first intervention examined is whether DWI enforcement can reduce the number of drunk driving crashes. Data were obtained from the Baltimore County Police Department on the number of citations for DWI given out in 1999 and 2000. In 1999, there were 1,715 citations given out and in 2000, 1,838 were given out. Examining the temporal and spatial aspects of the citations, it is clear that they tracked the crash behavior by month, day of week, and time of day (analysis not shown). Further, the spatial patterning of the citations seemed to track the location of DWI crashes. It appeared from the data that the Baltimore County Police Department were focusing their efforts on the times and locations with the highest likelihood of producing a DWI crash.

To test whether the citations actually reduced future DWI crashes, a non-linear (Poisson) regression was set up that related the number of DWI crashes that occurred in a TAZ in 2000 to the number of DWI citations given out in 1999 controlling for the number of DWI crashes in 1999. A second model tested whether the number of DWI crashes that occurred in a TAZ in 2001 was related to the number of DWI citations given out in 2000 controlling for the number of DWI crashes in 2000. In effect, we're asking whether prior DWI enforcement in zones during any one year led to reductions in DWI crashes in the following year. Both models produced similar results. If there is a relationship between DWI citations in one year and DWI crashes in the next, it should be negative (i.e., increased enforcement leads to lower number of crashes). Table 3 presents the results for the model predicting the number of DWI crashes occurring in 2001.

/Insert Table 3 here/

The results show a positive relationship between the number of crashes in 2000 and the number that occurred in 2001, as would be expected. But, contrary to expectations, there is also a positive relationship between the number of citations given out in 2000 and the number of crashes occurring in 2001. In other words, holding the number of DWI crashes that occurred in 2000 constant, the number of DWI citations given out in 2000 is positively related to the number of DWI crashes that occurred in the subsequent year, 2001. The results for the previous year were almost identical.

This is somewhat discouraging. Now, clearly, the positive coefficient for DWI citations does not imply that it is a causal factor (i.e., citations are not causing the crashes to occur). However, what these data suggest is that there is *momentum* in the DWI crash likelihoods in many zones and that the citations cannot reduce the number of crashes in the following year, at least for this two year period that was examined. In other words, the factors producing drunk driving and subsequent crashes are so strong that enforcement barely scratches the surface. As mentioned at the beginning, drunk driving is a repetitive behavior, similar to an addiction and ordinary enforcement does not appear to reduce the behavior much. This doesn't, of course, imply that there should be no enforcement because the problem might become worse without it. But, the enforcement is very limited in what it can accomplish. Thus, we turn to several alternative approaches to reduce the problem.

Effect of Interventions on High-risk Zones

One of the interesting findings in this study is that drunk drivers involved in crashes tend to be concentrated in certain neighborhoods. Figure 8 shows a map of 15 TAZs where seven or more drivers involved in DWI crashes resided. These 15 TAZs represent 2.8% of all the 532 origin zones but they contain 16% of all the offenders involved in drunk driving crashes. These zones tend to be in the more rural parts of the county and, in particular, on the eastern side. There is one TAZ on the western size that also has a higher concentration of DWI crash driver residences.

/Insert Figure 8 here/

If these zones could be targeted for special intervention, it is possible that substantial reductions in the number of DWI crashes could be obtained. What could these interventions be? First, one could concentrate "Don't drive while drinking" advertisements on these neighborhoods rather than disperse them throughout the region, particularly in the local establishments that sell alcohol. The concentration of advertising might attract more attention from drivers than seeing the occasional billboard while driving in the region.

Second, because drunk driving is generally a repetitive behavior, the jurisdiction will know the addresses of drivers convicted of prior DWI offences. One could have social workers intervene with these drivers to encourage them to seek psychotherapy or group support (e.g., Alcoholics Anonymous). Third, ignition interlock devices are a very effective technology that has been shown to reduce drunk driving (MADD, 2008; Marques, 2005; NTSA & GHSA, 2006). While most States require the implementation of this technology for different classes of drunk drivers (typically repeat offenders though sometimes minors too), in practice, few judges have been willing to impose this requirement as part of the sentencing. Emphasis by the jurisdiction and the press could increase the use of the technology, perhaps focusing on the high risk zones as a test case.

Fourth, identifying neighborhoods as having concentrations of drunk drivers residing can be a useful stimulus for broader community involvement. In Houston, for example, the Texas Department of Transportation initiated billboard signs along certain State roads that identified those roads as having a disproportionate number of DWI fatalities (Kaufman, 2008). While the community initially balked at the attention focused by the signs, they started to organize, particularly local businesses, and came up with alternative suggestions for highlighting the drunk driving problem in their area.

Let's assume that Baltimore County adopts one or more of these interventions and focuses on the 15 TAZ's with a higher concentration of resident DWI crash drivers. Let's further assume that the interventions are successful and that the number of DWI crashes that originate from these zones are reduced by 20%. The crime travel demand model can be used to test this proposition. Mechanically, the number of predicted crashes originating from these 15 TAZs was reduced by 20%. The rest of the model was then re-run including the balancing of predicted origins and predicted destinations, the distribution of the DWI crash trips from origins to destinations, and the assignment of the trips to likely routes. The net effect of reducing the number of DWI crash trips originating in the 15 zones was to reduce the total number of DWI crashes in the region by 3.5%. In other words, the simulation suggests that a concentrated effort at only 15 high risk TAZs (or 2.8% of the total number) can produce a sizeable reduction in the number of crashes.

Effect of Interventions in Crash Hot Spot Zones

Similarly, one can intervene at the high crash locations, the DWI crash hot spots. Nineteen of the destination TAZ's had 8 or more DWI crashes occur in them over the three year period from 1999-2001. In other words, 5.9% of the 325 destination TAZs accounted for 21% of the total DWI crashes in the county. Figure 9 shows a map of these zones. They tend to be in two sectors of the county, on the southeastern side and in the central west part of the county.

/Insert Figure 9 here/

As with identifying the high risk TAZs where drivers involved in DWI crashes reside, one could also concentrate resources on these 19 TAZs where DWI crashes are more likely to occur. Several types of interventions are possible. First, enforcement can be concentrated in these zones. As mentioned above, the police tend to do this anyway. But, their enforcement is spread over a much larger area than that defined by the 19 zones. If the police were to re-concentrate their efforts on these zones, there might be a more effective response with the general citation strategy. Second, since many of the drivers involved in drunk driving crashes live fairly close to the locations where they become involved in crashes (and, most probably to the bars where they drink), it might be possible to provide some form of para-transit service to keep drinkers away from driving. The para-transit could be a subsidized taxi service or a shuttle bus or even a campaign to encourage a non-drinking 'designated driver' for groups who will be drinking.

Third, it may be possible to provide engineering 'fixes' to some of these hot spots. There is a systematic traffic safety program that has long existed in the United States called the Hazard Elimination Program. Essentially, it's a federal funding stream tied to a methodology that identifies high crash locations, that determines the causes of the crashes, and then proposes improvements to locations through traffic control devices, improved signage and lane markers, or even the reconstruction of intersections if necessary. It is generally a strategy aimed at providing low-cost improvements on road segments or at intersections (more information on this can be found at H-GAC, 2004).

Again, let's assume that the county adopts one or more these strategies and focuses on the 19 TAZs that have a disproportionate number of DWI crashes. Further, let's assume that the interventions are successful and reduce the number of DWI crash trips to these zones by 20%.[9] Since we've already assumed that there will be a reduction in the number of drivers originating in the 15 high risk zones above, it is necessary to account for the cumulative effect of reducing crashes at both the origin locations and the destination locations. Mechanically, this was done in the model by iterating the reductions. The 20% reduction in the high risk origin zones reduced the total number; the subsequent 20% reduction in the high crash destination zones further lowered the total number. Again, the model was re-run through all three stages to see the net effects.

The simulation showed that the combined effect of targeting the 19 high crash destination TAZs along with the 15 high risk origin TAZs reduced the total number of annual DWI crashes by 21 (or 7.5% of the total over the three year period). Table 4 shows the results.

Table 4
Comparing Annual DWI Crash Trips Before & After "Interventions"

	Inter-zonal	Intra-zonal
Before "Interventions"	226	59
After "Interventions"	207	57
Expected Change	-19	-2

[9] This percentage is similar to what many traffic improvements are expected to produce. See H-GAC 2004 for more information.

In other words, modeling the combined effect of focusing on the high risk zones and the high crash zones leads the model to predict a substantial reduction in the total number of DWI crashes, particularly inter-zonal trips. The National Safety Council produces annual estimates of the economic and comprehensive costs of motor vehicle crashes (NSC, 2007). Using their estimates and assuming a distribution of injuries similar to a typical pattern (averages of 0.75% fatalities per crash; 1.12 injuries per crash; and 34.4% property damage only crashes), we estimated that reducing the number of DWI crashes in Baltimore County by 21 per year would yield an annual benefit of $492,788 in direct costs (in 2000 dollars) and $1,265,863 in comprehensive (life style) costs (again, in 2000 dollars).[10] The actual benefits would be much greater since these estimates were based on the sample of 862 DWI crashes for the three year period, which were only one-fourth the total number of DWI crashes that occurred. The jurisdiction could investigate whether these monetized benefits would exceed the costs of running such interventions. But, in general, safety improvements usually pay for themselves quite quickly.

Conclusions

The crime travel demand model is a dynamic framework that is superior to journey to crime analysis for understanding the travel behavior of offenders. First, it represents a sequenced and systemic model of travel behavior to be developed. Instead of depending on a single travel distance function, which is what most journey to crime and geographic profiling methodologies use, it sees travel distance as a by-product of predispositions, attractions, and cost. Travel distance is a result of the interaction of these three dimensions, rather than a fixed entity. It represents a more dynamic framework for understanding the travel behavior of offenders. Cities have different attractors as well as different road networks and travel mode opportunities. The crime travel demand model can be adapted to the specifics of each jurisdiction and region allowing for a flexible way to describe crime travel patterns.

[10] We used the 2000 National Safety Council cost estimates and calculated average injury costs. In 2000, the expected economic costs were $1,000,000 per fatality, $12,259 per injury, and $6,500 per property damage only crash. The comprehensive (quality of life) costs were $3,214,290 per fatality, $30,300 per injury, and $6,500 per property damage only crash. NSC, 2000.

Second, it allows the exploration of alternative interventions and policies. In this study, we examined the likely effects of targeted enforcement efforts, focusing on neighborhoods either where DWI offenders are more likely to live or where crashes are more likely to occur. While police have traditionally focused their DWI enforcement on the high crash neighborhoods, our analysis suggests that even more concentration will provide benefits in terms of reducing the number of drunk driving crashes. Currently, the Baltimore County Police Department is participating in a collaborative initiative between the National Highway Traffic Safety Administration and the Bureau of Justice Assistance to reduce crime and traffic accidents on targeted street segments through traffic enforcement. The Data Driven Approaches to Crime and Traffic Safety (DDACTS) project allocates police resources to street segments having high amounts of crime and traffic accidents. Police analysts are monitoring crime and accidents on the target locations to determine whether increased traffic enforcement is impacting crime and accidents.

Other scenarios could be examined using the crime travel demand model. We haven't done this, but one could explore other approaches, such as decentralized targeting compared to the concentrated targeting that we used in the simulation or the likely effects of increased enforcement at the entrance or exit ramps of the freeways compared to the neighborhoods where offenders live or where crashes occur. The advantage of the crime travel demand model is that, once calibrated on an existing data set, it can be used to explore alternatives.

The major disadvantages of the crime travel demand model are two-fold. First, it is a very intense data gathering process. A police department wanting to run such a model needs to devote resources to gathering a large amount of data together. There have to be sufficient numbers of events that are to be modeled as well as substantial socio-economic and network data that has to be obtained. A police department or other agency should be aware of the time demands that will be placed on the analyst to put together the datasets. However, once collected, it then becomes a much easier process to run the model even with alternatives being explored.

A second disadvantage is that it is a model, rather than a comprehensive description. Any model is an extreme oversimplification of reality, of course, and captures only some elements of the pattern. In other words, there is error in the model, and lots of it. A model is not reality. As we saw, for example, the predicted trip distribution captured only some of the major DWI trip links that existed. Still, models have been shown to be useful in being able to predict consequences. Once the datasets are gathered, it is a relatively inexpensive process to run alternative models. This would allow a police department to explore possible interventions quickly and at least filter out those that won't appear to produce any expected benefits. The focus then becomes on the likely benefits of the intervention relative to the expected costs in implementing it. The crime travel demand methodology, while not perfect, certainly provides insights into ways of reducing crime, in this case drunk driving.

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TABLES AND FIGURES

Table 1:

ZONAL PREDICTORS OF DRUNK DRIVING CRASH ORIGINS

Model result:	
Type of model:	Origin
DepVar:	DWI Crash Origins
N:	532
Df:	528
Type of regression model:	Poisson with over-dispersion correction
Log Likelihood:	-402.47
Likelihood ratio(LR):	137.29
P-value of LR:	0.0001
AIC:	818.94
SC:	848.88
Dispersion multiplier:	1.000
R-square:	0.38
Deviance r-square:	0.68

Predictor	DF	Coefficient	Stand Error	Tolerance	z-value	p
CONSTANT	1	-2.759	0.069	-	-39.87	0.001
POPULATION	1	0.0003	0.000	0.863	17.10	0.001
PCT WHITE	1	0.014	0.001	0.757	11.92	0.001
RURAL	1	0.441	0.069	0.556	6.39	0.001
# LIQUOR STORES	1	0.238	0.048	0.830	4.99	0.001
# BARS	1	0.150	0.028	0.819	5.39	0.001
AREA OF ZONE	1	-0.026	0.012	0.556	-2.07	0.05

Table 2:

ZONAL PREDICTORS OF DRUNK DRIVING CRASH DESTINATIONS

Model result:	
Type of model:	Origin
DepVar:	DWI Crash Destinations
N:	325
Df:	320
Type of regression model:	Ordinary Least Squares
R-square:	0.25
Adjusted r-square:	0.24

Predictor	DF	Coefficient	Stand Error	Tolerance	z-value	p
CONSTANT	1	0.291	0.082	-	3.51	0.001
POPULATION	1	0.0001	0.000	0.981	5.43	0.001
# BARS	1	0.214	0.034	0.896	6.21	0.001
COMMERCIAL ACRES	1	0.004	0.001	0.888	3.33	0.001
BELTWAY PASS THROUGH TAZ	1	0.314	0.099	0.989	3.18	0.01
AREA OF ZONE	1	-0.006	0.011	0.951	-1.71	n.s.

Table 3:
TESTING WHETHER DWI CITATIONS DECREASE DWI CRASHES
2000 Citations Predicting 2001 Crashes Holding 2000 Crashes Constant

Model result:	
Type of model:	Destination
DepVar:	Number of DWI Crashes in Zone: 2001
N:	325
Df:	322
Type of regression model:	Poisson with over-dispersion correction
Log Likelihood:	-543.02
Likelihood ratio(LR):	150.83
P-value of LR:	0.0001
AIC:	1092.05
SC:	1103.40
Dispersion multiplier:	1.000
R-square:	0.14
Deviance r-square:	0.81

Predictor	DF	Coefficient	Stand Error	Tolerance	z-value	p
CONSTANT	1	-0.288	0.111	-	-2.60	0.01
DWI Citations In 2000	1	0.058	0.011	0.774	5.34	0.001
DWI Crashes in 2000	1	0.129	0.045	0.774	2.87	0.01

Figure 1

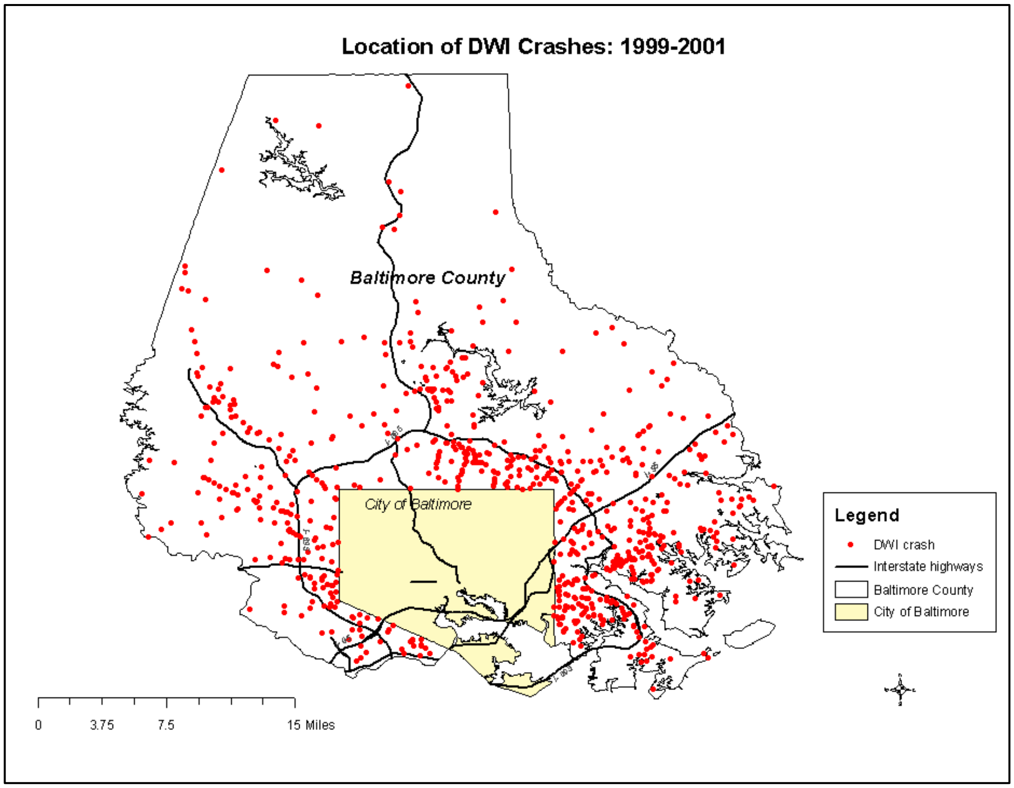

Location of DWI Crashes: 1999-2001
Baltimore County
City of Baltimore
Legend
DWI crash
Interstate highways
Baltimore County
City of Baltimore
0
3.75
7.5
15 Miles

Figure 2

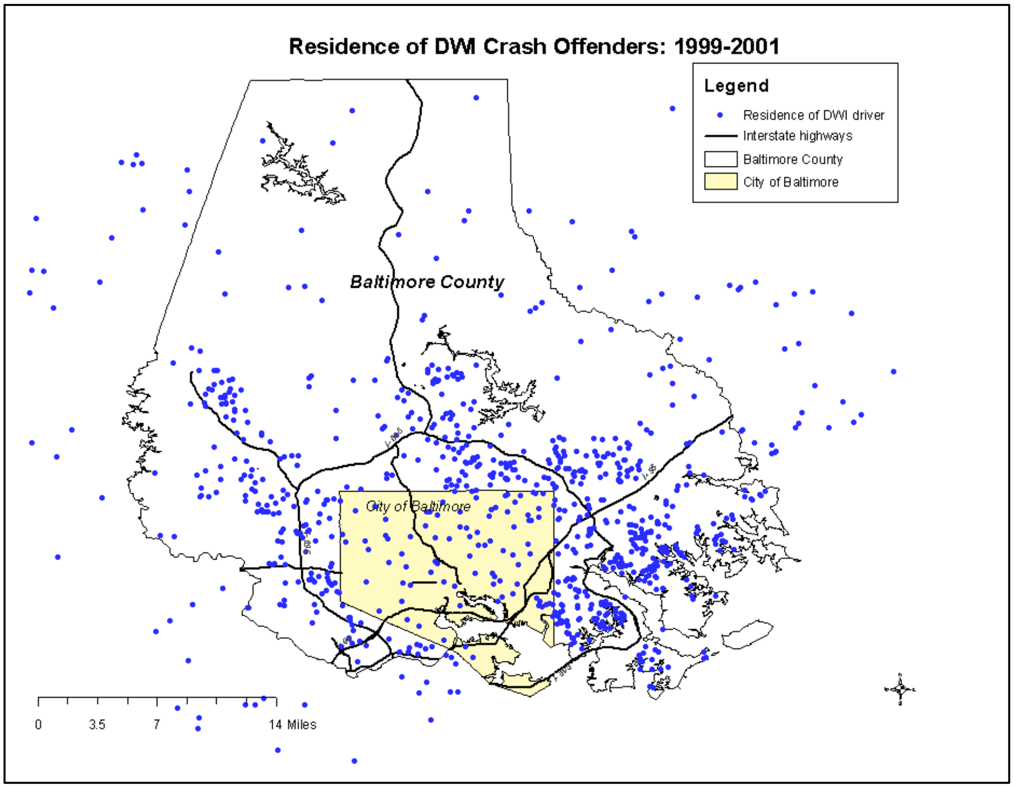

Residence of DWI Crash Offenders: 1999-2001
Legend
Residence of DWI driver
Interstate highways
Baltimore County
City of Baltimore
Baltimore County
City of Baltimore
0
3.5
7
14 Miles

Figure 3

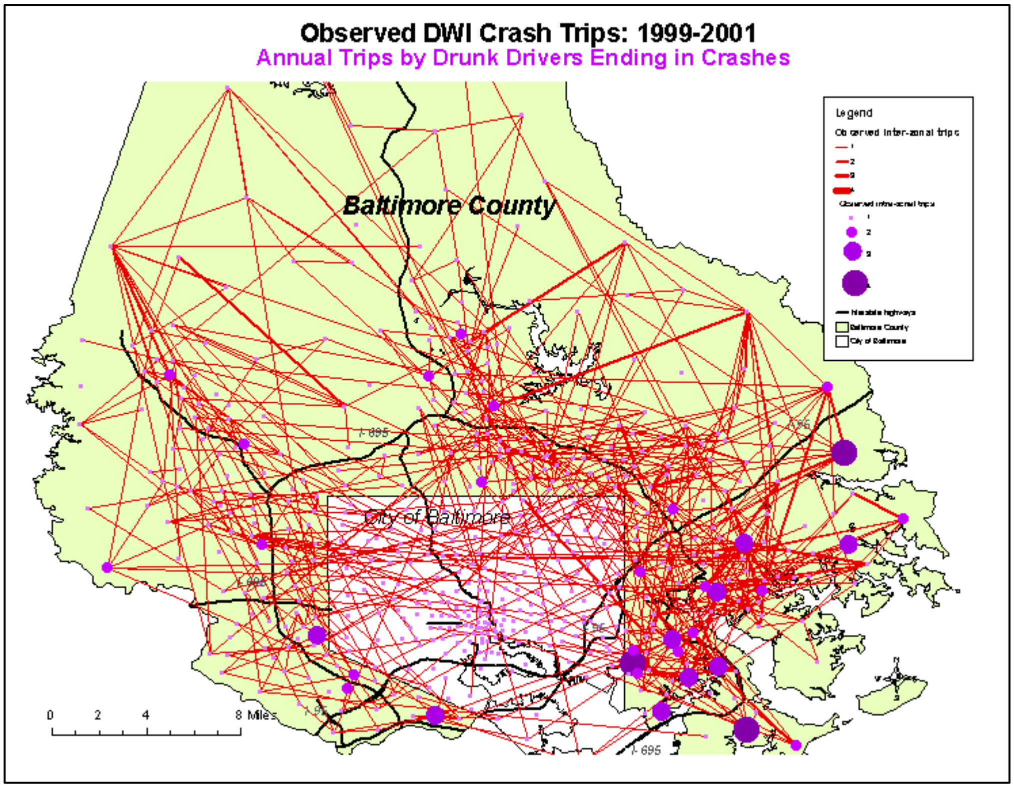

Observed DWI Crash Trips: 1999-2001
Annual Trips by Drunk Drivers Ending in Crashes
Baltimore County
City of Baltimore
I-695
Legend
Observed inter-zonal trips
1
2
3
4
1
2
3
0
2
4
8 Miles

Figure 4

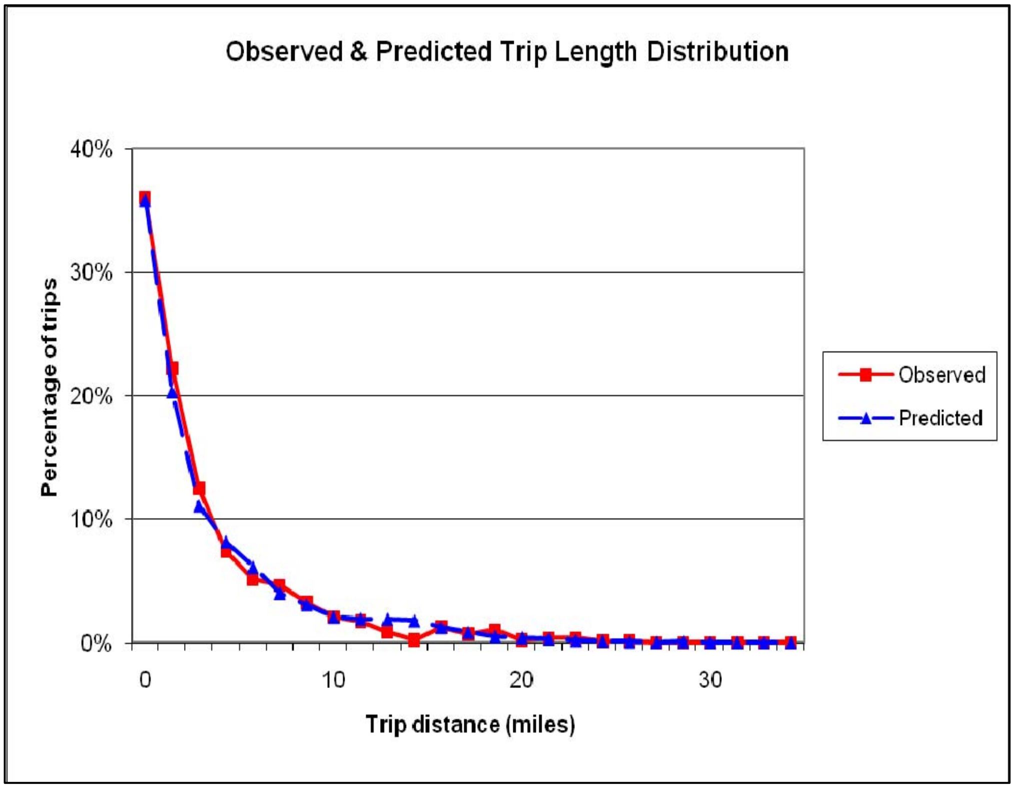
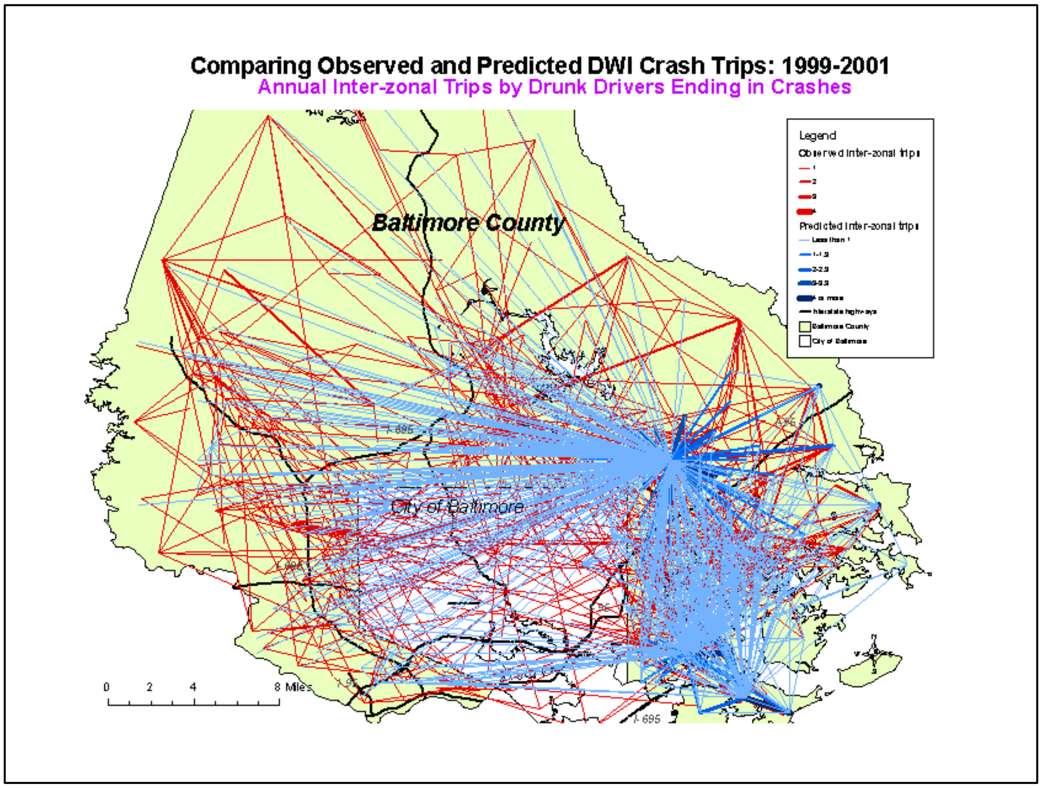
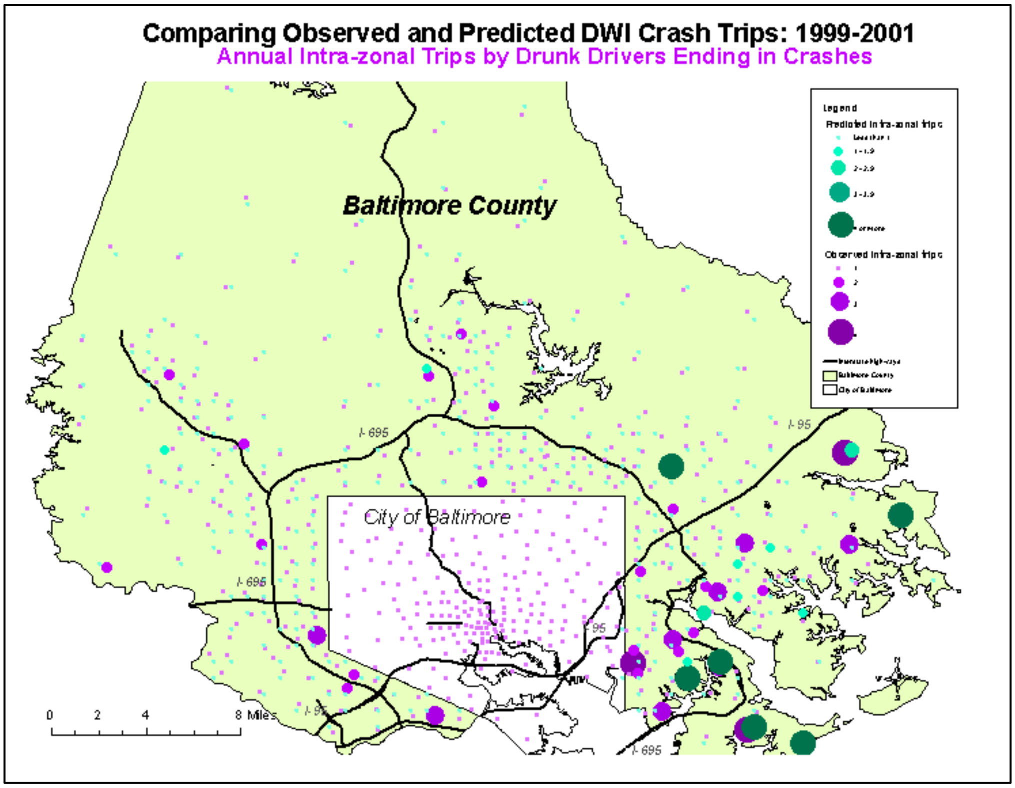

Observed & Predicted Trip Length Distribution
40%
30%
20%
10%
0%
Percentage of trips
0
10
20
30
Trip distance (miles)
Observed
Predicted

Figure 5



Comparing Observed and Predicted DWI Crash Trips: 1999-2001
Annual Inter-zonal Trips by Drunk Drivers Ending in Crashes
Legend
Observed inter-zonal trips
Predicted inter-zonal trips
Baltimore County
City of Baltimore
I-695
0 2 4 8 Miles

Figure 6



Comparing Observed and Predicted DWI Crash Trips: 1999-2001
Annual Intra-zonal Trips by Drunk Drivers Ending in Crashes
Baltimore County
City of Baltimore
I-695
I-95
Legend
Predicted intra-zonal trips
Observed intra-zonal trips
0 2 4 8 Miles

Figure 7

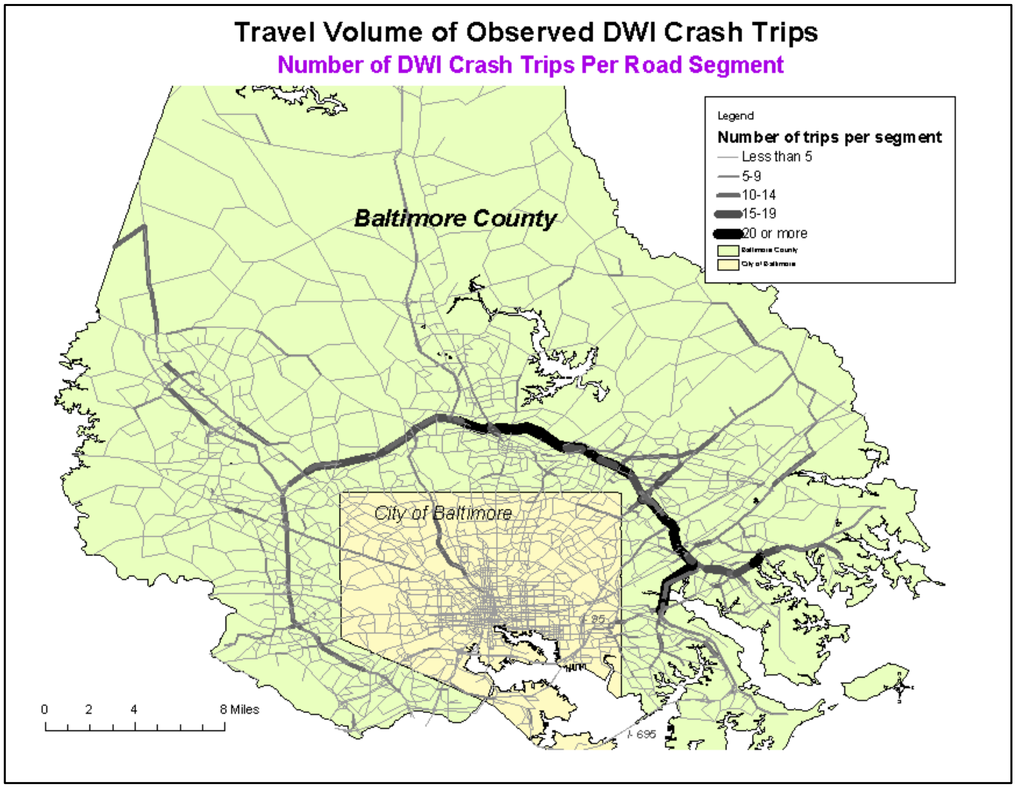

Travel Volume of Observed DWI Crash Trips
Number of DWI Crash Trips Per Road Segment
Legend
Number of trips per segment
Less than 5
5-9
10-14
15-19
20 or more
Baltimore County
City of Baltimore
0
2
4
8 Miles
I- 695

Figure 8

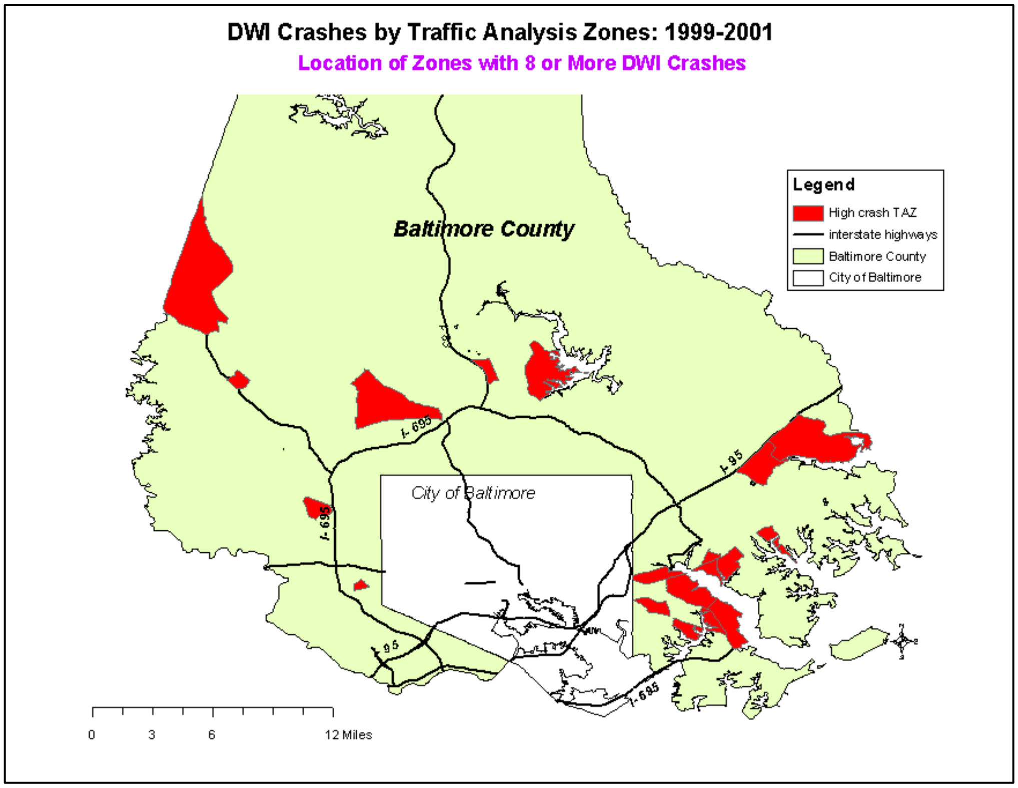
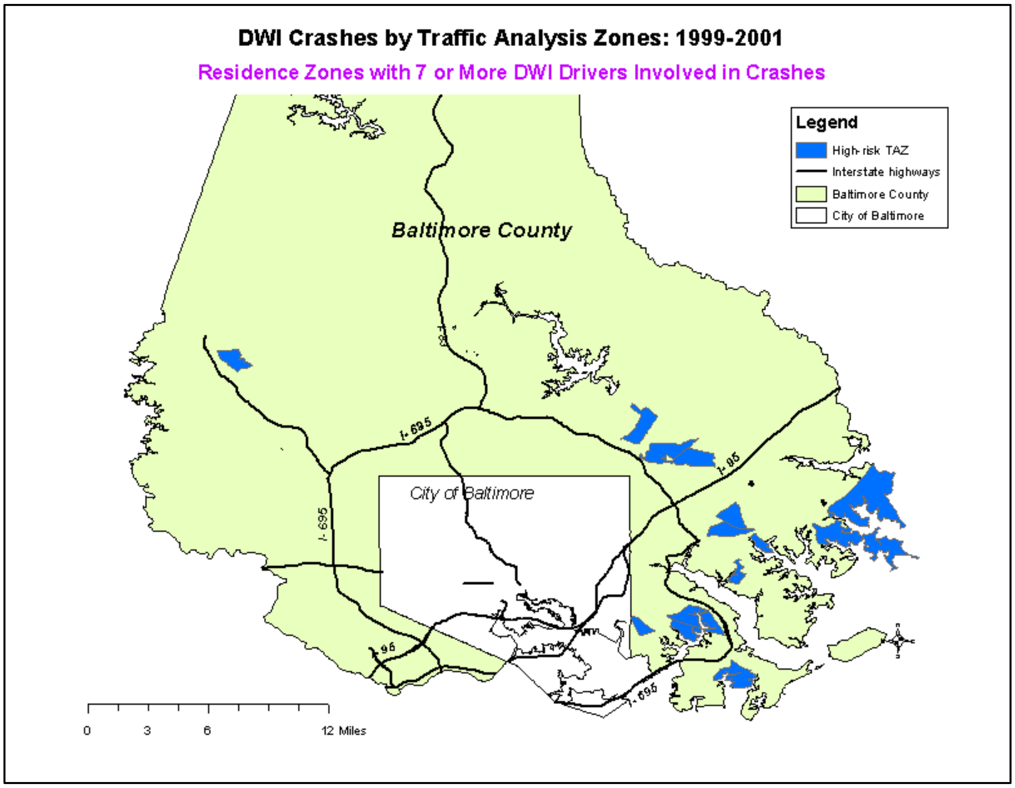

DWI Crashes by Traffic Analysis Zones: 1999-2001
Location of Zones with 8 or More DWI Crashes
Baltimore County
City of Baltimore
Legend
High crash TAZ
interstate highways
Baltimore County
City of Baltimore
I-695
I-95
I-695
95
I-695
0
3
6
12 Miles

Figure 9


DWI Crashes by Traffic Analysis Zones: 1999-2001
Residence Zones with 7 or More DWI Drivers Involved in Crashes
Legend
High-risk TAZ
Interstate highways
Baltimore County
City of Baltimore
Baltimore County
City of Baltimore
I-695
I-95
0
3
6
12 Miles