CrimeStat IV

Part VI: Crime Travel Demand Forecasting

Chapter 25:

Overview of Crime Travel Demand Modeling

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Chapter 25:

Overview of Crime Travel Demand Modeling

The next seven chapters present a module on crime travel demand modeling. Crime travel demand modeling is a framework for examining crime trips over an entire metropolitan area. In this chapter, an overview is presented. In this and the next five chapters, each of the separate components of crime travel demand modeling are presented. Finally, in Chapters 31 and 32, Richard Block and Dan Helms present case studies of the method applied to Chicago and Las Vegas crime data.

Much of the theoretical background was discussed in Chapter 13 (Journey-to-crime). Readers would be advised to review that material before proceeding with the crime travel demand model.

Travel Demand Forecasting

Crime travel demand modeling is an application of travel demand forecasting (or travel demand modeling). It is used by transportation planners for examining travel patterns over an entire metropolitan area and for forecasting future trends. It is a model of transportation patterns in a metropolitan area and is used for both forecasting and the analysis of the likely effects of building new roadways or installing new transit facilities. In the United States, it is required by Federal law to be used in every metropolitan area greater than 50,000 population as a basis for making decisions on highway and transit expenditures (USDOT, 2003: 23CFR450). It is also used for transportation planning in the metropolitan areas of many other countries of the world (Field & MacGregor, 1987).

The aim is to model travel over an urban area as a means for coordinating the approximately $36 billion dollars in transportation highway funds and $8.6 billion in transit funds that are spent *every* year in the U.S. (BTS, 2007). Rather than waste funds by building new roadways and transit facilities that will be little used, it is a lot more effective to first model the likely benefit of a new facility as a basis for making a decision to build it. In essence, Congress requires a transportation model be developed for every metropolitan area as part of an evaluation of the benefits to be obtained from particular transportation investments.

The framework has emerged slowly since the 1950s and is now starting its ‘third generation’. For the ‘first generation’ - what is used by most Metropolitan Planning Organizations (MPO) today, modeling is conducted entirely at a zonal level. The ‘second generation’ involves modeling individual level choices in travel mode taken within a zonal framework (Horowitz, Koppelman, & Lerman, 1986; McFadden, 2002), while a 'third generation' involves modeling individual-level trips in a framework known as 'activity-based' modeling (FHWA, 2009; Culp & Lee, 2005). In *CrimeStat IV*, we implement a modified 'first generation' model, primarily due to the lack of data on individual-level crime trips. In later versions, we may add individual-level choice components.

Need for More Complex Travel Model of Crime

Crime travel demand modeling is an application of travel demand theory targeted specifically to crime analysis. There are many reasons why such an approach is appropriate. First, current models of criminal travel behavior are too simple with respect to travel. As Chapter 13 discussed, journey-to-crime models assume that many offenders commit crimes in their neighborhoods. While this assumption is frequently empirically found, it is not a realistic model of modern day crime travel. Prior to World War II, Americans tended to live and shop almost exclusively in their residential community. Many people would grow up and live in a single community for most of their lives. Since World War II, however, American society has become very mobile. People move frequently, not just within metropolitan areas, but between metropolitan areas. For example, between 2009 and 2010, at the height of the Great Recession, 28.5 million persons moved homes (U.S. Census, 2010a). This was down from 1999-2000 where 43.4 million moved (Schacter, 2001) but still represented a substantial amount of movement. More than two-thirds of the households who moved (68%) stayed in the same county but 12 percent moved to a different State.

Second, the almost universal use of personal automobiles has increased daily mobility. For example, in the 2010 census, 91% of households owned at least one motor vehicle, an increase over 2000 where it was 86% (NHMC, 2012; U.S. Census, 2003; Aizcorbe & Starr-McCluer, 1996). For certain metropolitan areas, particularly in the west and in the south, motor vehicle ownership was greater than 92%. Even in cities with lower vehicle ownership, more than half the population do own vehicles (e.g., New York City had 56% of households with one or more vehicles in 2000; Wikipedia, 2012a).

Further, per capita vehicle travel has consistently increased over time. Since at least 1960, and probably before, the growth in vehicle miles traveled (VMT) has increased at a much faster rate than population, a trend that does not seem to be abating (NAP, 2009; BTS, 2003; FHWA, 1996). Essentially, automobile use has become almost ubiquitous. There is no reason to think that offenders would not be affected by these trends. Since there is no data available that could test whether offenders are less likely to own an automobile than non-offenders, it has to be assumed that more and more offenders have access to an automobile for the use of committing a crime. Clearly, the existence of an automobile makes crime travel much more fluid and difficult to model. While offenders will probably commit crimes in locales for which they are familiar, there is no reason to think that those locales will necessarily be the communities in which they live.

Third, the widespread availability of motor vehicles has allowed major shifts in intra-urban travel patterns. In the last census (2010), approximately half the U.S population lived in areas that would normally be called ‘suburbs’, even though the U.S. Census Bureau does not use this nomenclature (They use Outlying Counties within a Metropolitan Statistical Area type of Core Based Statistical Areas; Wikipedia, 2012b; OMB, 2010). Within metropolitan areas, approximately two-thirds of the population lives in suburban areas.

Much of the community-oriented crime patterns that were described by the so-called ‘Chicago School of Criminology’ in the 1920s and 1930s are no longer true (Burgess, 1925; Thrasher, 1927). Crimes have decreased in both the central cities and in the suburbs throughout the U.S. between 1990 and 2008 (Kneebone & Raphael, 2011). However, the differentials between the central city and the suburbs have decreased over time. In 1990, for example, the differential in violent crime between the central cities and the suburbs was 2.8 times whereas it was 2 times in 2008. Similarly, the differential in property crimes between the central cities and the suburbs decreased from 2 times to 1.7 times over that period. The researchers noted that this gap decreased in nearly two-thirds of metropolitan areas in the U.S. These decreases are associated with a dramatic drop in crime within the central cities but a more gradual drop in the suburbs.

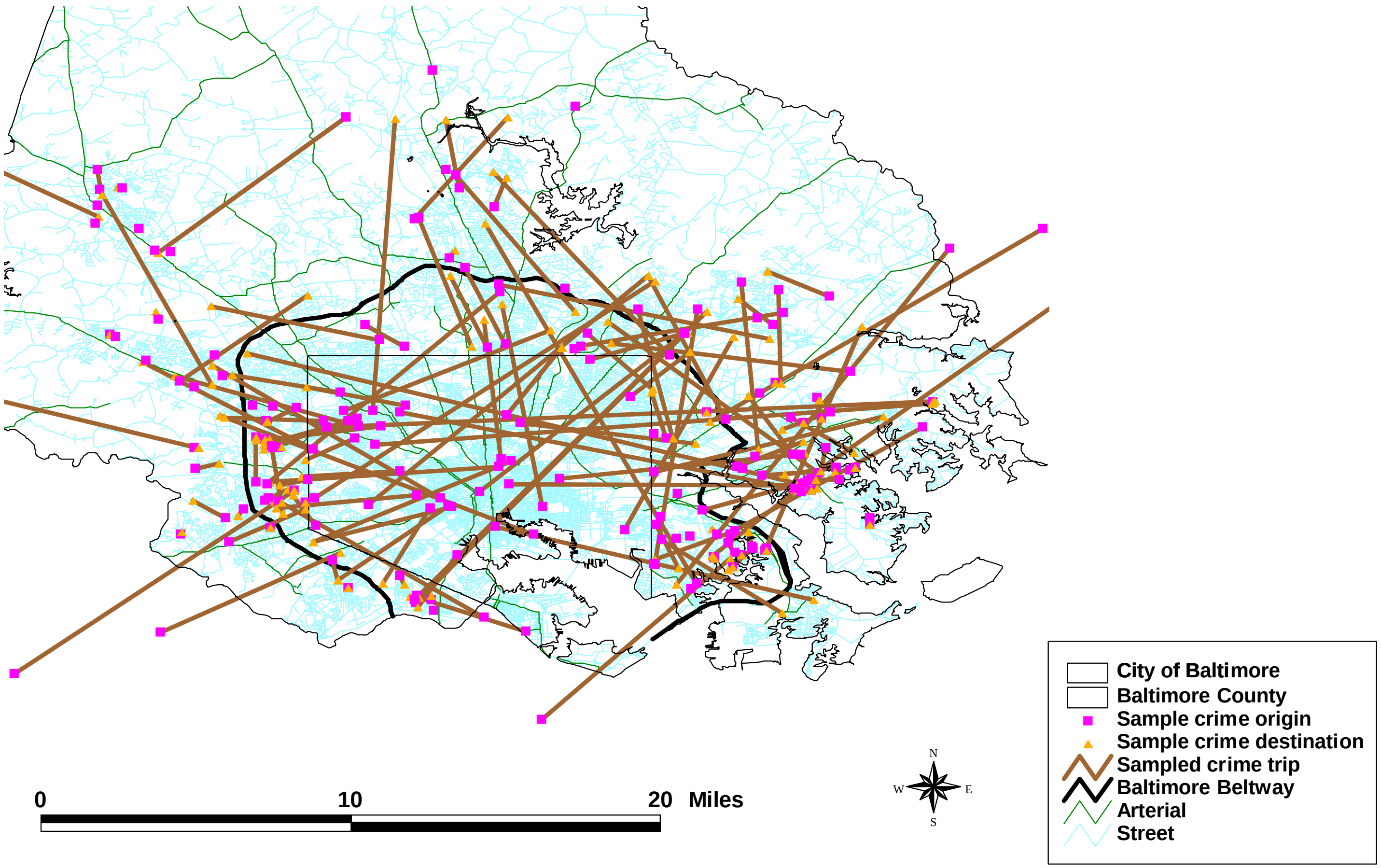
While crime has been decreasing in most metropolitan areas within the U.S., the travel patterns of offenders has become quite complex. Figure 25.1 below shows a sample of 200 crime trips in Baltimore County that occurred between 1993 and 1997. As seen, there is a complex pattern. Some of the trips are short; for some, the origin and destination are the same location. But, for other trips, the travel distances are substantial. In other words, there is a complex pattern of crime trips in Baltimore County which is not easily modeled by a simple distance decay-type function.

Fourth, an empirical examination of travel patterns shows considerable temporal variation. There are hourly variations, daily variations, and seasonal variation in crimes. Some of this can be understood as reflecting existing travel patterns in congested metropolitan areas. For example, in Baltimore County, crime travel distances were generally shorter during the peak afternoon ‘rush hours’ (4-7 PM) than at other times. Such a pattern suggests an adaptation to traffic by offenders, a not unreasonable assumption given the difficulties of traversing a metropolitan area during peak travel times.

Fifth, crime travel behavior represents a complex pattern in itself. Especially for personal crimes, there is an interaction in the travel patterns of offenders and victims that is very difficult

Figure 25.1:

Baltimore County Crime Trips: 1993-1997
Origins and Destinations
Sample of 200 Crime Trips



to even describe, least of all model. Many crimes are committed by multiple offenders and the existence of intermediate locations (e.g., ‘fences’ for the distribution of stolen goods, auto theft drop locations) makes crime travel even more of a complex pattern to be understood.

In short, American society has become very mobile, leading to larger travel distances, more frequent trips, and more complex trips. Again, offenders are going to be affected by these trends. Because of this, there is a need to understand crime patterns in terms of the complexity of travel rather than continue to rely on overly simple models of travel ‘distance decay’.

Crime Travel Demand Framework

Crime travel demand theory is a framework for understanding this complexity. There are two phases:

1. An inventory (or data gathering) phase; and
2. A modeling phase.

The data gathering involves putting together the necessary data to estimate the model. This involves selecting an appropriate zone system (since the model is estimated at the zonal level), obtaining data on crime ‘trips’ and allocating it to the zones, obtaining zonal variables that will predict trips (both on the production side and on the attraction side), creating possible policy or policing interventions, and obtaining one or more modeling networks.[1]

The modeling phase involves four distinct modeling steps (or stages) that represent a logical ‘causative’ pattern:

1. **Trip generation** - separate models are produced of crime trip productions (i.e., the number of crime trips that originate in each zone) and crime trip attractions (i.e., the number of crime trips that occur in each zone). The model may include policy or intervention variables as predictors as well as socio-economic variables. One of the major uses of the model is to explore how different interventions might alter the number of trips taken.

2. **Trip distribution** - a model that predicts the number of crime trips that will begin in every production zone and will end in every attraction zone.

[1] In the usual travel demand modeling framework, data gathering is called a *land use inventory* and involves estimating population and employment by different land uses, particularly retail trade and several other types of industry.

3. **Mode split** - a model that predicts, for each production-attraction zone pair, which travel modes will be taken (e.g., walking, bicycle, driving, bus).

4. **Network assignment** - a model that predicts, for each production-attraction zone pair by travel model, which route is liable to be taken.

The modeling is typically sequential following these steps. The output from each stage is then used as an input for the subsequent stage. Figure 25.2 below shows the sequence.

One can think of the model as a *plausible* behavioral representation. First, someone decides to make a trip (e.g., an offender decides to commit a robbery to get some money to purchase drugs). That would be the first stage. Second, that individual decides where to go to commit the robbery. This is the second stage. Third, the individual decides how to travel to that location (walk, drive, or take the bus). This is the third stage. Finally, the individual chooses a route; in the case of walking, biking, or driving, that is a deliberate choice whereas in the case of transit trips, it is dependent on the actual bus or rail network. This is the fourth stage.

However, the analogy to behavioral decisions quickly breaks down as alternative behavioral sequences can be generated (e.g., the offender first makes a trip and then decides to commit a crime; the offender first decides to commit a crime and chooses a destination, but then commits a crime at an intermediate location in the trip). As a behavioral model, this type of framework is actually not very accurate for predicting individual behavior as a number of studies have suggested (Ortuzar &Willumsen, 2001; Domencich & McFadden, 1975).

Consequently, it is important to understand this framework as a *zonal* model, rather than a behavioral explanation. The data are aggregated at the zonal level and the model is applicable to that level. The model is good at predicting total trips in a metropolitan area and for predicting the major trip links, and should be used only at that level.

Note in Figure 25.2 that there is feedback from the network assignment stage to the mode split stage. This is a function of transit use since the choice of travel mode is dependent on the availability of an appropriate network (e.g., one cannot have train trips if there are no trains nearby).[2]

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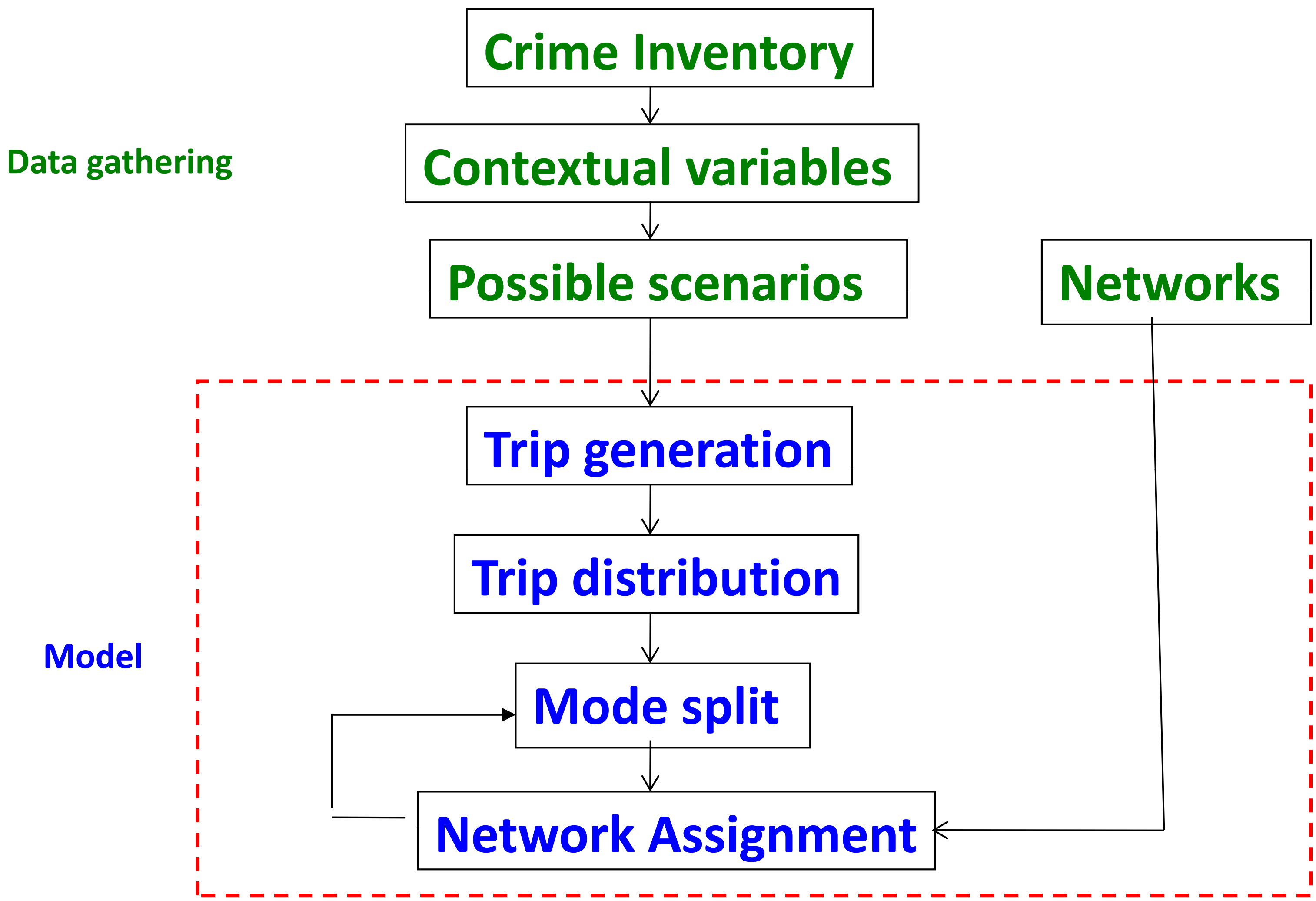
[2] In classic travel demand modeling, there are several feedback loops. One is from the network to the mode choice, as in the crime travel demand version. A second is from the network to both mode choice and trip distribution stage. If a particular route becomes very congested (having a traffic volume-to-capacity ratio greater than 1.0), it has been noted alternative destinations become more attractive. For example, people will often travel farther and more out of the way to avoid congested corridors. In short, there are a variety of feedbacks from later stages to earlier stages, and the model is quite flexible in being able to accommodate the different sequences.

Figure 25.2:

Crime Travel Demand Model



Also, crime travel demand modeling is a framework, rather than a specific theory. There is more than one way to implement the framework. In transportation modeling, there are many variations of the model and transportation planning organizations implement it in slightly different ways. For this reason, it is best thought of as a framework.

In this version of *CrimeStat*, we implement one particular version of the framework. It is a framework that is consistent and appears to produce reasonable predictions of crime travel behavior. But, clearly, it is not the only way that this could have been implemented.

The 'second-' and 'third-generation' travel demand models represent alternative ways of modeling travel in a metropolitan area. In the following chapters, these alternatives will be mentioned where appropriate. Nevertheless, the type of framework implemented in this version should be seen as a first step in developing a more realistic model of crime travel behavior.

Crime Travel Definitions

Let us start with two definitions.

Crime Trip

In the *CrimeStat* implementation, a **crime trip** is a round-trip journey from an offender's residence that includes a committed crime at a specified location. From a modeling perspective, the offender's residence will be considered the **origin** of the trip and the crime location will be considered the **destination**. Note that there may be intermediate trips between the origin and the destination, as Figure 25.3 below illustrates. But, at some point, the offender will probably return home to the initial origin. Defining a crime trip in this way avoids the issue of identifying the actual origin of the trip. As mentioned in Chapter 13, routine activity theory suggests that many crimes are committed while offenders are involved in other activities. The possibilities can become quite complex (e.g., an offender stays overnight at some other location than his/her residence and commits a crime as a part of that stay rather than while en route to home).

Nevertheless, by referencing all trips with respect to the offender's residence, a consistent set of estimates can be obtained. Since intermediate trips are almost never known, it is a hypothetical question whether modeling origins from offender residences will produce better estimates than modeling origins from other locations.[3]

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3 *If* it were possible to obtain data on intermediate locations during crime trips by offenders, then it would be possible to test whether modeling the origin with respect to these intermediate locations produces more stable and clearer predictions than with respect to the residences of the offenders. But, until that data is obtained, the question is speculative.

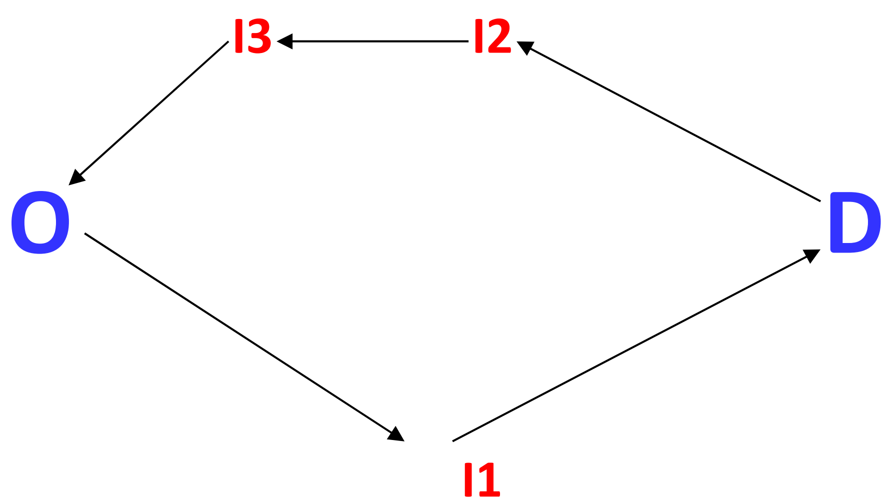
Figure 25.3:

Origin-Destination Links

There is an *origin* (residence)

There is a *destination* (crime location)

There may be *intermediate* links



In the usual travel demand forecasting framework, transportation modelers usually distinguish **productions** and **attractions** from origins and destinations. The reason is that origins are asymmetrical in time. For example, for a home-to-work (commuting) trip, the origin location in the morning is the residence while the destination is the work location. On the return trip, however, the origins and destinations are reversed (i.e., the work location is the origin while the home location is the destination). The models are referenced in the same way that is done here, namely from the residence location and the trips are assumed to be reciprocal. Thus, the production end of a trip is always the residence location and the attraction end of a trip is always the work location. The round-trip journey can be broken into different time sequences (e.g., morning home-to-work trips; afternoon work-to-home trips), but the production and attraction ends are always the same.

In crime travel demand modeling, there is usually data on intermediate trips. Consequently, some of the finer analysis cannot be done. Therefore, we adopt a similar logic, but with a slightly different terminology. As with the usual travel demand modeling, the production end is *always* the home location and the attraction end is *always* the crime location. However, we use origin and destination interchangeably with production and attraction since we cannot document the return part of a crime trip.

Crime Travel Demand

Crime travel demand is the number of offenders per unit time that are expected to travel on a given segment of the transportation system under a set of socioeconomic, land-use, and environmental conditions. That is, the final model output is an estimate of the number of trips (or offenders) that travel on any given segment of the transportation system at a given time under a given set of conditions:

$$\text{Number of trips} = \text{number of offenders traveling to crime} \tag{25.1}$$

First, as mentioned above, the model is estimated sequentially. In the first stage, trip generation, there is a prediction of the number of crime trips that originate from each origin zone and the number of crime trips that occur (end) in each destination zone. In this case, a crime **trip** is equated with an offender because of the nature of arrest records from which these estimates come. With most arrest records, there is a single record for each crime that an individual commits. Thus, the origin is the residence location of the offender while the destination is the crime location. If the individual committed more than one crime, there will be a separate record for each crime (or, at least, those that are known). If two individuals commit a single crime and both are arrested, then there will be two records in the data base. In other words, the nature of the data equates a crime trip with a single offender. Thus, the total number of crime trips estimated (whether from the production or attraction end) is equivalent to the number of offenders.

Aggregate Volume/count Model

Second, by a 'set of socioeconomic, land-use, and environmental conditions' is meant correlates of crime trips. At the aggregate level of a zone, predictors of crime trips (whether productions or attractions) are correlates of those trips. Since the number of trips are being predicted, the model estimates **volumes (**or counts), not rates.[4] That is, the number of crime trips originating in a zone or ending in a zone is a count of events. Aggregate counts, in turn, tend to be related to other aggregates, particularly population. Thus, in developing a predictive model, population is almost always one of the dominant variables. Sometimes it can be a sub-set of population, such as number of households, number of vehicles, or number of males aged 16-25. But, since the number of incidents is usually a function of the size, there can be difficulties in inferring individual characteristics from ecological models.[5] It is important to keep this distinction in mind and not make inferences about individuals.

In addition to population, variables that predict crime trips are also ecological variables - employment, retail space, number of bars, number of pawn shops, existence of a freeway, number of arterial lane miles, and so forth.

O-D Zone Pairs

In the second stage, trip distribution, a model is estimated of the number of crime trips that occur from any particular origin zone to any particular destination zone. Since the input to the second stage is the number of predicted crimes originating in each origin zone and the number of predicted crimes ending in each destination zone, the second stage estimates how many trips will be distributed from each origin zone to each destination zone. The result is an

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4 Some agencies have actually used it to predict rates. Since a rate is an event relative to a baseline, population is factored into the dependent variable. It is possible to apply the model as a rate, though the user needs to ensure that all the predictor variables are also rates.

5 The question of whether an ecological inference is valid or not has been studied extensively. Sometimes it holds and sometime it does not. An ecological inference occurs when data are aggregated with a *grouping* variable (e.g., state, county, city, census tract; see Freedman, 1999; Langbein & Lichtman, 1978). The relationship is often called an *ecological fallacy*, but that is an oversimplification. Typically, if the between-group variance (i.e., differences) is greater than those within groups, then the ecological relationship will be a lot stronger than at an individual level. Conversely, if the within-group variance is greater than the between-group variance, a relationship that holds at the individual level will not be seen at the aggregate level. There are other ecological characteristics that account for typically higher R^2 at the aggregate level - spatial autocorrelation, skewness in the dependent variable, and hetereoscedasticity (unequal estimation errors around a statistical estimate).

estimate of crime trips between zone pairs (an origin zone and a destination zone). There are different names that are used for this combination - zone-to-zone trips; zone pairs; zone-to-zone links, O-D links (for origin-destination links), O-D pairs, but in all cases the term refers to the number of trips that start in any one origin zone that go to any one destination zone.

Travel Mode

In the third stage, mode split, the number of trips by any O-D combination are then split into different travel modes - walking, biking, driving, bus (if available) or train (if available). In the usual travel demand modeling done by transportation modelers, some of these modes are broken down very finely (e.g., drive alone trips, car pooling trips, park-and-ride trips). There is no logical reason why mode split cannot be defined in multiple ways. For our purposes in modeling crime trips, simple choices are probably adequate because of a lack of data that would allow finer distinctions to be made.

Estimating Travel Routes by Mode

Finally, in the fourth stage, the number of trips from any origin to any destination by separate travel modes are assigned to a route on the transportation network. Thus, if the trip is by walking, biking, or driving, the model may predict a different route than if the trip is by transit since a transit system is limited to particular bus or rail routes. Hence, the final stage is an estimate of the total number of crimes that occur on any segment of a transportation network by separate travel mode.

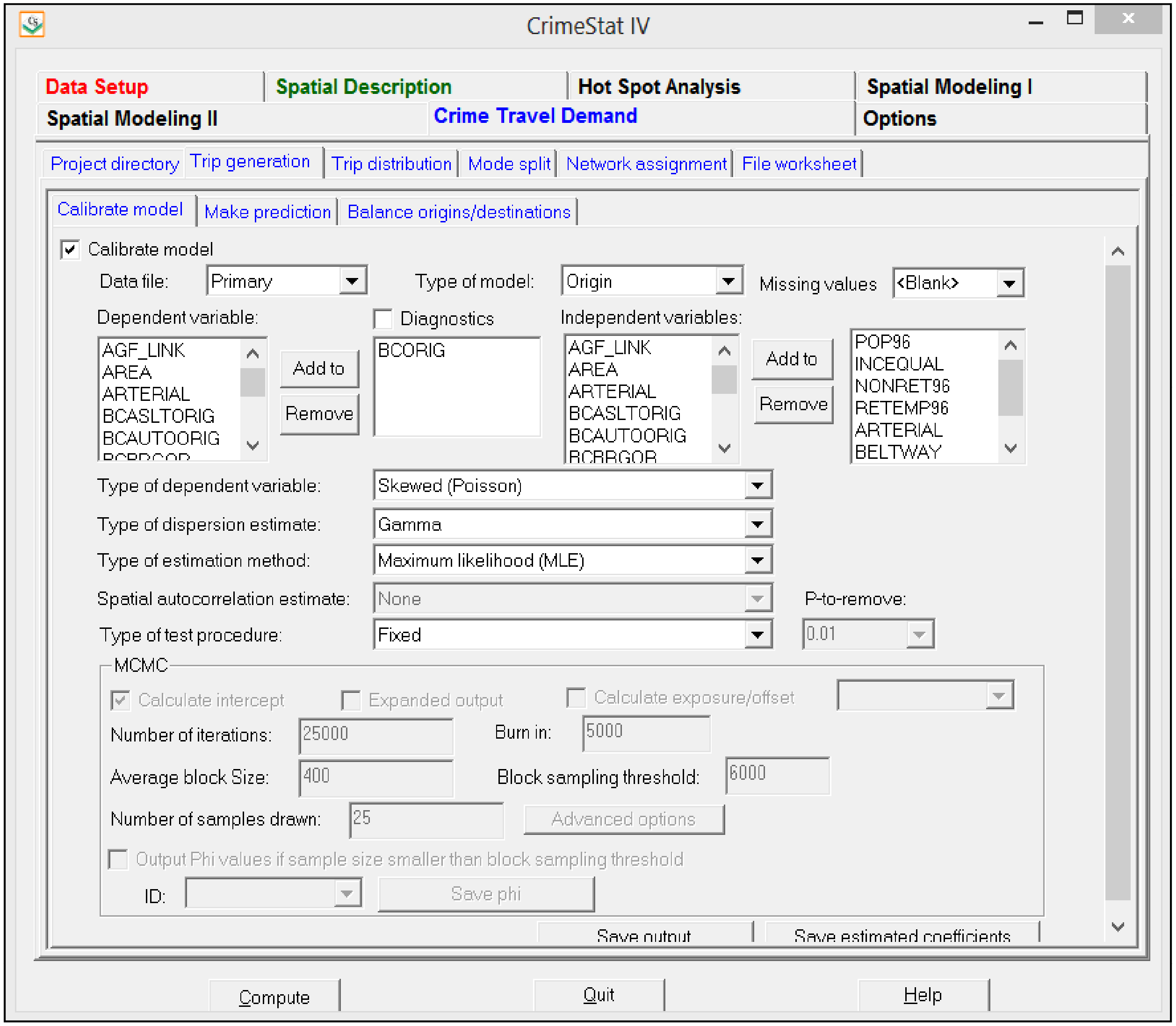
The *CrimeStat* Crime Travel Demand Module

The *CrimeStat* crime travel demand module follows this logic fairly closely, but adapts it to the nature of crime data. Figure 25.4 below shows a screen image of the module. There are five main sections (tabs). Four of them correspond to the four stages. Each of the four sections has several routines associated with them. These will be explained in the subsequent chapters.

In addition, there is a ‘File worksheet’ section. This allows the user to save the file names in order to keep track of them. The module is complicated and there are a lot of files used - 38 of them, many used multiple times. In addition, there are a variety of parameters that are used for the different files. The result is complex because not only is the model tested sequentially but there are multiple options available for each stage. The subsequent chapters, the file worksheet tab, and the online help menu will try to make the routines easy to understand. But, the user has to realize that it will take time to gather the data and to construct the model.

Figure 25.4:

Crime Travel Demand Module



Crime Travel Demand v. Journey-to-crime

A distinction should be made between crime travel demand and journey-to-crime. Crime travel demand modeling is not journey-to-crime modeling. Journey-to-crime modeling (and its use in geographical profiling) is a much simpler system. Research on journey-to-crime has been conducted since the 1930s (see Chapter 13). For the most part, journey-to-crime modeling is a descriptive framework. Estimates are made of the distance that offenders travel during particular crime trips. A distance decay-type function is estimated from these trips and comparisons are made between different types of crime or the same type of crime for different time periods.

There is very little in the way of theory for this type of model. Crime trips are a function of distance plus some other characteristics, such as the crime type or whether there is or is not a 'buffer zone; around the offender's residence (see Chapter 13). Most of the journey-to-crime studies have compared different types of crime by distance traveled, whether measured as average distance or by type of function as was used in Chapter 13. Almost exclusively, the key variable is travel distance. There are very few studies that have looked at travel time (see Kent, Leitner & Curtis, 2004 for an exception).

In other words, journey-to-crime modeling is a single-stage model, essentially a description, with the primary variable being distance. It is also 'non-adjustable' in the sense that the conditions cannot be varied since there is no model that predicts distance other than crime type (or buffer zone, for which we did not find evidence; see Chapter 13). There is very little in the way of predictions that the model can make other than to estimate the likely origin location of an offender (for events committed by a single offender).

Crime travel demand modeling, on the other hand, is a predictive framework. Crime trips are a function of productions, attractions, and impedance. Productions are a function of some socio-economic and policy variables. Attractions are a function of some other socio-economic and policy variables. Impedance is a function of cost and availability variables. Each of these components is predicted by different variables. Hence, the model can be adjusted (e.g., by adding or subtracting a policy intervention variable). One of its benefits is the ability to adjust conditions. For example, if it can be shown that the amount of policing in a zone impacts the number of crimes that either originate or end in that zone, then a subsequent run can 're-assign' police personnel to impact crimes in other zones.

The model is multi-stage since it is estimated sequentially and, therefore, can be used for prediction. Thus, once the model is estimated on one data set, it can be used on another set. Thus, it represents a calibration against a known data set. For example, one could calibrate the model on one year's worth of data and then use the estimated coefficients and parameters on a second year's worth of data. This, in fact, is how it is used in transportation modeling. The model is calibrated on a current year and then applied to a future year to make a forecast of future travel demand.

In short, crime travel demand is a theory of travel behavior whereas journey-to-crime modeling is but a simple description. In many ways, crime travel demand modeling is a quantum leap in complexity and analysis, requiring gathering a lot more data and calibrating many individual steps. Nevertheless, that complexity allows a far greater use of the model than the traditional journey-to-crime.

Models v. Description

A key distinction in the crime travel demand framework is that of an empirical description versus a model. The framework can be applied both as an empirical description and as a model, assuming that data can be obtained. An empirical description describes the data that have been collected. For example, for trip generation, it is a count of the number of crimes that originate in each zone and the number of crimes that occur in each zone. For trip distribution, it is the actual number of trips that go from each origin zone to each destination zone. For mode split, assuming that data could be obtained on travel mode, it is a count of the number of trips for each origin-destination pair that are taken by each travel mode. Finally, for network assignment, again assuming that data could be obtained on the actual routes taken, it is a documentation of the actual routes that are taken and a count of the number of trips on each segment of the transportation network. In other words, an empirical description is a count of the number of offenders, whether by origin location, destination location, O-D pair, travel mode, or route.

A model, on the other hand, is a simplified set of relationships that approximate the most important features of the actual count. The model is not reality, but is a rough approximation to it. Because it is rough, a model inevitably makes errors. Consequently, there always will be a difference between a model and the actual events to which the model approximates.

The two differ on other dimensions as well. A model has only a few variables whereas the actual events have many (perhaps hundreds). A model has a simplified set of relationships among the variables whereas the actual events have very complex relationships among the variables, often too complex to describe properly. By simplifying the relationships, a model produces, what Herbert Simon and Allen Newell called, an *analogy* to the actual situation, whereas the actual events are literal (Simon & Newell, 1963; Newell, Shaw & Simon, 1957).

The *CrimeStat* crime travel demand routines can be applied both to empirical data as well as modeled relationships. In fact, two of the routines are directly concerned with the differences between the model and the actual data. Both sets of endeavors have value in their own right, but they differ. An empirical description is most relevant to the present. For a police department trying to mitigate crime and catch offenders, the empirical description is probably of more use than an abstract model. As will be seen, the empirical description of crime trips will always be more complex than the estimated model. If the only purpose is to describe the actual patterns that are occurring, then a model is not needed.

On the other hand, a model has definite advantages that a description does not. First, it can be used for prediction. If a model is calibrated against a known data set, that model can then be applied to a new data set. For example, one could create an estimate of crime trip productions based on existing socioeconomic and land use data. Then, one could apply that model to a forecast data set of future socioeconomic and land use conditions. The result is a prediction of future crime levels. Of course, since the model was never completely correct in the first place, it will inevitably make errors.[6] Further, since there is no guarantee that past relationships will necessarily hold in the future, there is no certainty about whether the most important part of the predicted relationships will actually hold. Nevertheless, there has been enough success in demographic, economic, and transportation modeling that new fields of forecasting have emerged as legitimate research activities.

A second advantage of a model is that it can be manipulated. Variables can be modified to explore their effect. Distributions can be re-arranged to, again, understand their effect. For example, if relationships can be established between the number of crimes produced or attracted to zones, on the one hand, and the number of police personnel in a zone or to the existence of a large shopping mall, or to the existence of a drug treatment center, on the other hand, then scenarios could be run that explore the different arrangements. These 'What if?' types of scenarios can be very useful. For example, if a relationship exists between shopping malls and crime trips, what is liable to happen when a new shopping mall is built? One could take the model, add the new shopping mall (or the retail employment or acreage associated with the mall) and run the model to make a prediction about its likely impact. Or to take another example, if it can be shown that there is a negative relationship between the number of beat police officers and the number of crimes originating in zones, then it would be possible to evaluate the likely consequences of re-arranging police personnel across different beats.

In short, a model is a very powerful tool for evaluating policy or intervention type strategies. Rather than speculate or gather evidence from other metropolitan areas on their experience (which is valuable, of course), a model can be used to simulate the likely

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6 Simon and Newell described two kinds of errors: 1) errors of commission (Type I errors); and 2) errors of omission (Type II errors). The first kind represents relationships and predictions that do not exist (to use our terminology) while the second kind represents the failure to detect relationships that do exist. Any model will have both sets of errors. The point to keep in mind is whether a model captures the most important relationships and does not make too many Type I errors (Simon & Newell, 1963; Newell, Shaw, & Simon, 1957).

consequences of an action on crime levels. In transportation planning, the travel demand model is used all the time to evaluate the likely consequences of implementing particular projects. This does not mean that it is the only factor considered in making a decision or even the most important factor; clearly, politics, financing, and community support are also major components of any decision. Nevertheless, the travel model is a very important input into any decisions about future investments.

Uses of a Crime Travel Demand Model

Table 25.1 illustrates some possible uses of the crime travel demand model, assuming that data could be obtained.

Table 25.1:
Possible Uses of Crime Travel Demand Model

	Trip Generation	Trip Distribution	Mode Split	Network Assignment
Description	Identify correlates of crimes	Identify crime trip links	Identify crime travel models	Identify routes taken by offenders
Calibration	Estimate coefficients of predictor variables for crime origins & destinations	Estimate origin-to-destination coefficients for crime trips	Estimate formula for travel modes used by offenders	Estimate model for routes taken by offenders
Prediction	Predict future crime levels	Predict future crime trip links	Predict future crime travel modes	Predict future routes used by offenders

The model could be used for description, calibration, or prediction. In description, the emphasis is on describing the travel behavior of offenders. For trip generation, it involves identifying the correlates of crimes, both by origin zone and by destination zone. For trip distribution, it involves describing the actual crime trips taken between specific origin zones and specific destination zones. For mode split, it involves identifying the different modes that offenders are using, describing the proportion of each mode that are used, as well as describing the modes used for particular origin-destination links. Finally, network assignment involves describing the actual routes taken by offenders. In other words, the emphasis on description is identifying the specifics used in crime trips.

On the other hand, calibration involves selecting variables that can approximate the description and estimating coefficients for their use. The emphasis is on finding a limited number of general variables and coefficients that can produce a reasonable approximation to the actual travel behavior. Thus, in trip generation, the aim is to find a few variables that can predict reasonably accurately the number of crimes by origin zone and destination zone. In trip distribution, the aim is to estimate coefficients that can approximately describe the trips that are taken from particular origin zones to particular destination zones. In mode split, the aim is to develop coefficients that can approximate the travel modes used while in network assignment, the aim is to find an algorithm that approximates the actual travel routes used by offenders. The result of a calibration is a model that can be generalized whereas a description cannot be generalized.

Finally, in prediction, the calibration models are applied to other data, either forecast values of future levels of the predictive variables or data from other jurisdictions to see the similarities or differences. The existence of a model (ideally calibrated against a real data set) allows a forecast to be made whereas a description cannot be forecast.

Research Uses of a Crime Travel Demand Model

For research, a crime travel demand model has many different uses, only some of which are explored in the next five chapters. First, it organizes crime travel information in a systematic manner. The model is logical and proceeds in a systematic way. As opposed to a journey-to-crime-type model, which is just a description, the crime travel demand model systematically steps through the four stages in an understandable way. It is a very good way to organize information on crime travel, though, clearly, it is not the only way.

Second, compared to the journey-to-crime literature, it is a more realistic model of offender travel. For one thing, it incorporates information about origin locations. This helps answer the question of why certain areas produce more crimes than others (remember, it is not a behavioral explanation, but an ecological model). For another thing, it incorporates information about destination locations and helps answer the question of why certain areas attract more crimes than others. For a third thing, it models travel choice in a more complex manner. Instead of assuming that all offenders will travel to a crime in exactly the same way (e.g., by walking), the model allows the separation of different travel modes. For journey-to-crime models, distance is the only impedance variable, whereas for crime travel demand modeling, travel time and travel cost are often better predictors of travel behavior, especially in relationship to an available network. In short, it is a much more complex, yet realistic, representation of crime travel behavior.

Third, it is a dynamic analysis of travel behavior. Crime trips are seen as a product of neighborhood production factors, attractions, and travel costs (impedance). Since these change by various hours of the day, so too do the travel patterns change. The ability to model travel at different times of the day is one of the strengths of the travel demand type of framework.

Fourth, and finally, a crime travel demand model can allow comparisons between different types of crimes in the productions, the attractions, and the costs. So, too, can journey-to-crime models be used to compare different type of crimes. But those comparisons are uni-dimensional, essentially comparing different distance decay functions. The crime travel demand model can explain the 'distance decay' function and hence allow a more structural interpretation than was previously possible. For example, in comparing data sets from Baltimore, Chicago, and Las Vegas, Richard Block, Dan Helms and myself are finding that there may be very little difference in the cost function used for different types of crime trips, but that differences in these trips are more a function of the distribution of opportunities (attractions). To link this up to the early theme of this chapter, American society has become so mobile and the automobile so ubiquitous that distances are not as much a barrier to offenders as they used to be. In other words, the distribution of opportunities appears to be the more dominant factor predicting types of crimes than the limitations of neighborhoods and small communities. If this turns out to be true, then we are in for a major shift in the type of crimes that our society will experience over the next few decades. Mobility may replace neighborhood as a determining factor in crime behavior. In other words, the local 'community-based' offender is morphing into a metropolitan-wide and, perhaps, regional offender, a not very desirable prospect. The Kneebone and Raphael (2011) study may indicate that this has already started to occur.

Crime travel demand modeling allows for a more complex, more interventionist and, perhaps, deeper understanding of crime travel than previous types of model, particularly the journey-to-crime and serial walk type of model (see Chapter 13).

Utility for Policing and Law Enforcement

For police department and other law enforcement agencies, crime travel demand modeling has some advantages as well. First, it can be used to model different policing strategies, as suggested above. For example, it could be used to evaluate the likely effect of shifting patrol deployment. The 'What if?' nature of crime travel demand modeling makes it useful to explore alternative arrangements before they are actually implemented.

Second, it could be used for forecasting. As mentioned, if a model has been calibrated on one set of data, then it could be applied to another set to predict, for example, the distribution of crimes five or ten years later. Typically, police departments have not done forecasting, but they are often expected to be able to anticipate changes. This type of model can be useful for that purpose since Councils of Governments (COG) and Metropolitan Planning Organizations (MPO) systematically make forecasts of future population and employment levels.

Third, it can be used for modeling interventions. Aside from modeling different policing strategies, a range of land use and communities changes could be explored. For example, what would be the effect of introducing more drug treatment centers or more ‘weed and seed’ adolescent facilities? The logic is similar to forecasting. A model is calibrated against one data set. But, in addition to socioeconomic and land use variables, variables on facilities are added to the equation as predictors. If it can be shown that they have any effect (which we hope they do), then these can be used as variables in a modeling scenario.

Fourth, these types of models can be used for anticipating changes in the community. Again, this is similar to the forecasting purpose mentioned above. But, it is slightly different in that it anticipates structural changes. An example was given of anticipating changes from new shopping malls. In Baltimore County, for example, shopping malls were shown to be the strongest attractors of crime trips. In that context, what would happen if a new mall was built? This type of model can be used to model this scenario. Conversely, a lack of employment opportunities appears to be correlated with crime productions, at least in Baltimore County. What would happen to crime if local employment was increased in certain zones? Again, this type of model is useful for exploring that type of question.

Again, going back to an earlier point, there is, of course, a difference between a model and reality (an actual situation). Reality is complex; models are not, or are a lot simpler. Still, models as analogies can provide insight into mechanisms and allow police, law enforcement, and the policy community as a whole to try to simulate changes without having to commit to expensive, and perhaps disastrous, changes with little information. In other words, modeling in general, and crime travel demand modeling in particular, is a tool that may have wide utility for the law enforcement community.

References on Travel Demand Modeling

In this final section, some sources on travel demand forecasting are listed. There are a large number of sources, though there are few actual textbooks. A very good textbook on the subject is by Ortuzar and Willumsen (2001), while an older, out of print book is by Stopher and Meyburg (1975). There are several major handbooks on the topic (Hensher & Button, 2003;

ITE, 2003). Some good chapters on the subject are found in Beimborn (1995), Field and MacGregor (1987, Ch. 6) and by Engelen (1986, Ch 17). Discussions of ‘second’ generation models can be found in Domencich and McFadden (1975) and Ben-Akiva and Lerman (1985).

However, probably the best source for articles on the subject are found on the Federal Highway Administration (http://www.fhwa.dot.gov) and other web sites. Among the articles/presentations that can be found on that site are FHWA (2012), FHWA (2009), Jeannotte, Sallman, Margiotta, and Howard (2009), and McKeever and Griesenbeck (2009). Of particular interest is a study of bicycle and pedestrian travel modeling (Turner, Shunk, and Hottenstein, 1998), which may be relevant for crime analysis, and ‘third’ generation models.

Older sources, which are still good are by Oppenheim (1975, ch. 4) and Krueckeberg and Silvers (1974, Ch. 10), aside from the Stopher and Meyburg text mentioned above.

References

Aizcorbe, A. & Starr-McCluer, M. (1996). Vehicle Ownership, Vehicle Acquisitions, and the Growth of Auto Leasing: Evidence from Consumer Surveys. Finance and Economic Discussion Series, Federal Reserve Board of Governors: Washington, DC. http://www.federalreserve.gov/pubs/feds/1996/199635/199635pap.pdf. Accessed April 28, 2012.

Ben-Akiva, M. & Lerman, S. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press: Cambridge.

BTS (2007). Table 2: A matrix of transportation expenditure by source of finance and type of expenditure, *Government Transportation Financial Statistics*, Bureau of Transportation Statistics, U.S. Department of Transportation: Washington, DC., http://www.bts.gov/publications/government_transportation_financial_statistics/2007/html/table_02.html. Accessed April 28, 2012.

BTS (2003). U.S. Vehicle-miles (millions), Table 1-32. *National Transportation Statistics 2004*, Bureau of Transportation Statistics, U.S. Department of Transportation: Washington, DC. http://www.bts.gov/publications/national_transportation_statistics/2004/html/table_01_32.html. Accessed April 28, 2012.

Burgess, E. W. (1925). The growth of the city: an introduction to a research project. In Park, R.E., Burgess, E. W. & Mackensie, R. D. (ed), *The City*. University of Chicago Press: Chicago, 47-62.

Culp, M. & Lee, E. J. (2005). Improving travel models through peer review. *Public Roads*, 68 (6), FHWA-HRT-05-005. Federal Highway Administration, U.S. Department of Transportation: Washington, DC. http://www.fhwa.dot.gov/publications/publicroads/05may/07.cfm. Accessed April 28, 2012.

Domencich, T. & McFadden, D. (1975). *Urban Travel Demand: A Behavioral Analysis*. North Holland Publishing Company: Amsterdam & Oxford (republished in 1996). Also found at http://emlab.berkeley.edu/users/mcfadden/travel.html. Accessed April 28, 2012.

Engelen, R. E. (1986). Transportation planning. In So, F. S. *The Practice of State and Regional Planning*. American Planning Association: Chicago, Ch. 17, 431-453.

FHWA (2012). FHWA Resource Center Planning Team. Federal Highway Administration, U.S. Department of Transportation: Washington, DC. http://www.fhwa.dot.gov/resourcecenter/teams/planning/travel.cfm. Accessed April 29, 2012.

References (continued)

FHWA (2009). Integrated Urban Systems Modeling, *The Exploratory Advanced Research Program Fact Sheet*, FHWA-HRT-09-042. Federal Highway Administration, U.S. Department of Transportation: Washington, DC. http://www.fhwa.dot.gov/advancedresearch/pubs/interurbsys.pdf. Accessed April 28, 2012.

FHWA (1996). Latest VMT growth estimates, *Highway Information Update*, 1(1), Federal Highway Administration, U.S. Department of Transportation: Washington, DC., http://www.fhwa.dot.gov//ohim/vol1no1.html. Accessed April 28, 2012.

Field, B. & MacGregor, B. (1987). *Forecasting Techniques for Urban and Regional Planning*. UCL Press, Ltd: London.

Freedman, David A. (1999). Ecological inference and ecological fallacy. *International Encyclopedia of the Social and Behavioral Sciences*, Technical Report No. 549, October. http://www.stanford.edu/class/ed260/freedman549.pdf. Accessed March 26, 2012.

Hensher, D. A. & Button, K. J. (2002). *Handbook of Transport Modeling*. Elsevier Science: Cambridge, UK.

Horowitz, J. L., Koppelman, F. S. & Lerman, S. R. (1986). *A Self-instructing Course in Disaggregate Mode Choice Modeling*. Federal Transit Administration, U.S. Department of Transportation: Washington, DC. http://ntl.bts.gov/DOCS/381SIC.html. Accessed April 28, 2012.

ITE (2003). *Trip Generation* (7th edition). Institute of Transportation Engineers: Washington, DC.

Jeannotte, K., Sallman, D., Margiotta, R. & Howard, M. (2009). *Applying Analysis Tools in Planning for Operations*. FHWA-HOP-10-001, Federal Highway Administration: Washington, DC. http://ops.fhwa.dot.gov/publications/fhwahop10001/fhwahop10001.pdf. Accessed April 29, 2012.

Kent, J., Leitner, M., & Curtis, A. (2006). Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay algorithms. *Computers, Environment and Urban Systems, 30* (2), 181-200.

Kneebone, E. & Raphael, S. (2011). *City and Suburban Crime Trends in Metropolitan America*. Metropolitan Opportunity Series, Metropolitan Policy Program, Brookings Institution: Washington, DC. http://www.brookings.edu/papers/2011/0526_metropolitan_crime_kneebone_raphael.aspx. April 28, 2012.

References (continued)

Krueckeberg, D. A. & Silvers, A. L. (1974). *Urban Planning Analysis: Methods and Models*. John Wiley & Sons: New York.

Langbein, L. I. & Lichtman, A. J. (1978). *Ecological Inference*. Sage University Paper series on Quantitative Applications in the Social Sciences, series no. 07-010. Beverly Hills and London: Sage Publications.

McFadden, D. L. (2002). The path to discrete-choice models. *Access*, No. 20, Spring. 20-25. http://www.uctc.net/access/access20.shtml. Accessed April 28, 2012.

McKeever, M. & Griesenbeck, B. (2009). *Linking Transportation and Land Use*. Federal Highway Administration: Washington, DC. http://www.fhwa.dot.gov/policy/otps/innovation/issue1/linking.htm. Accessed April 29, 2012.

NAP (2009). Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions, Special Report 298. The National Academies Press: Washington, DC. http://www.nap.edu/catalog.php?record_id=12747. Accessed April 28, 2012.

Newell, A., Shaw, J. C. & Simon, H. A. (1957). Empirical Explorations of the Logic Theory Machine, Proceedings of the Western Joint Computer Conference, pp. 218-239.

NHMC (2012). Quick Facts: Resident Demographics. National Multi Housing Council: Washington, DC. http://www.nmhc.org/Content.cfm?ItemNumber=55508. Accessed April 28, 2012.

OMB (2012). 2010 Standards for Delineating Metropolitan and Micropolitan Statistical Areas. U.S. Office of Management and Budget, *Federal Register*, June 28, 2010, 37246. http://www.whitehouse.gov/sites/default/files/omb/assets/fedreg_2010/06282010_metro_standards-Complete.pdf. Accessed April 28, 2012.

Oppenheim, N. (1980). *Applied Models in Urban and Regional Analysis*. Prentice-Hall, Inc.: Englewood Cliffs, NJ.

Ortuzar, J. D. & Willumsen, L. G. (2001). *Modeling Transport* (3rd edition). J. Wiley & Sons: New York.

Schachter, J. (2001). Geographical mobility: March 1999 to March 2000. *Current Population Reports*, P20-538, March. U.S. Census Bureau: Hyattsville, MD.

Simon, H. A. & Newell, A. (1963). The uses and limitations of models. In Marx, M. (ed), *Theories of Contemporary Psychology*, Macmillan: New York, 89-104.

References (continued)

Stopher, P. R. & Meyburg, A. H. (1975). *Urban Transportation Modeling and Planning.* Lexington, MA: Lexington Books.

Thrasher, F. M. (1927). *The Gang*, University of Chicago Press: Chicago.

Turner, S., Shunk, G. & Hottenstein, A. M. (1998). *Development of a Methodology to Estimate Bicycle and Pedestrian Travel Demand*. Report 1723-S, Texas Transportation Institute: College Station. http://tti.tamu.edu/publications/catalog/record/?id=146. Accessed April 28, 2012.

U.S. Census (2010a). Geographic Mobility/Migration. U.S. Census Bureau, U.S. Department of Commerce: Washington, DC. http://www.census.gov/hhes/migration/data/cps/cps2010.html. Accessed April 28, 2012.

U.S. Census (2003). Net Worth and Asset Ownership of Households: 1998 and 2003 (Table A). *Current Population Reports*, P70-88. U. S. Census Bureau, U. S. Department of Commerce: Washington, DC. http://www.census.gov/prod/2003pubs/p70-88.pdf. Accessed April 28, 2012.

USDOT (2003). *Title XXIII*, *Part 450*. Code of Federal Regulations. Code of Federal Regulations, Title 23, Part 450, Volume 1. 23CFR450. Washington, DC.

Wikipedia (2012a). List of Cities with Most Households without a Car. Wikipedia. http://en.wikipedia.org/wiki/List_of_U.S._cities_with_most_households_without_a_car. Accessed April 28, 2012.

Wikipedia (2012b). Table of United States Metropolitan Statistical Areas. Wikipedia. http://en.wikipedia.org/wiki/Table_of_United_States_Metropolitan_Statistical_Areas#cite_note-MSA-0. Accessed April 28, 2012.