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## Neighborhood Crime and Travel Behavior: An Investigation of the Influence of Neighborhood Crime Rates on Mode Choice, MTI Report 07-02

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# Neighborhood Crime and Travel Behavior: An Investigation of the Influence of Neighborhood Crime Rates on Mode Choice



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MTI REPORT 07-02

**NEIGHBORHOOD CRIME AND TRAVEL  
BEHAVIOR:  
AN INVESTIGATION OF THE INFLUENCE OF  
NEIGHBORHOOD CRIME RATES ON MODE  
CHOICE**

**April 2008**

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# EXECUTIVE SUMMARY

## OVERVIEW

While there is a rich collection of studies that have investigated the connections between crimes, urban form, and socio-demographics, as well as a growing body of recent research on the links between urban form and the propensity to walk and exercise, little work has been done to look at the interactions between neighborhood crimes, urban form, and travel behavior. This exploratory research study collected individual crime records data from seven San Francisco Bay Area police departments for the year 2000 (or if unavailable, 2001) and calculated crime rate statistics by neighborhoods (as represented by Travel Analysis Zones, or TAZs) in these cities. These crime rates were then merged with travel survey data from the Bay Area Travel Survey for the year 2000, collected and provided by the Metropolitan Transportation Commission. A set of urban form and transit accessibility variables also were calculated and merged with the travel and crimes dataset in the form of a factor analytic score variable that removed most of the multicollinearity (where the predictor variables in a multiple regression are themselves highly correlated) effects found between these variables. These crime rate, urban form and transit accessibility, and other socio-demographic control variables were then analyzed using logistic regression techniques to identify the effects of neighborhood crime rates on mode choice.

## STUDY PURPOSES

The primary purpose of this study is to identify if there is a relationship between neighborhood crime rates and the propensity to choose non-automotive modes of travel for home-based trips. We hypothesize that people living in high-crime neighborhoods would be less likely to choose walking, bicycling, or transit.

This study also sought to look for relationships between urban form and crime rates. Because high-density, pedestrian-friendly, transit-rich neighborhoods tend to increase non-auto mode share, if crimes also tend to cluster in these areas, then we may find that there is a non-causal, positive correlation between crime rates and auto mode choice.

We also hypothesize that different crime types may have different spatial distributions. We could expect that violent and property crimes would have different patterns of distribution throughout urban space that may depend on the nature of the physical environment.

This project has the following policy and research implications:

1. Digital crime data with detailed location information are available from an increasing number of local police departments as computerized database record keeping systems are introduced. While these data can be difficult to obtain depending on the technical



sophistication and data-sharing policies of the police departments in question, the availability of these data for research and public policy analytic purposes is improving.

2. To the extent a causal relationship can be identified between neighborhood crime rates and mode choice, crime data may (with further research and substantiation) prove a useful supplement to the data collected and regularly analyzed for mode-choice models in travel demand forecasting models.
3. If a causal relationship is identified, policies and programs that seek to reduce neighborhood crime rates and increase a sense of personal security may be as or more cost-effective than efforts to increase transit services to a target neighborhood or more long-term efforts to increase urban density and pedestrian-friendly infrastructure improvements.

## **STUDY RESULTS**

This exploratory study covered seven San Francisco Bay Area cities—ranging from the urban core environment of San Francisco to suburban communities such as Concord and Sunnyvale—and found substantiation for the proposition that neighborhood crime rates have an influence on the propensity to choose non-automotive modes of transportation for home-based trips. Specifically, high vice and vagrancy crime rates were associated with a lowered probability of choosing transit in suburban cities for both work and non-work trips, high property crime rates were associated with a lower probability of walking for work trips in urban/inner-ring suburban cities, high violent crime rates with a lower probability of walking for work trips in suburban study cities, and higher property crime rates in San Francisco were associated with an increased probability of walking for non-work trips. While the signs of these significant relationships generally conformed to our expectations (i.e., that high crime rates reduce the probability of choosing non-automotive modes of travel), we did not find statistically significant relationships for all city/trip-type model runs, suggesting that these relationships differ depending on the urban-form and trip-type contexts.

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## LITERATURE REVIEW

Literature review activities for this project focused on identifying studies that measured the effects of neighborhood crime on travel behavior. Because there are very few studies that have specifically addressed this question, studies also were evaluated that measured the effects of crime on physical activities. These studies suggested that there may be a difference between the effects of the actual number of crimes in a neighborhood (i.e., the crime rate) and the perceptions people have of the threats of crime for them personally. Studies of perception and crime and the effects of the physical and social environments on crime rates and perceptions were identified and analyzed.

### THE EFFECTS OF CRIME ON TRAVEL BEHAVIOR

While there are very few studies that have directly investigated the effects of crime on travel behavior, a few are noteworthy. A common thread found in these studies is a complex interaction between urban environment, crime levels, perceptions of crime, and travel behavior.

Atkins et al. studied the effects of street lighting on neighborhood crime levels and perceptions of crime in the London borough of Wandsworth. They found no detectable changes in travel behavior among neighborhood residents. Specifically, people still seemed to engage in the same patterns of avoiding certain streets and places in both the before and after conditions of the study despite the fact that poor lighting fell from the most frequently cited reason for avoiding these areas to a minor ranking among reasons listed.<sup>1</sup> These results suggest that changes to the physical environment alone (i.e., improved street lighting) might not be sufficient to reduce residents' fear of crime in certain locations and will not encourage them to walk in these areas.

Nevertheless, our perceptions of safety appear to be intimately connected to our assessment of our physical environment. Different behavioral responses to the introduction of street lighting were provided by Painter, who conducted surveys of residents in two neighborhoods in London, UK, "before" and "after" street lighting improvements were made. She found that incidents of crime and disorder as well as the general fear levels of crime dropped markedly while pedestrian activity increased significantly after dark in the study areas after lighting improvements.<sup>2</sup>

Research conducted by Ingalls et al.<sup>3</sup> suggests that the different behavioral responses to street lighting found by Atkins et al.<sup>4</sup> and Painter<sup>5</sup> may be explained by differences in the urban context of the study areas they worked in. Ingalls et al. studied how concerns for personal safety affect people's propensity to ride transit in small-city environments. Their results suggest that our culture's perceptions of urban environments play a key role in determining a sense of personal safety and a willingness to use transit. They surveyed both residents and bus

riders in Greensboro, North Carolina, and found that the city's residents rarely used transit (i.e., most transit riders were from out of town). While both groups were found to be concerned for their personal safety and residents were two to three times as concerned as bus riders, neither was specifically concerned for the safety of the transit system itself, but rather were most concerned for their safety in their communities as a whole. The authors concluded that people associate their fear of crime and feelings of insecurity in downtown areas with the bus system even though they may feel that the bus system itself is safe. They further concluded that this fear of crime is a major impediment to transit ridership growth.<sup>6</sup>

This conclusion is supported by the findings of Yoh et al. They studied the factors that contributed to the nationwide gains in transit ridership seen during the economic boom times of the 1990s. They found that among other factors, a major increase in immigrants living near subway stations and a reduction in crime and fare evasion contributed to increased ridership on some transit systems.<sup>7</sup>

## **THE EFFECTS OF CRIME ON PHYSICAL ACTIVITY**

A related body of research has studied the effects of the physical environment and neighborhood crime on people's propensity to engage in physical activities. This area of research has seen a burst of activity over the last decade. A common element in these studies are findings that women and ethnic minorities are likely to consider neighborhood crime levels as a significant impediment to their willingness to engage in regular, physical activities (e.g., bicycling and walking).

However, a number of studies have found seemingly contradictory results with regard to the importance of neighborhood crime levels in determining physical activity patterns. The results of Wilcox et al. are a good example. They compared the leisure time physical activity of rural and urban women in the United States, and found that the key environmental barriers to leisure time physical activity for urban women are a lack of sidewalks and streetlights, high crime, a lack of access to exercise facilities, and infrequently seeing others exercise in their neighborhood, among other factors. Rural women were significantly more likely to report the presence of unattended dogs as an important impediment. While these univariate statistical findings point to crime as one key factor that correlates with physical activity levels, multivariate analyses did not find crime among the significant determinants of a sedentary lifestyle for either rural or urban women.<sup>8</sup>

The findings of several studies have suggested that gender, age, and race combine to form an intricate web of causality underlying how neighborhood crime levels affect the propensity to exercise. King et al. did not find a significant role for crime levels in influencing inactivity in middle-aged and older American women.<sup>9</sup> However, in a study that focused on the inactivity levels of adolescents in the United States, Gordon-Larsen et al. found that high neighborhood crime levels were associated with a decreased likelihood of study adolescents falling into the highest category of moderate to vigorous activity levels.<sup>10</sup>

These apparent contradictions may be explained by the different effects of actual, reported crimes and a person's perceptions of the dangers of crime in their neighborhood. The findings of Humpel et al. support this distinction. Their review of the existing literature found that while reported crime levels were not statistically related to the propensity to exercise, residents' perceptions of their relative levels of safety from crime in their neighborhood was a statistically significant factor.<sup>11</sup> Race appears to be another important variable mediating perceptions of safety and physical activity levels. In another meta-analysis, Seefeldt et al. reviewed the research to date on the causes of physical inactivity. They found strong evidence that high crime rates and fears for personal safety were two important factors that have proven significant in reducing levels of physical activity among ethnic minorities.<sup>12</sup> Similarly, Eyler et al. studied physical activity levels in women from a variety of ethnic backgrounds and found that safety from crime (i.e., the perception of crime levels) and the presence of sidewalks were two of a small number of significant environmental factors that correlated with higher levels of physical activity among African American women.<sup>13</sup> These findings suggest that perceptions of crime can be just as important (if not more so) as reported crimes in affecting how willing people are to walk or bicycle in their neighborhoods. They also suggest that just as perceptions are influenced by our physical environment (e.g., crime levels), they also may be influenced by the social and psychological constructs that result from race, gender, education levels, and age.

## PERCEPTIONS AND CRIME

Evidence that perceptions of crime may be a more important determinant of travel behavior than reported crime levels (e.g., Seefeldt et al.,<sup>14</sup> Eyler et al.<sup>15</sup>) leads to two questions:

- What are the factors that influence the perceptions of both perpetrators and non-perpetrators of neighborhood crime?
- To what extent do perpetrators use environmental factors to determine their choice of locations and times for engaging in criminal activities?

Research suggests that there are two primary factors that influence both our perceptions of neighborhood crime: the physical and the social environments.

## ENVIRONMENTAL FACTORS

### The Effects of the Physical Environment

Wilson and Kelling proposed the now famous “broken windows” theory of neighborhood deterioration and crime. They suggested that neighborhoods that provide a space where “small” or relatively less serious crimes are tolerated or go unpunished send a message to criminals that this is an area where they can successfully commit more serious crimes. Therefore, signs of neighborhood disrepair—such as a broken window that remains un-repaired or an abandoned car that is not towed away—cause residents to feel less safe and leads to a reduced level of community involvement and vigilance, creating a fertile

environment for more serious criminal activity.<sup>16</sup> This theory has had a profound impact on the approach to crime deterrence in the United States. While previous efforts largely concentrated on crime deterrence through punishments of the penal system, Wilson and Kelling's theory turned attention towards preventing crimes by altering our perceptions of the physical environment and its likelihood to support or deter criminal behavior. Kelling and Sousa provide support for the broken windows theory in their study of the causes of sharp declines in crimes seen in New York City in the 1990s. They found that these declines were not due to the improving economy, an aging population, and declining crack cocaine use, as had been suggested, but rather that laws against minor crimes, known as "broken windows" policing, was a statistically significant cause of the decline in violent crimes.<sup>17</sup>

Research by Doran and Lees has drawn a direct link between perceptions of neighborhood disorder and crime levels in New South Wales, Australia. Their findings suggest that graffiti, one of the most prevalent forms of physical disorder found, was most spatially correlated with concentrations of crime.<sup>18</sup>

Research on crime at the ten most dangerous (from a crimes perspective) Los Angeles bus stops by Loukaitou-Sideris found a long list of "negative" environmental attributes that contribute to a sense of fear on the part of bus riders, including a lack of "defensible space" at these locations (Figure 2). Most of these ten bus stops were located in downtown commercial areas at the intersections of multi-lane streets, and are often not visible from nearby shops and lack adequate lighting, public phones, or a nearby police presence. Many are located near vacant lots and abandoned buildings, with easy escape routes for criminals in alleys and mid-block connections, and generally dilapidated conditions (i.e., "broken windows").<sup>19</sup>



**Figure 1 Typical High-Crime Bus Stop**



**Figure 2 Typical Low-Crime Bus Stop**

However, several researchers have concluded that perceptions of neighborhood disorder (i.e., the physical environment) are less important than the social and economic conditions of the neighborhood in question. Sampson and Raudenbush performed a longitudinal study of crime and neighborhood disorder in 1,966 Chicago neighborhoods. They found that both crime and physical disorder were a result of two other social factors: concentrated poverty and what they termed “collective efficacy.” They defined collective efficacy as the level of social cohesion among neighborhood residents and their ability to establish and maintain a set of accepted norms that govern the control of public spaces there.<sup>20</sup> These results suggest that while perceptions of the physical environment may play a role in determining crime levels, the social and economic constructs of the neighborhood may play a more important role.

As suggested in the previous discussion of perceptions of crime and levels of physical activities, perceptions of neighborhoods and their relative safety from crime are determined by both the characteristics of the perceiver and the characteristics of the neighborhood. Taylor conducted a longitudinal study of the links between social disorder, physical disorder, fear of crime, and incidence of crime. He found that in neighborhoods with high property values, property crimes decreased faster or increased more slowly than they did in less economically well-off neighborhoods. In general, the amount of physical and social disorder in each neighborhood at the beginning of the study period did not affect changes in the fear of crime in study neighborhoods; rather, the economic status of the neighborhoods appeared to play the most important role in the levels of fear of crime there.<sup>21</sup>

### *Transit Environs*

Cozens et al. used virtual reality walkthrough scenes to test people’s fear of crime in the British rail system environs, and found that rail station designs that provided high levels of visibility for passengers were perceived as offering high levels of perceived safety.<sup>22</sup> They concluded that station designs that provide high visibility are good examples of effective crime prevention through environmental design.

### *The Effects of Street Lighting on Crime and Perceptions of Crime*

Seen as a relatively inexpensive means to reduce neighborhood crime, a number of researchers have studied the effects of enhanced street lighting on crime levels. As described earlier, Atkins et al. found no change in people's perceptions of safety in the study neighborhood after street lighting was introduced.<sup>23</sup>

Wallace et al. studied the effects of transit safety measures, including improved lighting in transit facilities and vehicles, on passenger levels of perceived safety. They found that increased police presence and improved lighting were two of the most highly visible interventions studied and the most effective in terms of reducing the safety concerns of transit patrons.<sup>24</sup>

According to Farrington and Welsh, there are two hypothetical reasons for why improved street lighting would have a beneficial effect on crime levels. The first reason is that improved lighting encourages surveillance of potential offenders on the street both through improved visibility and by increasing the number of people on the street in general. The second reason is that improved lighting sends a signal to potential criminals and the community in general that the neighborhood is improving and that there will be increased community pride, cohesiveness, and informal social controls. They performed a meta-analysis of sixteen studies of the effects of street lighting on crime. In their analysis of eight U.S. studies, they found mixed results: roughly half showed a significant effect of improved lighting on crime whereas the other half found none. They found no clear reasons for these differing results, although those studies that found a significant effect were more likely to have measured the crime levels during both daytime and nighttime periods.<sup>25</sup> This suggests that the beneficial effects of street lighting may be due to the second reason mentioned by Farrington and Welsh—that improved lighting affects community perceptions of the neighborhood, sending a signal that the area is improving and strengthening the informal social controls there.

### *Crime Prevention Through Environmental Design (CPTED)*

Even before Wilson and Kelling first proposed their broken windows theory of neighborhood deterioration and crime,<sup>26</sup> researchers had begun to investigate ways of altering the physical environment to reduce crime. According to Clarke, traditional criminological theories concentrated on criminality and delinquency and did not pay attention to crime itself. More specifically, any theory of crime should explain and describe the interactions between the propensity for criminal behavior (i.e., criminality) and the opportunities for crime presented in the environment. Traditional criminology has assumed that explaining the behavioral dispositions for criminal behavior is the same as explaining crime. Based on this opportunity-based theoretical perspective, Clarke listed four different objectives to reduce crime opportunities: (1) to increase the perceived difficulty of crime, (2) to increase the perceived risks of crime, (3) to reduce the anticipated rewards of crime, and (4) to remove excuses for crime.<sup>27</sup>

Some of the first researchers to articulate the relationships between crime and environment were Mayhew et al.<sup>28</sup> and Jeffery,<sup>29</sup> who proposed that crime prevention should be approached

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from the perspective of reducing the opportunities for crime rather than on enforcement and sentencing. Crime prevention was therefore a matter of redesigning urban physical spaces to reduce the opportunities for crime. This approach has become known as “Crime Prevention Through Environmental Design” or “CPTED.” Since the early 1970s, a number of crime researchers and practitioners have worked to articulate and refine specific CPTED interventions, techniques, and principles.

Newman was the first to articulate the theory of “defensible space,” which has become an organizing principle of CPTED. Defensible space is the concept that people feel safe from crime in environments that allow them to mark out and protect their territory, and feel that they can easily see and monitor all non-private spaces around them. His initial research focused on large, high-rise apartment buildings. Newman found that high-rise buildings with lobbies, fire escapes, roofs, and corridors that are hidden from public view had much higher crime rates than did low-rise buildings. He proposed that apartment blocks should be designed to maximize the amount of public space under public surveillance at all times. He also proposed three critical factors that linked crime and public housing design: territoriality, natural surveillance, and image and milieu. The first, territoriality, asserted that people naturally mark out and protect their territory. He proposed that physical design should encourage this tendency and that there should be clear demarcations between spaces intended for public, private, and other shared uses. His conceptualization of natural surveillance proposed that people who are engaging in their natural territorial tendencies should be encouraged by a physical design that allows them to easily see all non-private parts of their housing development. Image and milieu refer to the poor image of many housing projects, which in turn create opportunities for criminal activities there. To counteract these negative images, housing projects must be well integrated into the surrounding neighborhoods.<sup>30</sup>

Geason and Wilson placed emphasis on physical design changes to residences and neighborhoods as opposed to increased police activities as an important and effective means to reducing crime. They noted that traditionally, increasing criminal activities have been met with increased policing and tougher sentencing to punish criminals after the crimes already have taken place. They listed a number of physical design elements that are potentially effective at reducing neighborhood crime: houses and their entrances are situated so they are clearly visible from the street, sufficient street and property lighting, children’s play areas that are clearly visible from residences, wide and straight streets that are easy for patrolling police to observe, residences have off-street parking that is visible from the owner’s house, the use of cul-de-sacs to control access to homes, residences are designed with “defensible space” by providing adequate building setbacks, clustered houses, the intended use of space is clear, and adequate recreational space for social cohesion.<sup>31</sup>

Newman and Franck used path analysis to identify a number of factors influencing crime and instability in housing sites in urban areas across the United States: socioeconomic characteristics, management effectiveness, quality of city police and security services, and form of ownership. Supporting the CPTED perspective of Newman’s earlier work, they found that



both physical (i.e., built environment) and social factors accounted for the most variation in the path analysis models. The two physical factors were the size of the development and the number of units sharing a common building entrance. The two social factors were the number of families on welfare and the ratio of teens to adults in the development. These factors together accounted for roughly 69 percent of the fear, 67 percent of the community's instability, and 39 percent of the crime against persons.<sup>32</sup>

Newman also reported on the results of an effort to reduce crime in the Dayton, Ohio, neighborhood of Five Oaks. Newman's plan as implemented was to restrict automobile traffic to the neighborhood and break it up into "mini-neighborhoods," thereby enhancing its defensible space. Gates were installed at key entrance points to the new mini-neighborhoods, excluding cut-through automobile traffic but allowing pedestrian access. One year after implementation, the city found that 67 percent of cut-through traffic through Five Oaks had been reduced and that traffic accidents had been reduced by 40 percent. Reported crimes in the neighborhood also had been reduced by 26 percent and violent crimes by 50 percent while crime in the city of Dayton as a whole went up 1 percent over the same period. Fears of crime displacement from the study area to surrounding neighborhoods also were shown to be unfounded since crime in the communities immediately surrounding Five Oaks dropped by 1.2 percent during the same period. A university survey of residents in Five Oaks found that 53 percent thought that there was less crime and that 4 percent felt safer,<sup>33</sup> suggesting that neighborhood design can play an important role in preventing crimes.

Further support for the CPTED perspective comes from Carter et al. They studied the effects of zoning, physical design changes, and community policing initiatives in the "crime-ridden" North Trail area of Sarasota, Florida. With local-resident and business-owner cooperation, city planners created a new zoning ordinance that required all new developments to submit site plans with design elements based on CPTED principles. Recommendations (which were often willingly complied with) included outside lighting, landscaping that allowed visibility, mixed uses, porches, balconies, and residential space above retail to allow "eyes on the street," and shared parking. Analysis of local land-use links to crime revealed that prostitution was enabled in the area by the presence of an abundance of small hotels. Review of these sites revealed that many were unable to renovate and expand due to restrictive street-setback requirements, and parking and drainage requirements that greatly increased the costs of renovating old businesses or building new ones. Focused police interventions included working closely with local business owners and residents, high-visibility patrols, and undercover investigations to identify and arrest pimps and drug dealers. The study looked at changes in four measures of crime over a 9-year period in the study area and the rest of Sarasota: calls for police service, crimes against persons or property, narcotics crimes, and prostitution. Using linear regression techniques, the researchers found that calls for police service fell in the North Trail area and rose in the rest of the city. The changes in the number of crimes against people or property fell in both the study area and the city, and were statistically indistinguishable. While the changes in the number of narcotics crimes in both areas rose during the study period, the rate of increase in the North Trail area was significantly lower than that for the city. Finally, the

number of prostitution police reports during the study period fell in the North Trail area and rose in the city as a whole.<sup>34</sup>

## **The Effects of the Social Environment**

A study by Loukaitou-Sideris et al. speaks directly to the influences of the social environment on crimes and focused in particular on neighborhoods surrounding transit stations. They found that there were more crimes against people at stations within low-income neighborhoods, with more persons per household, and higher concentrations of youth than in comparison neighborhoods. The researchers also found a strong correlation between station crime and the presence of liquor stores in the station neighborhood. In addition, they found that the busiest stations (i.e., those with the highest transit ridership) tended to incur the most serious crimes. Less serious crimes, such as vandalism, tended to be concentrated at stations in dense neighborhoods with high percentages of the population with less than a high school education. Taken together, these two studies indicate that the ridership levels, station area design and environmental characteristics, and neighborhood characteristics play a role in determining crime levels at transit stations.<sup>35</sup>

### *Transit Crime*

When the decline of transit use in the United States during the post-war period is considered, explanations often point to people's associations of transit with dense, often crime-ridden, urban areas. With the growth of the suburbs came the commonly held perception of these new neighborhoods as sanctuaries from the crime that resides in older urban areas. Furthermore, the lack of transit in suburbs often leads people to associate transit with crime. The expansion of transit lines into wealthy, suburban areas is often fought by locals fearing that transit services will import crime into their neighborhood.

Research on this subject provides somewhat conflicting evidence on whether there is a causal link between transit and crime. Liggett et al. studied the effects of the introduction of light rail service along the Los Angeles Green Line on crime levels in its surrounding neighborhoods. This line passes through low-income, high-crime areas and terminates in the affluent areas of west Los Angeles. The researchers analyzed five years of crime data in the neighborhoods surrounding the Green Line "before" and "after" its introduction. They found that the transit line did not have a significant effect on crime trends or crime dislocations in the station areas, and did not transport crimes from high-crime areas to low-crime areas.<sup>36</sup>

However, Block and Davis mapped and compared street robberies in four Chicago police districts with rapid transit stations—two with low overall crime rates and two with high-crime rates. In the low-crime districts, street robberies were concentrated near the rapid transit stations while in the high-crime districts, street robberies tended to be more dispersed. Street robberies near the stations in the low-crime districts also tended to have a more temporal pattern, with most incidents occurring during the off-peak transit ridership hours when there were fewer police patrols and observers.<sup>37</sup> These findings suggest that crimes may

indeed concentrate around rapid transit stations in low-crime areas, taking advantage of the spatial and temporal concentration of pedestrians. These conclusions are supported by Loukaitou-Sideris et al. They studied crime patterns at light rail stations in Los Angeles and found that the busiest stations (i.e., those with the highest transit ridership) tended to suffer from concentrations of the most serious crimes. Less serious crimes, such as vandalism, tended to be concentrated at stations in dense neighborhoods with high percentages of the population with less than a high-school education. Taken together, these studies indicate that the ridership levels, station area design and environmental characteristics, and neighborhood characteristics play a role in determining crime levels at transit stations.<sup>38</sup>

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## RESEARCH METHODS

### RESEARCH OBJECTIVES

This research project has several objectives, which focus on different aspects of identifying the relationships between neighborhood crime and mode choice and identifying the potential for routinely collecting, analyzing, and incorporating crime measures into the transportation modeling and policy arenas. The objectives are:

1. **Measure the Influence of Neighborhood Crime Rates on the Use of Non-Automotive Modes:** We hypothesize that higher neighborhood crime rates will discourage residents from walking, bicycling, or riding transit due to concerns for their personal safety. In high-crime neighborhoods, people will prefer to travel in the relative security of their personal automobiles, controlling for other factors that determine mode choice such as income, auto ownership, neighborhood accessibility, and urban form.
2. **Determine Availability of Disaggregate Crime Data:** Because most police departments have only recently introduced the combination of computer database systems for crime records keeping in tandem with the new Federal Bureau of Investigation (FBI) UCR (Urban Crime Reporting) system, a wealth of previously inaccessible data has or will soon become available to researchers and the public. However, many departments are still in the process of implementing these systems and developing the staff expertise to routinely handle requests from those outside government for these data. Therefore, one of our research objectives was to gauge the level of effort needed to acquire these datasets, and of those jurisdictions where we made requests for data, how many we would receive data from and in what condition the data would arrive. To be useful for fine-grained, disaggregate travel behavior analysis, it is necessary to obtain crime data that is similarly disaggregated (i.e., each database record represents an individual crime event) and has geographically specific identifiers such as an address, street intersection, or at a minimum, a police beat, census tract, or other neighborhood-scale location.
3. **Differentiate and Distinguish Between the Influences of Neighborhood Crime and Urban Density on Mode Choice:** It is our hypothesis that both the academic and political discourses in this country have confused and conflated the effects of urban density and crime rates on travel behavior. In particular, while the New Urbanism, Transit-Oriented Development, and Neo-Traditional movements have lauded the positive aspects of dense, mixed-use, and pedestrian-oriented urban forms, most Americans tend to associate these environments with high-crime rates and a lack of personal safety. It seems likely that while dense, high-accessibility transit- and pedestrian-oriented forms increase the use of non-automotive modes of travel, the concentration of residences and attractions is offset by the concentration of crime in urban spaces—more dense urban spaces means more dense concentrations of criminal activities—at least in spatial terms.<sup>39</sup> Therefore, while density is likely to increase transit, pedestrian, and bicycle mode shares, higher concentrations of

crime work in the opposite direction, discouraging people from venturing out of their homes and into their neighborhoods, keeping them in the relative security of their automobiles. By identifying and distinguishing between the effects of density and crime, we also can understand the relative benefits of various proposals that will serve to increase non-automobile mode share. While increasing neighborhood density may increase transit, pedestrian, and bicycle mode shares, it may be more cost-effective and easy to implement crime-reduction programs in the project neighborhood that will increase a sense of safety among the area's current residents and visitors. Here again, due to the limited resources available for this study and the paucity of research on the relationships between crime and travel behavior, we cannot draw definitive conclusions from this study as to the prospects for increasing non-auto mode share through crime prevention measures; however, our results would provide an indication of the prospects for further research that could investigate these relationships in more depth.

4. Determine the Potential for Using Neighborhood Crime Data in Travel Demand Modeling: Contingent on our success at meeting the first two objectives (i.e., crime data availability and the influence of crime rates on travel behavior), we sought to determine the degree to which crime variables might make a useful addition to travel demand modeling practices, particularly as an independent variable in mode-choice models. Because this is the first research effort to our knowledge that is seeking to identify a correlation between neighborhood crime rates and non-auto mode choice, it is unlikely that we will conclude that this project will clearly indicate the true potential of using these data in travel-demand models.

## DATA SOURCES

### Crime Data

The objectives listed earlier served to guide our efforts at identifying and collecting the appropriate data sources for this project. Accordingly, this research focused on developing binomial logistic mode choice regression models to determine the influence of neighborhood crime and urban form on the choice of non-automotive modes. We sought disaggregate crime data, ideally geocoded to specific street addresses. Starting in January 2006, the police departments of thirty-six cities in the San Francisco Bay Area were contacted via e-mail or a letter requesting crime data for the year 2000. Of the 36 cities contacted, seven (Berkeley, Concord, Oakland, Santa Clara, Walnut Creek, San Francisco, and Sunnyvale) ultimately shared their data.

### *Crime Categories*

The UCR Program was established by the federal government to coordinate the collection of crime data at local, state, and federal levels. The UCR defines two categories of crimes: Parts 1 and 2.

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### **Crime Categories–Part 1**

Part 1 crimes are considered the more serious crimes and are therefore most likely to be reported by law enforcement agencies.<sup>40</sup>

Part 1 crimes are considered the more serious crimes and include the following offenses:

1. Criminal homicide
2. Forcible rape
3. Robbery
4. Aggravated assault
5. Burglary
6. Larceny-theft
7. Auto theft
8. Arson

For the purposes of this study, Part 1 crimes were broken down into two categories:

1. Part 1 Violent Crimes: homicide, rape, robbery, aggravated assault
2. Part 1 Property Crimes: burglary, larceny-theft, auto theft, arson.

Abbreviations for these categories are respectively P1V (Part 1 violent) and P1P (Part 1 property).

### **Crime Categories–Part 2**

As Part 2 crimes are described as all other crimes outside of Part 1 crimes, the list given in the UCR Handbook is comprehensive. Based on these UCR categories, we developed a more fine-grained list of crime categories for the purposes of this study to group Part 2 crimes.

The five Part 2 categories were determined as follows.

1. Part 2 Violent Crimes: The UCR Handbook describes crimes such as simple assault, and assault and battery as Part 2 crimes. These crimes were considered for this study as P2V, or Part 2 violent crimes. Other violent crimes that fell into this category include sexual offense crimes, kidnapping, and carjacking.
2. Part 2 Crimes Against Property: Crimes involving stolen property are in the P2P category.
3. Broken Window Crimes: This category captures Part 2 crimes that affect the appearance of a neighborhood, such as vandalism and graffiti. The broken window theory proposes that issues of graffiti, vandalism, and overall neglect mark a decline in a neighborhood and create an environment susceptible to crime. For the purposes of this study, it was determined that these types of crimes have an impact on the probability of pedestrians' use of public transportation, or walkability. Residents were thought to be less likely to use public transportation if their neighborhood seemed to be neglected, run down, and potentially harboring criminal activity. Crimes of graffiti and vandalism are Part 2 type crimes put into the Broken Window category. In the City of Oakland, note that data were

available regarding abandoned cars. For this city, these data were included in the Broken Window category. This category is abbreviated as BROKWIN.

4. Vice and Vagrancy Crimes: Part 2 crimes to be captured by this study are, for example, prostitution and drug- and weapon-related offenses. These activities are expected to have an impact on walkability. These crimes describe criminal activity, as opposed to the Broken Window crimes which refer to the environment or appearance of the neighborhood. The abbreviation for this category is VICEVAG.
5. Crimes That Do Not Affect Walkability: Many Part 2 type crimes were determined to not have an impact on whether residents will walk, bike, or take public transportation. Crime data given to the study in some cases included all police activity such as assistance provided to outside agencies, be-on-the-lookout notices, work regarding lost and found property, and reports on vehicle accidents ranging from fender benders and hit-and-run accidents to accidents involving major or minor injuries. These crimes or records of police activity were considered as not having an impact on whether residents would walk, bike, or take public transportation. The abbreviation for this category is NOTAFFEC.

### *Final List of Crime Categories*

Thus altogether, seven categories were developed to group Part 1- and Part 2-type crimes. The seven categories and their abbreviations are:

1. Part 1 Violent Crimes (P1V)
2. Part 1 Crimes Against Property (P1P)
3. Part 2 Violent Crimes (P2V)
4. Part 2 Crimes Against Property (P2P)
5. Broken Window Crimes (BROKWIN)
6. Vice and Vagrancy Crimes (VICEVAG)
7. Crimes That Do Not Affect Pedestrians' Probability of Walking (NOTAFFEC).

A detailed list of these crime categories and their constituent crime types is provided in [Table 32](#) in [Appendix A](#)

### **Travel Survey Data**

In searching for a travel survey data source for this research, priority was placed on obtaining data that reported the amount of each individual's activity and travel behavior as discrete records, including detailed individual and household demographic information for survey participants and geographically precise data on residential, employment, and other recorded activity information. Because we requested crime data from San Francisco Bay Area police departments, we needed travel and activity data for Bay Area residents as well. Data sources that were reviewed included U.S. Census Journey to Work data, and the Metropolitan Transportation Commission's (MTC) Bay Area Travel Survey (BATS) conducted in 2000. We ultimately selected the BATS 2000 dataset for two reasons: First, because Journey to Work

data are provided in aggregate form, they are not suitable for use in a disaggregate mode choice model. Second, it is a distinct possibility that neighborhood crime rates may have different effects on different trip purposes. Because the Census data only reports commute trips and the BATS 2000 data survey and report the full spectrum of trip types, we felt our research would benefit from a wider range of trip purposes.

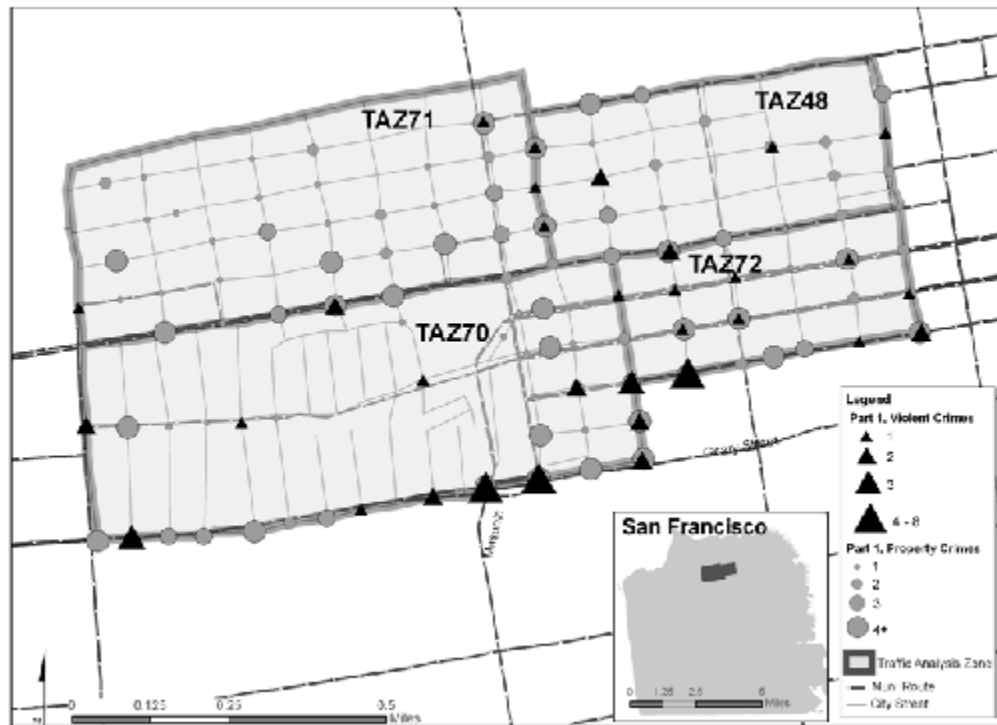
This dataset provides detailed activity diary records for 14,563 households, which represents roughly 0.6 percent of the 2,429,257 total households in 1998 in the San Francisco Bay Area. The surveyors utilized a geographically stratified sample, with the stratification based on counties and MTC's predefined traffic "superdistricts" within counties. To ensure a representative sample of the two counties with the lowest population densities—Napa and Marin—the surveyors chose to fix a minimum number of households ( $n = 600$ ) for each of these counties. The other seven counties were randomly sampled according to the stratification method mentioned earlier.

These data are used by MTC to calibrate the region's travel demand model. Because it contains detailed activity records for each individual, including travel purpose and mode choice, and detailed geographical location information for each activity, including trips, it can be combined with data on the distribution of employment to establish the relative accessibility of each surveyed residence to retail shopping opportunities.

### **Urban Form Data**

To determine the influence of urban form on transit, pedestrian and bicycle mode choice, three measures of urban form were developed: the number of four-legged intersections per acre, the residential population per acre, and the residential and employment population per acre. For the residential and employment population density variables, we hypothesized that higher density values would promote the provision and use of non-auto modes by providing more local opportunities to use transit, walk and ride bicycles. For the four-legged intersection density measure, we hypothesized that the higher the density value, the more the neighborhood street network conforms to a traditional "gridiron" design that provides the greatest level of point-to-point connectivity within the neighborhood, reducing travel distances and encouraging the use of non-automotive modes. The greater point-to-point connectivity offered by a gridiron street network with a large number of four-legged intersections is shown in Figure 2, which shows the street patterns in a 9-square-mile area of San Francisco and Walnut Creek.





**Figure 3 Gridiron Versus Suburban Street Network Patterns**

The number of four-legged intersections per acre variable was calculated by counting the number of four-legged intersections per TAZ and then dividing the total count by the area of the TAZ. The street intersection map and the TAZ GIS map data files were both obtained from the MTC, and the number of employees per census tract data were obtained from the Association of Bay Area Governments (ABAG). Employment census tract data were converted to TAZ-level data using census tract to TAZ correspondence tables, also provided by MTC.

Both the residential and the residential plus employment population density variables were calculated by dividing the total residential or residential plus employment population of each study TAZ by the area of that TAZ. The TAZ-level residential data were obtained from MTC and the employment population data were obtained from the ABAG in census tract form. Using census tract to TAZ correspondence tables also provided by MTC, the employment per census tract estimates were converted to employment per TAZ estimates.

### Accessibility Data

To determine the influence of urban geography and travel times on the transit, pedestrian, and bicycle mode choice, a measure of the relative accessibility to attractions around the Bay Area (e.g., shopping centers, central business districts, etc.) for each survey respondent in the BATS

2000 dataset was developed. Data on the geographical distribution of shopping opportunities were obtained from the ABAG, which provides estimates of employees at the TAZ level for the Bay Area.<sup>41</sup>

Each household's accessibility to attraction opportunities was calculated using a gravity-based measure based on the total number of employees, as shown in the following formula:

$$A_i = \sum_j \{Jobs_j * F_{ij}\}$$

where:

$F_{ij}$ =Time<sub>ij</sub>

Jobs=# of jobs in TAZ

Time=network travel

i=residential zone

j= employment zone

— = an empirically calculated friction factor using BATS 2000 data.

## TRAVEL BEHAVIOR MODELING APPROACH

### Factor Analysis

Preliminary pedestrian and bicycle mode choice models showed a high degree of multicollinearity between crime variables and the urban form/accessibility variables, and among the urban form/accessibility variables themselves. As a result, model runs with these variables included would often result in unanticipated changes in the sign and significance of these variables when one of its collinear partners was inserted or removed from the list of independent variables included in a model run. A number of approaches were tested, including factor variables that were developed from factor analysis using all of these crime and urban form/accessibility variables together to create two factor component variables: one representing crimes and the other representing urban form/accessibility. However, in testing these factor variables in the logistic model runs, we found that the crime factor variable would often produce a positive sign, indicating that increased crime rates were associated with an increased probability of survey participants choosing transit, bicycle, or pedestrian modes. Based on our earlier tests of logistic model runs, we suspected that the violent crimes variable was causing these unexpected results. Earlier logistic model tests with the violent crime variable would often produce a statistically significant and strongly positive relationship between pedestrian mode choice and high crime rates while the property crime variable was often negative and significant. We suspect that this may be due to an ecological fallacy, where violent crimes have a tendency to cluster in crime “hot spots” more than do property crimes, which are more spatially dispersed. Because these violent crime hot-spot clusters are likely to

locate in dense, urban traffic analysis zones/neighborhoods where people are more likely to choose walking, bicycling, or transit, this may explain why we have found these counterintuitive results and lead us to conclude that the violent crime rate variable may not be a good choice for transportation mode choice modeling efforts.

As a result of these initial factor analysis runs, we chose to run the final logistic regression models with only the property crime rate variable, which we have concluded is more spatially dispersed and is less likely to cause an ecological fallacy. Multicollinearity between the three urban form/accessibility variables was removed by running factor analysis and creating a single urban form/accessibility factor variable. Each model type (i.e., pedestrian, bicycle, and transit) exhibited different patterns of multicollinearity between its independent variables. Furthermore, each model run with different groups of cities similarly displayed somewhat different patterns of multicollinearity between the urban form/accessibility and the crime variables. Therefore, for each model run, a separate factor analysis run and separate set of factor score variables were produced. After testing a number of combinations of urban form and accessibility measure variables, a combination of the following input variables yielded results consistent with theoretical assumptions without substantial collinear effects. These are the number of four-legged intersections per acre in each TAZ, the number of jobs plus the number of residents per acre in each TAZ, and the transit accessibility measure for each TAZ.

## Binary Logistic Regression Modeling

This study used a binary logistic regression modeling approach to estimate the impact of a set of independent variables on a person's probability of taking a particular transportation mode. Maximum likelihood estimation technique was used to estimate the coefficient parameters.

A binary logit model is defined as:

$$P(Z) = \frac{\exp Z}{1 + \exp Z}$$

where P is the probability of a binary outcome [e.g., a person taking transit (P = 1) or not taking transit (P = 0)], and  $Z = \alpha + \beta X$ , where X is a vector of individual, household, urban form, and transit accessibility, and  $\beta$  is the slope of the variables.

A person's individual characteristics included age, income, race, employment status, and status as the head of household. The household characteristics included the number of vehicles per licensed driver and the number of bicycles per household. The urban form & transit accessibility was a factor variable that grouped such urban form variables as number of four-legged intersections per acre and population per acre, with the transportation accessibility variable measured as accessibility to transit. The neighborhood crime characteristics were measured as the number of crimes per 1,000 residents of each TAZ (i.e., the crime rate).

Three sets of logistic regression models were run. The three model sets estimated the impact of independent variables on a person's probability to take transit, bike, and walk for work and non-work trips.

## DATASET PREPARATION

### Travel Survey Data

BATS 2000 data were prepared for analysis by first importing the BATS 2000 data files into a Microsoft Access database. Because BATS 2000 data are distributed by MTC as text files, these files were converted into Access format. The BATS data are provided as three separate files:

1. Household File: Contains coded data descriptions of each household that participated in the survey. Household data include household income, number of household vehicles, number of persons in the household, type of dwelling, location of the household (i.e., city and TAZ), and other variables that describe the household.
2. Person File: Contains coded data descriptions of each person in each household who participated in the survey. Person data include personal income, gender, race, and other descriptive variables.
3. Activities File: Contains coded data describing the activities of each person in each household over the 2-day survey period. Each record is a separate activity, and activities are coded into the categories shown in Table 1.

**Table 1 BATS 2000 Activity Code Key**

1 = Driving, riding, walking, biking, flying
2 = Household chores and personal care
3 = Meals (at home, take-out, restaurant, etc.)
4 = Recreation/Entertainment
5 = Sleep
6 = Work or work related (in or out of home)
7 = School or school related (college/day care)
8 = Shopping (at home)(by Internet, catalog or television)
9 = Shopping (away from home)
10 = Personal services/bank/government
11 = Social activities
12 = Relaxing
13 = Volunteer/civic/religious services
14 = Sick or ill/medical appointment
15 = Non-work (non-shopping) Internet use
16 = Pick-up/drop off passenger
17 = Changed type of transportation
990 = Out of town/moved out

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996 = Other

998 = Don't know

999 = Refused

Source: MTV BATS 2000 Activity Survey File

The location of each activity also is identified by TAZ number, and if an activity is a trip, the origin and destination TAZs as well as the mode used for each trip also are provided.

1. Vehicle File: Describes each vehicle in the survey household. This data table was not utilized for this research effort.
2. Unlinked Trip File: Describes each trip link taken by each person in the BATS survey. This file is actually a subset of the Activities data file described earlier, with only trip data records.
3. Linked Trip File: Describes the trip purpose of each trip link in terms of the ultimate destination of the combined, linked trip. For instance, a trip in the Unlinked File with a trip purpose listed as Pick Up/Drop Off Passenger or Changed Type of Transportation are re-labeled with the ultimate trip destination's purpose such as Social Activities or Work or Work Related. This file is actually a subset of the Activities data file described earlier, with only trip data records. This file also identified the primary travel mode for each set of linked trips, identifying which mode of travel used in the linked trip sequence was most important (in that it covered the greatest distance). Trip linking and the identification of the primary mode of travel were performed by the MTC. This process is explained in greater detail in "Trip Linking Procedures" working paper.<sup>42</sup>

Our first step was to create data tables that combined data from the various files described earlier. Mode choice analysis is typically done at a disaggregated level, meaning that each data record in the analysis tables needs to represent a single trip taken by a single person; however, each trip record needs to have data from multiple data files—household, person, and trip data—all in one record on one table. Therefore, we organized the BATS 2000 data tables into a relational database structure in Access, linking different data file records by common identifiers for household, person, and activity.

Because the largest share of trips taken by a person during a typical travel day are home-based and because the mode of travel chosen for a home-based trip plays an important role in determining the mode choice of trips throughout the travel day, it is our assumption that neighborhood crime levels will have their greatest effect on mode choice in a person's home neighborhood. Therefore, we selected trip data records for analysis that were home-based.

Trips were categorized into five categories: auto, transit, walk, bicycle, and other. Only trips identified as auto, transit, walk, or bicycle were used for our analysis. To run the pedestrian binary logistic regression model, a "dummy" variable was constructed where pedestrian trips were coded with a "1" and all other trip types were coded with a "0." Similar dummy variables were constructed for each of the other three modes of travel to use as dependent variables in the transit and bicycle binary logistic regression models.

There are several peculiarities of how trips are coded in the BATS 2000 dataset. We chose to use the Unlinked Trips File for our pedestrian and bicycle binary logistic model runs while we used the linked trips file for our transit analysis. We came to the conclusion that this was the most efficacious approach because home-based transit trips are under-represented in the Unlinked Trips File. Because very few people step directly out of their front doors onto a waiting transit vehicle, the transit trip is often the second, third, or later link in a trip chain, and the origin of this trip link will therefore not be coded as the home but rather as the bus stop, BART station, ferry terminal, or other transit station where the transit trip started. To reliably link the home's neighborhood data (i.e., crime rates and transit accessibility) to each transit trip that began as a linked trip from the home, we used the Linked Trip File for the transit mode choice analysis. This way, transit trips that required a short walk or bicycle ride from home to reach the transit stop would be coded as home-based despite the fact that the origins of these individual trip links are actually located at the transit stop where the traveler boarded the transit vehicle. Pedestrian and bicycle trips were analyzed using the Unlinked Trip File because these modes are most likely to be used directly from the home.

### **Assessment of Crime Data Collection Process and Activities**

Starting in January 2006, the police departments of 36 cities in the Bay Area were contacted via e-mail or hard copy letter requesting crime data for the year 2000. At each police department, follow-up phone calls were made to inquire as to the status of our request. Of the 36 cities contacted, five cities ultimately shared their Parts 1 and 2 data for the year 2000 or 2001 while three additional cities shared just the Part 1 data for the year 2000 or 2001.

Most city police departments that were unable to comply with our requests cited a lack of available staff to do the work of compiling and sending us their data. Some departments indicated that their policy was to charge the data requester for the staff time required to gather and send their data. In one case, we were told they would need to charge us up to \$2,000 to gather and send their data.

Reasons given for not providing data also included:

- Need to charge \$5 per (record with) address; too time consuming;
- Understaffed and cannot help;
- Have no data analysis unit. Have 40,000 reports/year (records/year). Do not have enough manpower to provide the data.
- Crime database system is periodically purged; only past 6 months currently available;
- Unable to collect data due to large amount; and
- Too time consuming for the single person crime analysis.

While there were many negative or slow responses to our requests, one city responded within a week with the data and the GIS information. It is our assumption that two factors contribute to the willingness and ability of a police department to provide these detailed crime data records. The first is, as suggested by the negative responses summarized earlier, a lack of staff

resources to collect and send the data. This includes both the availability of staff to perform the tasks as well as the expertise among staff to produce the data. The second factor is likely the degree to which a police department has made a successful transition from paper records or older generation database systems to more up-to-date and user-friendly systems. The data used in the study were collected by September 2006, 9 months after the process was started.

To facilitate future work involving crime data analysis (both academic research and analysis at the local, police-department level), we recommend that a national- or state-level policy be developed that would (perhaps as a supplement to the UCR system) encourage local police departments to digitally store historical crimes data. These data are extremely valuable, and our experience with police departments that routinely purge their historical data indicates that some departments do not understand the importance of storing and maintaining historical datasets. Although resources are often limited, researchers and other individuals who can analyze trends and patterns for reducing crime would be greatly helped by having comprehensive access to this information. This need presents opportunities for joint funding of crime database improvements by research institutions, universities, non-profit organizations, and government agencies in cooperation with individual police departments and the criminal justice agencies within state and federal governments. These opportunities should be explored and pilot-tested as a potential avenue for enhancing access to this potentially rich source of data.

### **Crime Data Coding**

Five cities used in this study provided both Part 1 and Part 2 crime data. The cities of Berkeley, Concord, Oakland, and Walnut Creek provided both Part 1 and Part 2 data for the year 2000. The city of Santa Clara provided Part 1 and Part 2 data for the year 2001. The cities of San Francisco and Sunnyvale were able to provide only Part 1 data. Details regarding the coding process for these cities are given next.

#### *Berkeley*

The crime data for Berkeley had 12,818 records of police activity for the year 2000. Each record has sufficient descriptive information for easy categorizing into the seven crime groupings. A total of 9,306 of the records provided (or 72.6 percent) were successfully geocoded and used for this study.

#### *Concord*

The crime data for the City of Concord contained 22,528 records of police activity for the year 2000. Of these records, 703 had addresses outside of the city of Concord. These records were not included in the analysis.

After the geocoding was done, 19,216 records, 85.3 percent, remained that were successfully geocoded with sufficient descriptive information for each record for the purposes of categorizing. All records had unique case numbers.

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### *Oakland*

The City of Oakland provided the most comprehensive dataset. We received 193,131 records of Part 1 and Part 2 crimes and incidents for the year 2000; however, these records included entries with either follow-up information on crimes which had been reported previously or entries with supplemental information for all persons involved in one crime. These duplicate and supplemental entries were removed from the dataset.

After these records were removed, other entries were found where either the crime description or the incident location was left blank. In some cases, the incident location given was unknown. City of Oakland personnel were unavailable for questions regarding these data. Consequently, these records also were removed from the dataset.

The remaining records were categorized and geocoded. A number of records were found to fall outside of the Oakland city limits. These records were removed from the study. The final number of records successfully geocoded and included in this study for the city of Oakland was 68,513 (or 35.5 percent).

### *Santa Clara*

The City of Santa Clara provided 15,634 records of Part 1 and Part 2 crimes for the year 2001. Because this was the earliest year for which data were available, we used 2001 data as a proxy for 2000 data. While crime levels and geographic distributions undoubtedly change from year to year, we believe that these changes over the course of a single year are minimal. These data came with only code numbers to describe crimes. For this reason, categorizing these data was more challenging. Personnel at the city of Santa Clara made themselves available to help with interpreting and understanding the crime codes. For Santa Clara, 12,644 records (or 80.9 percent) were geocoded successfully.

### *Walnut Creek*

The City of Walnut Creek provided 33,981 records of Part 1 and Part 2 crimes for the year 2000. Of these records, 25,023 (or 73.7 percent) geocoded successfully and fell within the bounds of the city limits.

The cities of San Francisco and Sunnyvale provided only Part 1 crime data for our study. Sunnyvale provided Part 1 data for the year 2000 while San Francisco provided Part 1 data for 2001.

### *Sunnyvale*

A total of 2,123 Part 1 crime data records were provided for the year 2000 by the City of Sunnyvale. Street addresses were not provided for these crimes—only police department Reporting District information was provided; therefore, we were not able to geocode crimes in Sunnyvale at the address- or even intersection-level. However, an electronic map outlining Reporting Districts was made available, and we used it to create a GIS shapefile for Reporting



Districts. This shapefile was then used to geocode a total of 2,120 records (or 99.9 percent) of the original dataset provided.

### *San Francisco*

The City of San Francisco provided 22,429 Part 1 crime records for the year 2001. Data from San Francisco were received with no case numbers. A case number was created by concatenating the date, time, and address information for each record. For the concatenation, the Excel program transformed the given date from the date format into the numerical date value. For example, “12/7/2001” became the numerical date value 37232.

Addresses provided in the San Francisco data were “blocked” for reasons of confidentiality.

To geocode the San Francisco addresses, “XX”s were replaced with “00.” This effectively placed all crime locations that fell on a particular block at the corner adjacent to the lowest, even-numbered address on that block. While this reduced the accuracy of our crime geocoding for San Francisco, the fact that all crimes were aggregated to and summarized at the TAZ level made this loss of accuracy virtually inconsequential.

Cases where a range of addresses were given, such as “0001–2499 STOCKTON ST.”, the leading characters (in this case, namely “0001–”) were removed, leaving “2499 STOCKTON ST.” as the address for the geocoding. The final number of geocoded records was 19,169 (or 85.5 percent) of the San Francisco dataset.

## **STUDY HYPOTHESES AND RESEARCH QUESTIONS**

Because the nature of this research effort was primarily exploratory, the methods we applied were primary exploratory in nature as well. Therefore, our approach, methods, and working hypotheses are somewhat informal and do not seek “ironclad” scientific confirmation of a set of working hypotheses but can be more accurately described as an exploration of a set of research questions and expectations. Our research questions and expectations can be summarized as follows:

1. Different crime types will have different spatial distributions: It is our understanding from a review of the crime research literature that property crimes will be more evenly distributed spatially than will violent crimes. In other words, violent crimes will tend to cluster into “hot spots” more than will property crimes. These differences may play a role in determining which crimes—property or violent crimes—are more appropriate for use as predictor variables of mode choice.
2. Do higher density environments have higher or lower crime rates? Jane Jacobs was one of the most vocal and prominent advocates for dense, active urban environments, in part, reasoning that such neighborhoods serve to deter crime by having more “eyes on the street.” Because dense, urban areas typically have higher levels of transit services as well, we would reason that dense, transit-rich areas may have lower crime rates and, consequently, higher non-auto mode shares attributable to all three factors (i.e., high

density, high transit service levels, and lower crime rates). However, research related to this question provides somewhat mixed results. Cozens et al. found that well-lit transit station areas provide an enhanced feeling of safety from crime, and Loukaitou-Sideris et al. found that the introduction of the Green Line light rail system to Los Angeles did not increase crime rates in the station areas. Ingalls et al. found that people's perceptions of high crime rates in urban, transit-rich environments was an impediment to transit ridership growth, and Block and Davis<sup>46</sup> found that crimes tend to concentrate around rapid rail stations in Chicago. Therefore, we will explore two alternative relationships between density, transit service levels, and crime:

- a. Transit-rich and high-density environments have lower crime rates.
  - b. Transit-rich and high-density environments have higher crime rates. If true, then we might expect some difficulties in measuring crime rates using TAZ aggregations of crimes due to the increased potential for an ecological fallacy.
3. Higher crime rates will discourage non-automotive mode share: Controlling for individual, household, and urban form factors, we would expect high neighborhood crime rates to lead to a lower probability of choosing pedestrian, transit, and bicycle modes, and would increase the probability of traveling by automobile for home-based trips. Specifically, a public perception of high neighborhood crime rates will engender a feeling that these neighborhoods are unsafe to walk or ride a bicycle in and, by extension because people typically walk or ride bicycles to transit, will deter transit ridership as well.
  4. Self-Selection Bias: Attitudes toward crime and non-auto modes of travel are important, but unmeasured in this study. We can assume that people who have chosen to live in dense, urban, transit-rich environments have done so in part because they value the lifestyles these places provide. It is reasonable to assume that one reason they have chosen to live in dense cities is to enjoy the benefits of high transit accessibility and pedestrian-friendly environments. Therefore, if these urban environments also have higher crime rates, then those who have chosen this lifestyle have decided that they will not be dissuaded by high crime rates from enjoying their transit-oriented lifestyles. In these areas, we might expect to find high levels of transit use, walking, and bicycle usage despite the high crime rates. As a result, for cities such as San Francisco, Oakland, and Berkeley, we actually may find a positive correlation between crime rates and non-automotive mode share.

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## OVERVIEW OF CITY, CRIME AND TRAVEL DATA

This section provides descriptive statistics for each study city, including the crimes data provided by each study city's police department as well as an overview of the travel data for each city grouping obtained from the BATS 2000 survey. We present socio-demographic data in this section (e.g., household income) using Census 2000 data to provide an overview of each city's socio-demographic makeup. We then give similar data using the BATS 2000 data used to run the logistic regression models to compare and contrast the trip data populations with the city-level census data.

Regarding Part 1 violent and Part 2 violent and vice-vagrancy crimes, the counts of crimes per 1,000 residents for Walnut Creek are the lowest of all the study cities. For property crimes, Part 1 property, Part 2 property, and broken window crimes, Walnut Creek is comparable to or above the average of the other study cities (Table 2).

**Table 2 Crime Rates for All Study Cities**

	PIV	PIP	P2V	P2P	BROKWIN	VICEVAG	NOTAFF
<b>Berkeley</b>	1.2945	55.376	8.7695	0.4867	9.7914	7.8837	7.2122
<b>Concord</b>	2.2556	40.1062	13.9285	2.8318	10.7510	11.6482	76.5656
<b>Oakland</b>	7.5098	48.9440	14.8569	1.2191	10.7691	26.6423	61.5655
<b>San Francisco</b>	6.4308	18.2482					
<b>Santa Clara</b>	1.1536	26.1721	6.1156	0.1075	8.3821	12.8955	60.0131
<b>Sunnyvale</b>	1.1536	14.9362					
<b>Walnut Creek</b>	0.9332	30.3751	6.1901	9.0985	10.6850	6.3768	325.5257
<b>All Cities</b>	5.4193	31.8894	12.0810	1.8681	10.3192	18.4630	78.0471

Source: Crime data from all study city police departments

BROKWIN = "Broken Windows" Crimes Category

VICEVAG = "Vice & Vagrancy" Crimes Category

NOTAFF = "Does Not Affect Mode Choice" Crimes Category

Table 3 provides general descriptive statistics for each study city for the purposes of comparison and analysis. More detailed descriptive statistics and discussion are provided in Appendix B.

**Table 3 General Statistics of Study Cities**

	Pop	Density/ sq. mi.	4-legged int/ac	# crimedata	Median Income	% White	% Black	% Hispanic
<b>Berkeley</b>	102,743	9,823.20	0.1108	9,306	44,485	63.7	15.3	9.7
<b>Concord</b>	121,780	4,041.00	0.0130	19,204	55,597	75.8	3.8	21.8
<b>Oakland</b>	399,484	7,126.66	0.0321	68,513	40,055	34.7	37.6	21.9
<b>San Francisco</b>	776,733	16,634	0.1274	19,169*	55,221	53.0	8.6	14.1
<b>Santa Clara</b>	102,361	5,566.20	0.0328	11,771	69,466	59.6	2.8	16.0
<b>Sunnyvale</b>	131,760	6,006.50	0.0213	2,120*	74,409	56.7	2.7	15.5
<b>Walnut Creek</b>	64,296	3,229.60	0.0075	25,023	63,238	86.8	1.5	6.0

\* part 1 data only

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

## SUMMARY STATISTICS OF MODEL VARIABLES

Based on analysis of the data summaries just presented, pilot test logistic regression model runs, and the local knowledge of the research team members, we summarized and analyzed the travel diary survey data based on grouping the study cities into four sub-groups: urban core (San Francisco only); inner-ring (Oakland & Berkeley); suburbs with Parts 1 and 2 data (Walnut Creek, Santa Clara, & Concord); and All Suburbs Combined (Walnut Creek, Santa Clara, Concord, and Sunnyvale). Preliminary logistic model runs showed that combining the data into these sub-groups improved overall goodness-of-fit results. Furthermore, the relationships between the crime, density, and travel behavior were the most internally consistent (within groups) when the cities were organized in this fashion. Groupings of individual variables (e.g., race into “white” and “non-white” and household income into four groups) were based on a combination of the researchers’ past analytic experience, understanding of the research literature, and the iterative process of testing various combinations of variable groupings in the process of determining the ultimate structure and components of the final logistic regression models. The summary data and model results that follow are reported using these groups for the purposes of facilitating comparisons between the descriptive statistics on travel behavior and the model outputs.

## TRANSIT MODEL TRIPS DATA

Frequency distributions of categorical-level variables are listed in [Table 4](#) for work trips using public transportation or transit mode and in [Table 5](#) for non-work trips using transit mode. These models were run for San Francisco alone; for Oakland and Berkeley; for Concord, Santa Clara, and Walnut Creek; and for all suburban cities, Concord, Santa Clara, Sunnyvale, and Walnut Creek.

The distributions closely parallel the Census Journey to Work data in all cases. For example, the census data describe San Francisco as having 31.1 percent using transit for their work commute while [Table 4](#) lists 26.7 percent for this model’s dataset (i.e., all trip records less than 5 miles in length). Comparing household income data, the distributions listed in and for the transit models do not follow the patterns seen in the census data. In the models, the percentages for household income below \$15,000 are much lower than that of the general population described in the census data. The percentages for the highest income level, above \$75,000, are all higher than that of the general population described in census data. However, for incomes above \$75,000, the suburban cities have higher percentages than San Francisco, and Oakland and Berkeley, as was the case in the census data.

**Table 4 Frequency Distribution of Categorical-Level Variables: Transit File—Work Trips**

Variable	Percentage of Observations			
	SF Only	Oakland & Berkeley	Walnut Creek, Santa Clara, Concord	All Suburbs
<b>Trips</b>				
Transit	26.72	17.46	9.64	7.04
Non-Transit	73.28	82.54	90.36	92.96
<b>Income</b>				
Household income under \$15,000	1.11	2.29	0.92	0.67
Household income \$15,000–49,999	22.16	27.54	19.95	16.93
Household income \$50,000–74,999	22.93	24.45	22.30	20.33
Household income above \$75,000	53.80	45.72	56.83	62.07
<b>Age</b>				
Age 19–39	52.44	45.71	34.97	40.44
Age 40–59	42.68	46.97	56.50	51.97
Age over 59	4.88	7.32	8.53	7.59
<b>Gender</b>				
Male	57.01	52.64	54.08	55.54
Female	42.99	47.36	45.92	44.46
<b>Head of Household</b>	63.13	60.58	60.27	59.93
<b>Race</b>				
White	76.05	74.56	80.99	77.06
Non-White	23.95	25.44	19.01	22.94
<b>Number of bicycles in household</b>				
0	39.04	35.07	37.49	37.33
1	24.09	23.09	18.90	18.39
2	23.72	20.25	22.60	23.10
3	7.41	11.11	9.22	9.33
4	4.45	5.28	7.56	6.95
5	0.68	2.36	2.42	3.02
6	0.49	1.81	1.36	1.33
7	0.00	0.47	0.23	0.32
8	0.00	0.00	0.23	0.18
9	0.12	0.55	0.00	0.00

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)



**Table 5 Frequency Distribution of Categorical-Level Variables: Transit File—Non-Work Trips**

Variable	Percentage of Observations			
	SF Only	Oakland & Berkeley	Walnut Creek, Santa Clara, Concord	All Suburbs
<b>Trips</b>				
Transit	13.96	6.48	2.05	1.55
Non-Transit	86.04	93.52	97.95	98.45
<b>Income</b>				
Household income under \$15,000	5.53	7.07	0.90	0.91
Household income \$15,000–49,000	26.34	30.62	23.52	21.86
Household income \$50,000–74,000	20.56	18.97	20.94	20.91
Household income above \$75,000	47.58	43.34	54.64	56.33
<b>Age</b>				
Age 19–39	43.31	38.94	27.96	33.09
Age 40–59	38.85	38.07	44.20	41.12
Age over 59	17.85	22.99	27.84	25.80
<b>Gender</b>				
Male	48.97	44.18	43.25	44.12
Female	51.03	55.82	56.75	55.88
<b>Head of Household</b>	67.46	65.62	58.38	57.85
<b>Race</b>				
White	80.10	79.04	85.86	83.73
Non-White	19.90	20.96	14.14	16.27
<b>Number of bicycles in household</b>				
0	42.11	39.82	36.97	36.23
1	24.76	21.96	16.53	17.47
2	20.73	19.14	21.29	21.58
3	6.86	8.00	9.47	10.29
4	3.86	5.59	9.58	8.25
5	1.14	2.00	3.25	3.48
6	0.38	1.95	2.13	2.07
7	0.11	1.03	0.34	0.30
8	0.00	0.00	0.39	0.30
9	0.05	0.51	0.00	0.04
10	0.00	0.00	0.00	0.00
11	0.00	0.00	0.06	0.00

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

Descriptive statistics for the transit mode datasets (all trips greater than 0.5 miles in length) are shown in Table 6 through Table 13. As expected, the number of vehicles per licensed driver is lowest in San Francisco and highest in the suburban cities.

**Table 6 Descriptive Statistics of Categorical-Level Variables: Transit File—Non-Work Trips**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	3	0.8218	0.4502
Total number of bicycles in household	0	9	1.1902	1.2651
Part 1 property crimes per person in TAZ	0.0007	0.2059	0.0137	0.0156
Urban form & transit accessibility factor score	-2.3369	4.9703	-0.0084	0.9762

N = 1599

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 7 Descriptive Statistics for Continuous Variables for Berkeley and Oakland: Work Trips—Transit Mode (All Trips Greater than 0.5 Miles)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	4	0.9570	0.3904
Total number of bicycles in household	0	9	1.4901	1.6091
Part 1 property crimes per person in TAZ	0.0118	0.4141	0.0444	0.0293
Urban Form & Transit Accessibility Factor Score	-2.8738	4.7595	-0.0007	0.9661

N = 1255

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 8 Descriptive Statistics for Continuous Variables for Concord, Santa Clara and Walnut Creek: Work Trips—Transit Mode (All Trips Greater than 0.5 Miles)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	4	1.0639	0.3713
Total number of bicycles in household	0	8	1.4565	1.5473
Vice & vagrancy crimes per Jobs + Population in TAZ	0	0.0259	0.0061	0.0054
Urban Form & Transit Accessibility Factor Score	-1.7124	4.4424	0.1898	1.1061

N = 1314

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 9 Descriptive Statistics for Continuous Variables for All Suburbs: Work Trips—Transit Mode (All Trips Greater than 0.5 Miles)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	4	1.0637	0.3608
Total number of bicycles in household	0	8	1.4723	1.5499
Part 1 violent crimes per person in TAZ	0	0.0125	0.0012	0.0012

**Table 9 Descriptive Statistics for Continuous Variables for All Suburbs: Work Trips—Transit Mode (All Trips Greater than 0.5 Miles)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Urban Form & Transit Accessibility Factor Score	-2.0542	4.2671	0.1941	1.0600

N = 2176

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 10 Descriptive Statistics for Continuous Variables for San Francisco Only: Non-Work Trips—Transit Mode (All Trips Greater than 0.5 Miles)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	4	0.7912	0.4576
Total number of bicycles in household	0	9	1.1148	1.2609
Part 1 property crimes per person in TAZ	0.0007	0.2059	0.0151	0.0178
Urban Form & Transit Accessibility Factor Score	-2.3369	4.9703	0.0543	1.0146

N = 1795

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 11 Descriptive Statistics for Continuous Variables for Berkeley and Oakland: Non-Work Trips—Transit Mode (All Trips Greater than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	3	0.9242	0.3992
Total number of bicycles in household	0	9	1.4012	1.6610
Part 1 property crimes per person in TAZ	0.0118	0.4141	0.0447	0.0301
Urban Form & Transit Accessibility Factor Score	-2.8738	4.4784	0.0364	0.9643

N = 1923

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 12 Descriptive Statistics for Continuous Variables for Concord, Santa Clara and Walnut Creek: Non-Work Trips—Transit Modes (All Trips Greater than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	3	1.0426	0.3185
Total numbers of bicycles in household	0	11	1.6095	1.6956
Part 1 property crimes per person in TAZ	0	0.0259	0.0053	0.0052
Urban Form & Transit Accessibility Factor Score	-1.7124	4.4424	-0.0502	0.9750

N = 1781

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 13 Descriptive Statistics for Continuous Variables for Suburbs: Non-Work Trips—Transit Mode (All Trips Greater than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0	4	1.0415	0.387
Total numbers of bicycles in household	0	11	1.5918	1.6573
Part 1 violent crimes per person in TAZ	0	0.0053	0.0010	0.0010
Urban Form & Transit Accessibility Factor Score	-2.0542	4.2971	-0.0355	0.9919

N = 2698

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

### Pedestrian Model Work Trips Data

Descriptive statistics for the variables used in the pedestrian work trip binary logistic regression model are shown in Table 14. For work trips starting in suburban cities less than 1 mile in length, 30 percent are pedestrian trips while the corresponding figures for San Francisco and Oakland, 80 percent and 69 percent, respectively, conform to expectations that people who live in more pedestrian-friendly, urban cities tend to choose walking more often than do people in the suburbs. This pattern is repeated for the non-work pedestrian trip variables as seen in Table 15. From the same dataset, the percentage of households in each income level group is roughly consistent across the three city groupings, indicating that the BATS 2000 sampling techniques were effective.

**Table 14 Frequency Distribution of Categorical-Level Variables: Persons Reporting Work Trips Under One Mile in Length**

Variable	Percentage of Observations		
	SF Only	Oakland & Berkeley	Suburbs
<b>Trips</b>			
Pedestrian trips	80.16	69.07	30.32
Non-pedestrian trips	19.84	30.93	69.77
<b>Income</b>			
Household income under \$15,000	0.83	2.85	2.21
Household income \$15,000–49,000	25.07	30.70	27.21
Household income \$50,000–74,999	27.00	23.32	28.68
Household income above \$75,000	47.11	43.12	41.91
<b>Age</b>			
Age 19–39	56.67	57.56	43.75
Age 40–59	38.97	38.02	45.00
Age over 59	4.36	4.43	11.25
<b>Gender</b>			
Male	52.05	51.30	45.63
Female	47.95	48.70	54.38

**Table 14 Frequency Distribution of Categorical-Level Variables: Persons Reporting Work Trips Under One Mile in Length**

Variable	Percentage of Observations		
	SF Only	Oakland & Berkeley	Suburbs
<b>Head of Household</b>	68.46	64.72	64.38
<b>Race</b>			
White	80.16	75.27	2.28
Non-white	19.84	24.73	17.72
<b>Number of bicycles in household</b>			
0	47.18	40.92	31.88
1	26.67	25.04	16.88
2	13.59	16.03	20.63
3	7.69	9.31	13.13
4	4.10	5.34	8.75
5	0.51	2.29	6.88
6	0.26	0.46	0.63
7	0.00	0.15	0.63
8	0.00	0.00	0.63
9	0.00	0.46	0.00

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

**Table 15 Frequency Distribution of Categorical-Level Variables: Persons Reporting Non-Work Trips Under One Mile in Length**

Variable	Percentage of Observations		
	SF Only	Oakland & Berkeley	Suburbs
<b>Trips</b>			
Pedestrian trips	60.00	42.65	18.77
Non-pedestrian trips	40.00	57.35	81.23
<b>Income</b>			
Household income under \$15,000	6.67	2.85	3.57
Household income \$15,000–49,000	32.00	30.70	20.66
Household income \$50,000–74,999	21.94	23.32	20.41
Household income above \$75,000	39.39	29.38	55.36
<b>Age</b>			
Age 19–39	49.30	47.04	33.26
Age 40–59	37.95	35.70	38.81
Age over 59	12.76	17.27	27.93
<b>Employed persons</b>	70.38	65.54	57.05
<b>Gender</b>			
Male	48.54	45.23	39.45
Female	51.46	54.77	60.55
<b>Head of Household</b>	67.35	69.85	60.77
<b>Race</b>			

**Table 15 Frequency Distribution of Categorical-Level Variables: Persons Reporting Non-Work Trips Under One Mile in Length**

Variable	Percentage of Observations		
	SF Only	Oakland & Berkeley	Suburbs
White	83.20	79.58	87.61
Non-white	16.80	20.42	12.39
<b>Number of bicycles in household</b>			
0	44.11	38.27	35.61
1	25.73	25.77	15.35
2	19.78	17.65	20.26
3	5.08	6.06	10.87
4	4.22	4.64	9.59
5	0.54	2.96	3.84
6	0.54	2.58	3.20
7	0.00	1.29	0.64
8	0.00	0.00	0.64
9	0.00	0.77	0.00

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

The frequency distributions for the work and non-work mode trips for all cities as used in the bicycle binary logistic regression models are listed in [Table 16](#).

**Table 16 Frequency Distribution of Categorical-Level Variables: Persons Reporting Work and Non-Work Trips Under Five Miles in Length**

Variable	Percentage of Observations	
	All Cities—Work	All Cities—Non-Work
<b>Trips</b>		
Bike trips	5.13%	2.14%
Non-Bike Trips	94.87%	97.86%
<b>Income</b>		
Household income under \$15,000	1.99	5.34
Household income \$15,000–\$49,000	24.85	27.11
Household income \$50,000–74,999	23.01	19.93
Household income above \$75,000	50.15	47.63
<b>Age</b>		
Age 19–39	47.47	39.36
Age 40–59	45.73	38.69
Age over 59	6.80	21.95
<b>Employed Persons</b>	XXX	63.64
<b>Gender</b>		
Male	52.87	44.33
Female	47.13	55.67
<b>Head of Household</b>	62.37	64.36

**Table 16 Frequency Distribution of Categorical-Level Variables: Persons Reporting Work and Non-Work Trips Under Five Miles in Length**

Variable	Percentage of Observations	
	All Cities—Work	All Cities—Non-Work
<b>Race</b>		
White	78.58	83.11
Non-White	21.42	16.89
<b>Number of bicycles in household</b>		
0	37.50	39.94
1	21.83	21.76
2	21.63	19.44
3	9.40	8.15
4	5.37	5.88
5	2.67	2.41
6	1.17	1.66
7	0.20	0.46
8	0.03	0.08
9	0.20	0.19
10	XX	XX
11	0.00	0.02

Source: Census 2000, Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454)

As expected, a higher percentage of people in the study cities bicycled for work purposes (roughly five percent) than for non-work purposes (roughly two percent)—a function of the relative predictability of work trips compared to non-work trips, and the fact that non-work trips often require carrying purchased goods home—an activity that can be difficult on a bicycle. There also appears to be a slightly higher percentage of people from lower income categories who traveled for non-work purposes, most likely a result of the fact that unemployed people have lower incomes and will, by circumstance, take only non-work trips.

Regarding the descriptive statistics of continuous variables for the pedestrian work-trip and non-work trip models, the information is consistent with what has been observed in the census data.

For example, as to be expected, for the total number of vehicles per licensed driver in household, the mean is closer to “1” for the suburban cities (See [Table 19](#)) than it is in the San Francisco (See [Table 17](#)) or the Oakland/Berkeley models (See [Table 18](#)), indicating that suburban residents tend to have more cars per licensed driver than those in urban cities.

Interestingly, in San Francisco’s pedestrian work trips model’s dataset, that city has mean of 0.9744 bicycles per household while in the suburban model, the figure is 1.8 bicycles. This range also is seen in the non-work pedestrian model datasets.

Also of note, Part 1 property crime rates are consistently highest in Oakland for the work and non-work pedestrian models when compared to the other city groupings. Descriptive statistics for all these models are listed in the next eight tables (Table 17 through Table 24).

**Table 17 Descriptive Statistics for San Francisco: Work Trips—Pedestrian Model (All Trips Less than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.3333	2.5	0.8697	0.3342
Total number of bicycles in household	0.0	6.0	0.9744	1.1974
Part 1 property crimes/TAZ population	0.0007	0.1800	0.0136	0.0169
Urban Form & Transit Accessibility Factor Score	-2.0704	4.9979	0.3108	1.1106

N = 273

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)

**Table 18 Descriptive Statistics for Oakland and Berkeley: Work Trips—Pedestrian Model (All Trips Less than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.20	2.5	0.8791	0.3300
Total number of bicycles in household	0	9	1.2580	1.4794
Part 1 property crimes/TAZ population	0.00066	0.41	0.0298	0.0381
Urban Form & Transit Accessibility Factor Score	-1.44394	5.9904	0.4264	1.0914

N = 499

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)

**Table 19 Descriptive Statistics for Suburban Cities: Work Trips—Pedestrian Model (All Trips Less than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.3333	3	0.9995	0.3581
Total number of bicycles in household	0	8	1.8	1.7331
Part 1 Violent crimes/TAZ population	0	0.0053	0.0018	0.0016
Urban Form & Transit Accessibility Factor Score	-1.4486	4.4804	0.3870	01.0732

N = 155

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)



**Table 20 Descriptive Statistics For San Francisco: Non-Work Trips—Pedestrian Model (All Trips Less than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.3333	4	0.8898	0.3841
Total number of bicycles in household	0	6	1.0335	1.2015
Part 1 Property crimes/TAZ population	0.0007	0.1700	0.0136	0.0139
Urban Form & Transit Accessibility Factor Score	-2.0704	4.1007	0.2572	1.0087

N = 689

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)

**Table 21 Descriptive Statistics for Oakland and Berkeley: Non-Work Trips—Pedestrian Model (All Trips Less than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.2	4	0.9240	0.3271
Total number of bicycles in household	0	9	1.4407	1.7624
Part 1 Property crimes/TAZ population	0.01	0.25	0.0462	0.0329
Urban Form & Transit Accessibility Factor Score	-2.0704	4.1007	0.4877	1.1355

N = 643

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)

**Table 22 Descriptive Statistics for Suburban Cities: Non-Work Trips—Pedestrian Model (All Trips Less than 1 Mile)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.3333	2	1.0265	0.2861
Total number of bicycles in household	0	8	1.7484	1.8059
Part 1 Violent crimes/TAZ population	0	0.0053	0.0012	0.0012
Urban Form & Transit Accessibility Factor Score	-1.5070	4.4804	0.1750	1.0201

N = 463

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)

**Table 23 Descriptive Statistics for All Cities: Work Trips—Bicycle Model (All Trips Less than 5 Miles)**

	Descriptive Statistics			
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.2	4	0.9531	0.3336
Total number of bicycles in household	0	9	1.3857	1.4957
Part 1 Property crimes/TAZ population	0	0.41	0.0240	0.0289
Urban Form & Transit Accessibility Factor Score	-1.5194	7.2021	0.2700	1.0989

**Table 23 Descriptive Statistics for All Cities: Work Trips—Bicycle Model (All Trips Less than 5 Miles)**

Descriptive Statistics				
	Minimum	Maximum	Mean	Standard Deviation
N = 2666				

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1454)

**Table 24 Descriptive Statistics for All Cities Except Richmond: Non-Work Trips—Bicycle Model (Trips Less than 5 Miles)**

Descriptive Statistics				
	Minimum	Maximum	Mean	Standard Deviation
Total number of vehicles per licensed driver in household	0.2	4	0.9789	0.3455
Total number of bicycles in household	0	11	1.3643	1.5692
Part 1 Property crimes/TAZ population	0	0.41	0.0238	0.0252
Urban Form & Transit Accessibility Factor Score	-1.5194	5.7514	0.1811	1.0519
N = 5275				

Source: Census 2000, Metropolitan Transportation Commission 2000 Transit Analysis Zones (1554)



## MODELING RESULTS

### TRANSIT MODEL FACTOR ANALYSIS

The dataset used for each factor analysis run was defined by selecting all trip records in the transit trips dataset with trip origins in the group of study cities being analyzed (i.e., trips with origins in San Francisco for the San Francisco model, Oakland or Berkeley for the Oakland & Berkeley model, and Walnut Creek, Santa Clara, Concord, or Sunnyvale for the Suburbs Only model, and the same suburban cities minus Sunnyvale for the Suburbs Not Sunnyvale model).

The factor loadings for each factor analysis output variable and the variance in the input variables explained by the factor analysis component variables is shown in [Table 25](#).

**Table 25 Urban Form & Transit Accessibility Factor Analysis Component Loading for Transit Model Runs**

Variables	Component Factor Loadings			
	SF Only	Oakland & Berkeley	Suburbs Only	Suburbs Not Sunnyvale
Jobs+Pop Density	0.794	0.747	0.732	0.792
4-legged intersections per acre	0.844	0.819	0.784	0.818
Transit accessibility	0.716	0.617	0.698	0.571
% of variance explained	61.8	53.7	54.6	54.1

Extraction Method: Principal Component Analysis

In general, the component loading values for all four models/city groupings show that the Jobs+Pop Density and the four-legged Intersection per Acre variables have the highest factor loading coefficients and, therefore, generally have the dominant role in contributing to the final factor variable score. The relative contribution of the Transit Accessibility variable varies in importance from city grouping to city grouping, attaining its maximum influence for the San Francisco Only model and the lowest for the Suburbs Not Sunnyvale model. The variability in the input variables explained by the component output variable ranges from roughly 54 to 62 percent.

Factor scores for each component were saved as variables in the pedestrian/bicycle dataset and used as independent variables in the pedestrian and bicycle binary logistic model runs.

### PEDESTRIAN AND BICYCLE MODEL FACTOR ANALYSIS

The dataset used for each factor analysis run was defined by selecting all trip records in the pedestrian/bicycle trips dataset with trip origins in the group of study cities being analyzed

(i.e., trips with origins in San Francisco for the San Francisco model, Oakland or Berkeley for the Oakland & Berkeley model, and Walnut Creek, Santa Clara, Concord, or Sunnyvale for the Suburbs Only model, and all of these cities together for the All Cities model [used only for the bicycle mode choice model runs because there were not enough bicycle trip records in the BATS 2000 dataset to perform model runs for individual cities or city sub-groupings]).

The factor loadings for each factor analysis output variable and the variance in the input variables explained by the factor analysis component variables are shown in Table 26.

**Table 26 Urban Form & Transit Accessibility Factor Analysis Component Loadings for Pedestrian & Bicycle Model Runs**

Variables	Component Factor Loadings			
	SF Only	Oakland & Berkeley	Suburbs Only	All Cities
Jobs + Pop density	0.845	0.737	0.737	0.780
4-legged intersections per acre	0.790	0.822	0.822	0.706
Transit accessibility	0.716	0.609	0.609	0.703
% of variance explained	61.7	53.0	53.4	59.0

Extraction Method: Principal Component Analysis

In general, the component loading values for all four models/city groupings show that the Jobs+Pop Density and the four-legged Intersection per Acre variables have the highest factor loading coefficients and, therefore, generally have the dominant role in contributing to the final factor variable score. The relative contribution of the Transit Accessibility variable varies in importance from city grouping to city grouping, attaining its maximum influence for the San Francisco Only model and the lowest for the Oakland & Berkeley and Suburbs Only models. In the All Cities model, the component loading coefficient for Transit Accessibility is roughly on par with those for the other two variables. The variability in the input variables explained by the component output variable ranges from roughly 53 to 62 percent.

Factor scores for each component were saved as variables in the pedestrian/bicycle dataset and used as independent variables in the pedestrian and bicycle binary logistic model runs.

## BINARY LOGISTIC MODEL RUN RESULTS

### Transit Work Trip Logistics Model Results

Because transit trips are typically more than a half-mile in length, trip records were selected for all transit mode choice analysis model runs a half-mile in length or longer, regardless of the mode of travel reported. Four separate models were run. As mentioned earlier, only Part 1 crime data were available for San Francisco and for Sunnyvale whereas both Part 1 and Part 2 crime data were available for Berkeley, Oakland, Walnut Creek, Santa Clara, and Concord.

Hence, a separate model, examining the impacts of both Part 1 and Part 2 crimes, was run for Berkeley, Oakland, Walnut Creek, Santa Clara, and Concord.

**Table 27 Binomial Logistic Regression Results for Transit Work Trips**

	SF Only	Oakland & Berkeley	Suburbs Only	Walnut Creek/Santa Clara/Concord
<b>Household Income</b>				
Under \$15,000	-0.1497	-1.0773	1.0294	0.7684
\$15,000–49,000	-0.1138	-0.3764*	-0.3665	-0.4985*
\$50,000–74,999	0.1981	-0.3005	-0.1411	-0.3386
Over \$75,000	Referent	Referent	Referent	Referent
Household vehicles per licensed driver	-1.2430** *	-1.2117** *	-.06954	-0.7963***
Household bicycles	-0.2016** *	-0.0412	-0.1009	-0.1113
<b>Age</b>				
19–39 years	Referent	Referent	Referent	Referent
40–59 years	-0.3163**	-0.4166**	-0.5242**	-0.4245
Over 59 years	-0.8961**	-1.0936**	-1.3301**	-1.1899**
Gender (1= Male, 0 = Female)	0.0899	0.0457	-0.1510	-0.0917
Householder (HHR) (1=HHR, 0=Non-HHR)	0.1131	0.2486	0.3460*	0.3821*
Race (1= White, 0= Non-White)	-0.3205**	-0.3791**	0.0629	0.0099
Urban Form & Transit Accessibility Factor Score	0.0656	0.127	-0.6142** *	-.05879***
Violent Crimes per Person	N/A	N/A	-67.8786	N/A
Property Crimes per Person	2.7136	1.0748	N/A	N/A
Vice Crimes per Person	N/A	N/A	N/A	-51.2522*
Constant	0.3779	0.0812	-1.4331** *	-0.7554
N	1392	1111	1903	1162
Nagelkerke R Square	0.125	0.078	0.078	0.097

Notes:

\* =  $p < 0.10$

\*\* =  $p < 0.05$

\*\*\* =  $p < 0.01$

N/A = Not applicable

### *Goodness of Fit*

Nagelkerke R<sup>2</sup> results for the four transit logistic model runs indicate that the models explain between 8 and 13 percent of the variation in the dataset.

### *Household Income Results*

While household income is generally thought to play an important role in determining mode choice, among the four binary mode choice models run to predict transit work trips, the income dummy variables were statistically insignificant on two occasions—in the Oakland & Berkeley model and in the Walnut Creek/Santa Clara/Concord model—where the people with incomes between \$15,000 and \$49,999 were found to have a lower probability of taking transit to work than those with incomes greater than \$75,000. These counter-intuitive negative and statistically insignificant findings may suggest that if transit is available and then controlling for other exogenous factors such as age and race, people of all income groups are equally likely to use it.

### *Household Vehicle and Bicycle Availability Results*

Consistent with our theoretical assumptions, the higher the number of vehicles, the less likely a household member will choose to take transit to work. The variable measuring the number of household vehicles per licensed driver had a negative sign and was highly statistically significant for all four transit work trip models. The variable measuring the number of bicycles per household was statistically significant only for the San Francisco model, indicating that bicycles might not be a very good substitute for transit except for very dense urban environments such as those found in San Francisco.

### *Person Age Results*

Consistent with our theoretical assumptions, taking transit to work appears to be an activity for the young. In all four city groupings' model runs, dummy variables representing people aged 40 years and older were generally statistically significant, and all age variables possessed negative signs. These findings suggest that in general, people aged 19 to 39 years are more likely to take transit to work than those who are older.

### *Gender Results*

Results for the Gender (Male) dummy variable from all four models were statistically insignificant, indicating that gender does not play an important role influencing transit mode choice in these city groupings.

### *Householder Status*

Those who were identified in the BATS 2000 survey as the “householder” were represented in the analysis datasets with a “1” whereas all other survey participants received a “0.” This variable was statistically insignificant for the San Francisco, and Oakland & Berkeley models. However, those from the suburbs who identified themselves as the “householder” were significantly less likely to take transit to work than were other household members. This finding suggests that the more limited modal options in the suburbs (i.e., higher car dependence) affects the most “time-starved” and busy persons in the typical household—the householder.

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### *Race Variable Results*

Those who were identified in the BATS 2000 survey as “White” or “Caucasian” were represented in the analysis datasets with a “1” whereas all other survey participants received a “0.” Results for this variable for the San Francisco only model and for the Oakland & Berkeley model were statistically significant, indicating that in San Francisco and in Berkeley and Oakland, white residents are less likely to take transit to work. For the models run on suburban cities, this variable was statistically insignificant, indicating that race does not play an important role influencing transit mode choice in these city groupings.

### *Urban Form & Transit Accessibility Factor Score Variable Results*

Because the variables developed to represent various aspects of urban form and transit accessibility were found in initial model runs to be collinear, we used factor analysis to develop a combined factor score variable that represents all three of these individual variables (See description of how these variables were developed for each city grouping/model run in the “Pedestrian and Bicycle Model Factor Analysis” section). For all two of the four transit model runs, this factor variable was statistically significant at the  $p = .01$  level or better and possessed a counter-intuitive negative sign. Our theoretical assumption was that the higher the urban form/accessibility variable score, the more likely a household member is to take transit to work from all four city groupings/model runs; however, the models findings suggest that this variable either had no or counter-intuitive negative impact on the probability that a resident will take transit to work. To determine the specific urban form/accessibility component variable or variables that may be causing this counter-intuitive result, we ran the work model without the urban form/accessibility factor variable and instead entered in the component variables of this factor variable. We found that while the transit accessibility variable had a positive sign and was statistically significant, the population density and four-legged intersection density variables had negative signs and were statistically significant. From these exploratory model runs, we determined that the two density (i.e., population and intersection) variables were causing the factor variable to have a negative sign. Because the variables only had negative signs for the two suburban cities’ transit model runs, we interpreted these findings as indicative of the unique land use and street network configurations in suburban TAZs with high levels of transit service (and transit ridership). Because all four of our suburban study cities (Walnut Creek, Concord, Sunnyvale, and Santa Clara) have either BART or light rail stations, and because the TAZs for these station neighborhoods are likely to have some of the highest levels of transit ridership in these cities, they also have counter-intuitive relationships between urban form and the propensity for residents to choose transit. Furthermore, these high transit service/high transit ridership suburban TAZs tend to have freeways running adjacent to or surrounding their rail transit stations (e.g., in Walnut Creek and Concord), with park-and-ride lots surrounding these stations, and/or tend to be located in TAZs dominated by employment uses and low-density, arterial street networks. Therefore, while the proximity of rail transit stations tends to increase the probability that people living in these zones will choose transit, the dominance of suburban, auto-oriented development



patterns there result in low population densities, low four-legged intersection densities, and a negative relationship between these two variables and the probability of choosing transit for work trips.

### *Neighborhood Crime Rate Variable Results*

Neighborhood crime variables were selected for each model run based on performance in preliminary modeling exercises and on theoretical considerations. For three models—San Francisco Only; Oakland & Berkeley; and Suburbs Only—crime variables calculated as the number of crimes per TAZ resident/population tended to yield statistically significant results. For the Walnut Creek/Santa Clara/Concord model, the number of crimes per TAZ resident/population plus the number of TAZ employees yielded statistically significant results. For the San Francisco Only and the Oakland & Berkeley model runs, property crime rates were found to yield the best results; for the Suburbs Only model run, violent crime rates worked best; and for the Walnut Creek/Santa Clara/Concord model, vice crime rates worked best.

For three of the four model runs—San Francisco Only, Oakland & Berkeley, and Suburbs Only—the crime variables were statistically insignificant. The crime variable, measured as vice crime rate per TAZ, was statistically highly significant for the Walnut Creek/Santa Clara/Concord model and possessed a theoretically expected negative sign. These results suggest that although Part 1 crimes do not seem to impact the probability of a resident taking transit to work, certain Part 2 crimes (e.g., vice and vagrancy crimes in the case of Walnut Creek/Santa Clara/Concord model) may be associated with a lower probability of a neighborhood resident taking transit to work. We think it is important for future studies to estimate the impact of all crime types, not just major violent and property crimes (i.e., Type 1 crimes), on residents' probability of taking transit for work trips.

### **Non-Work Transit Trip Logistic Regression Analysis**

Since transit trips are typically more than a half-mile in length, trip records were selected for all transit mode choice analysis model runs a half-mile in length or longer, regardless of the mode of travel reported. Four separate models were run. As mentioned earlier, only Part 1 crime data were available for San Francisco and for Sunnyvale whereas both Part 1 and Part 2 crime data were available for Berkeley, Oakland, Walnut Creek, Santa Clara, and Concord. Hence, a separate model examining the impacts of both Part 1 and Part 2 crimes was run for Berkeley, Oakland, Walnut Creek, Santa Clara, and Concord.

**Table 28 Binomial Logistic Regression Results for Transit Non-Work Trips**

	SF Only	Oakland & Berkeley	Suburbs Only	Walnut Creek/Santa Clara/Concord
<b>Household Income</b>				
Under \$15,000	0.7648**	-0.0655	3.1275***	3.5688***
\$15,000–49,999	0.3985**	0.3063	0.9024**	0.9549*
\$50,000–74,999	-0.1806	0.0394	0.1937	0.4395
Over \$75,000	Referent	Referent	Referent	Referent
Household vehicles per licensed driver	-1.2599** *	-2.0745** *	-1.5337	-0.9428
Household bicycles	-0.1086	-0.1356	-0.0170	-0.0565
<b>Age</b>				
19–39 years	Referent	Referent	Referent	Referent
40–59 years	-0.1919	-0.5637**	-0.8456*	-0.8470
Over 59 years	-0.6924**	-0.6471*	-0.2097	-0.4092
Gender (1 = Male, 0 = Female)	-0.4141** *	-0.2763	-0.2097	-0.1819
Householder (HHR) (1 = HHR, 0 = Non-HHR)	-0.1530	0.2817	-0.0756	0.0879
Race (1 = White, 0 = Non-White)	-0.3934**	-.6633***	0.4286	0.1276
Employed (1 = yes, 0 = no)	0.0210	-0.1013	-0.1104	-0.0214
Urban Form & Transit Accessibility Factor Score	-0.0145	0.0674	-0.0858	0.22152
Violent crimes per person	N/A	N/A	-149.0680	N/A
Property crimes per person	5,2930	-3.0513	N/A	N/A
Vice crimes per person	N/A	N/A	N/A	-87.4330
Constant	-0.7185**	-0.1436	-2.6405	0.2152
N	1533	1621	2258	1511
Nagelkerke R Square	0.130	0.170	0.082	0.106

Notes:

\* =  $p < 0.10$ \*\* =  $p < 0.05$ \*\*\* =  $p < 0.01$ 

N/A = Not applicable

### *Goodness of Fit*

Nagelkerke R<sup>2</sup> results for the four non-work trip purpose transit logistic model runs indicate that the model runs explained between 8 and 17 percent of the variation in the dataset.

### *Household Income Results*

The four binary mode choice models run to predict transit non-work trips found that the income dummy variables were generally statistically significant, indicating that lower income residents are more likely to take transit for non-work trips. However, the findings were statistically insignificant for the Oakland & Berkeley model.

### *Household Vehicle and Bicycle Availability Results*

Consistent with our theoretical assumptions and the findings from the work trip transit models, the higher the number of vehicles available to the household, the less likely a household member will choose to take transit for non-work purposes. However, availability of bicycles, except for the Oakland & Berkeley model, did not seem to have a statistically significant impact on residents' probability of taking transit for non-work trips. The overall findings for the availability of bicycles are consistent with the transit work models: a bicycle does not seem to be a viable alternative to taking transit.

### *Person Age Results*

Consistent with our theoretical assumptions and the pedestrian work trip model runs, taking transit for non-work trips appears to be primarily for the young. In three of four city groupings' model runs, dummy variables representing people aged 40 to 59 years were statistically significant (with the exception of Suburbs Only model) and possessed negative signs. In two of four city groupings' model runs, dummy variables representing people aged 59 years and older were statistically significant (with the exception of the Suburbs Only model and the Walnut Creek/Santa Clara/Concord model) and possessed negative signs. These findings suggest that in general, people aged 19 to 39 years are more likely to take transit for non-work trips than those who are older.

### *Gender Results*

Results for the Gender (Male) dummy variable for three of four models were statistically insignificant, indicating that gender does not play an important role influencing transit mode choice in these city groupings. The gender variable was statistically significant and possessed a positive sign for the San Francisco model, indicating that males are more likely to take transit to non-work activities in San Francisco.

### *Householder Status*

This variable was statistically insignificant for all four city groupings' model runs, suggesting that this variable is not useful for predicting the mode choice of non-work trips.

### *Race Variable Results*

Results for this variable for the suburban cities models for non-work transit model runs were statistically insignificant, but highly significant (at the  $p < .05$  level and above) and negative for the San Francisco Only model and the Oakland & Berkeley model. This finding suggests that survey participants who identified themselves as "White" were less likely than people who described themselves as members of some Non-White category to take transit to non-work activities in San Francisco and in Oakland & Berkeley. This may be due to the fact that a large majority of the non-white population in these large urban cities are African American—a group very likely to be the primary user of transit for non-work activities.

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### *Employment Status Variable Results*

Those persons identified as “employed” in the survey were represented with a “1” while all other survey participants were coded with a “0.” Results for this variable were statistically insignificant for all transit non-work trip model runs.

### *Urban Form & Transit Accessibility Factor Score Variable Results*

Contrary to our theoretical assumptions, the urban form & accessibility variable score did not have a statistically significant impact on residents’ probability of taking transit to non-work activities in any of the four models.

### *Neighborhood Crime Rate Variable Results*

Neighborhood crime variables were selected for each model run based on performance in preliminary modeling exercises and on theoretical considerations. For three models—San Francisco Only, Oakland & Berkeley, and Suburbs Only—crime variables calculated as the number of crimes per TAZ resident/population tended to yield statistically significant results. For the Walnut Creek/Santa Clara/Concord model, the number of crimes per TAZ resident/population plus the number of TAZ employees yielded statistically significant results. For the San Francisco Only and Oakland & Berkeley model runs, property crime rates were found to yield the best results; for the Suburbs Only model run, violent crime rates worked best; and for the Walnut Creek/Santa Clara/Concord model, vice crime rates worked the best.

Consistent with the findings of the transit work-trip model runs, for three of the four model runs for the transit non-work trips—San Francisco Only, Oakland & Berkeley, and Suburbs Only—the crime variables were statistically insignificant. The crime variable, measured as vice crime rate per TAZ, was statistically highly significant for the Walnut Creek/Santa Clara/Concord model and possessed a theoretically expected negative sign. These results suggest that although Part 1 crimes do not seem to impact the probability of a resident taking transit for non-work trips, certain Part 2 crimes (e.g., vice and vagrancy crimes in the case of the Walnut Creek/Santa Clara/Concord model) may be associated with a lower probability of a neighborhood resident taking such transit trips. We think it is important for future studies to estimate the impact of all crime types, not just major violent and property crimes (i.e., Type 1 crimes), on residents’ probability of taking transit for non-work trips.

### **Pedestrian Work Trip Logistic Model Results**

Because walk trips are typically less than 1 mile in length, trip records were selected for all pedestrian mode choice analysis model runs 1 mile in length or shorter, regardless of the mode of travel reported.

**Table 29 Binomial Logistic Regression Results for Transit Non-Work Trips**

Variable	SF Only	Oakland & Berkeley	Suburbs Only
<b>Household income</b>			
Under \$15,000	N/D	-0.7859	-15.9758
\$15,000–49,000	-0.800	-0.2919	1.5469**
\$50,000–74,000	-0.4008	-0.0719	1.7556***
Over \$75,000	Referent	Referent	Referent
Household vehicles per licensed driver	-1.1895**	-1.1291** *	-2.4607**
Household bicycles	-0.3175**	-0.3381** *	-0.2925*
<b>Age</b>			
19–39 years	Referent	Referent	Referent
40–59 years	-0.1488	-0.8163** *	-0.9891*
Over 59 years	-2.4040** *	-2.2562** *	-0.4527
Gender (1 = Male, 0 = Female)	0.2374	0.1712	-0.6456
Householder (HHR) (1 = HHP, 0 = Non-HHR)	0.2078	0.1786	-1.1310**
Race (1 = White, 0 = Non-White)	0.6191	0.2614	0.6697
Urban Form & Transit Accessibility Factor Score	0.6004**	-0.4806** *	0.5460**
Violent crimes per person	N/A	N/A	-277.3119 *
Property crimes per person	-21.43323	-12.0730* *	N/A
Constant	2.7785***	2.7978	2.0275
N	247	443	129
-2 Log likelihood	209.74	443	129
Nagelkerke R Square	0.217	0.260	0.394

Notes:

\* =  $p < 0.10$ \*\* =  $p < 0.05$ \*\*\* =  $p < \text{Not Applicable}$ 

N/D = No Data

*Goodness of Fit*

While the Nagelkerke R<sup>2</sup> results for the three pedestrian logistic model runs indicate that their predictive power is relatively low, our experience with these models and similar model results from our review of the literature suggests that this model is performing at a high level, explaining between 22 and 39 percent of the variation in the dataset.

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### *Household Income Results*

While household income is generally thought to play an important role in determining mode choice, the three binary mode choice models run to predict pedestrian work trips found that the income dummy variables were statistically significant only in the Suburbs model, where people from households with incomes between \$15,000 and \$75,000 per year have a higher probability of walking to work than do those with higher household incomes. The lack of statistically significant findings for more urban city models (i.e., the San Francisco and Berkeley & Oakland models) might suggest that due to the relative lack of pedestrian- and transit-friendly environments and infrastructure in suburban cities, those with low or moderate incomes are more likely to get out of their cars and walk to work as a way to save on commute costs.

### *Household Vehicle and Bicycle Availability Results*

Consistent with our theoretical assumptions, the higher the number of vehicles and bicycles available to the household, the less likely a household member will choose to walk to work. These two variables had a negative sign and were highly statistically significant for all three pedestrian work trip models.

### *Person Age Results*

Consistent with our theoretical assumptions, walking to work appears to be an activity for the young. In all three city groupings' model runs, dummy variables representing people aged 40 years and older were generally statistically significant (with the exception of ages 40 to 59 in the San Francisco Only model and those over 59 in the Suburbs Only model), and all age variables possessed negative signs. These findings suggest that in general, people aged 19 to 39 years are more likely to walk to work than are those who are older.

### *Gender Results*

Results for the Gender (Male) dummy variable from all three models were statistically insignificant, indicating that gender does not play an important role in influencing pedestrian mode choice in these city groupings.

### *Householder Status*

This variable was statistically insignificant for the San Francisco Only and Oakland & Berkeley Only models. However, those from the suburbs who identified themselves as the “head of the household” were significantly less likely to walk to work than other household members. This finding suggests that the more limited modal options in the suburbs (i.e., higher car dependence) affects the most “time-starved” and busy persons in the typical household—the householder.

### *Race Variable Results*

Results for this variable from all three models were statistically insignificant, indicating that race does not play an important role in influencing pedestrian mode choice in these city groupings.

### *Urban Form & Transit Accessibility Factor Score Variable Results*

Because the variables developed to represent various aspects of urban form and transit accessibility were found in initial model runs to be collinear, we used factor analysis to develop a combined factor score variable that represents all three of these individual variables (See description of how these variables were developed for each city grouping/model run in the “Pedestrian and Bicycle Model Factor Analysis” section). For all three pedestrian model runs, this factor variable was statistically significant at the  $p = .05$  level or better and possessed a positive sign. Therefore, consistent with our theoretical assumptions, the higher the urban form/accessibility variable score, the more likely a household member is to walk to work from all three city groupings/model runs. This suggests that neighborhoods with a high density of population and employment, with a traditional grid street network (with a high density of four-legged intersections), and with high transit accessibility tend to increase the probability that a resident will walk to work. These consistent findings also suggest that our factor analytic variable has effectively mitigated the multicollinearity problems found between the three urban form/accessibility variables.

### *Neighborhood Crime Rate Variable Results*

Neighborhood crime variables were selected for each model run based on performance in preliminary modeling exercises and on theoretical considerations. For all pedestrian model runs, crime variables calculated as the number of crimes per TAZ resident/population tended to yield statistically significant results consistent with our theoretical expectations more than those calculated as the number of crimes per TAZ resident/population plus the number of TAZ employees. For the San Francisco Only and Oakland & Berkeley Only model runs, property crime rates were found to yield the best results whereas for the Suburbs Only model run, violent crime rates worked best.

Of the three model runs, the crime variables were statistically significant and possessed a negative sign for the Oakland & Berkeley Only and Suburbs Only model runs. While the crime variable in the San Francisco Only model run was statistically insignificant, its sign also was negative, lending some consistency to the results for this variable across the three model runs. These results suggest that higher crime rates were associated with a lower probability of a neighborhood resident walking to work.

## Non-Work Pedestrian Trip Logistic Regression Analysis

Because walk trips are typically less than 1 mile in length, trip records were selected for all pedestrian mode choice analysis model runs 1 mile in length or shorter, regardless of the mode of travel reported.

**Table 30 Binomial Logistic Regression Results for Pedestrian Non-Work Trips**

Variable	SF Only	Oakland & Berkeley	Suburbs Only
<b>Household income</b>			
Under \$15,000	0.0357	0.2101	-0.3486
\$15,000–49,000	0.2084	-0.8301** *	0.3863
\$50,000–74,999	0.2127	-0.1752	0.4254
Over \$75,000	Referent	Referent	Referent
Household vehicles per licensed driver	-0.4380	-1.1127** *	-1.0848*
Household bicycles	-0.0551	-0.1265**	-0.0662
<b>Age</b>			
19–39 years	Referent	Referent	Referent
40–59 years	-0.3431*	-0.2984	-0.5468*
Over 59 years	-1.1220** *	-0.9909** *	-1.2944** *
Gender (1 = Male, 0 = Female)	-0.1073	0.0424	-0.0975
Householder (HHR) (1 = HHR, 0 = Non-HHR)	-0.1612	0.3166	-0.0887
Race (1 = White, 0 = Non-White)	0.6159***	0.0379	0.2188
Employed (1 = Yes, 0 = No)	-0.3293	-0.2009	-0.4689
Urban Form & Transit Accessibility Factor Score	0.1361	0.7186***	0.3724***
Violent crimes per person	N/A	N/A	-57.8984
Property crimes per person	31.4834**	-2.7835	N/A
Constant	0.5965	1.1880**	0.1739
N	605	544	373
-2 Log likelihood	772.23	658.52	328.21
Nagelkerke R Square	0.091	0.192	0.133

Notes:

\* =  $p < 0.10$

\*\* =  $p < 0.05$

\*\*\* =  $p < 0.01$

N/A = Not Applicable

N/D = No Data

### Goodness of Fit

Nagelkerke R<sup>2</sup> results for the three non-work trip purpose pedestrian logistic model runs indicate that their predictive power is low compared to that found for the pedestrian work trip model runs. While the work trip model runs explained between 22 and 39 percent of the



variation in the dataset, the non-work trip model runs explained between 9 and 13 percent. In general, our experience is that non-work mode choice models tend to have somewhat lower goodness-of-fit results than do the work trip models. From a theoretical perspective, this makes sense because work trips are more regimented in terms of their origins, destinations, trip times, and travel choices available and therefore lead to a more consistent choice of travel mode.

### *Household Income Results*

Similar to the findings from the work trip pedestrian models, the three binary mode choice models run to predict pedestrian non-work trips found that the income dummy variables were generally statistically insignificant. For the non-work pedestrian models, the only statistically significant finding for these variables was in the Oakland & Berkeley model, where people from households with incomes between \$15,000 and \$75,000 per year have a lower probability of walking to work than do those with higher household incomes. This finding is somewhat in contrast to the findings of a statistically significant, positive relationship from the suburban cities pedestrian work model for the same income category. These different findings may be due to the different lifestyles of those living in the older, more urban cities of Oakland and Berkeley versus those living in more suburban cities.

### *Household Vehicle and Bicycle Availability Results*

Consistent with our theoretical assumptions and the findings from the work trip pedestrian models, the higher the number of vehicles and bicycles available to the household, the less likely a household member will choose to walk for non-work activities. However, while all the work trip pedestrian models had statistically significant coefficients and negative signs for these two variables and while all the signs for these variables were negative for the non-work model runs, significant findings were only found for vehicle availability and household bicycles from the Oakland & Berkeley model and for the Household Vehicles per Licensed Driver for the suburban non-work model runs. The fewer number of statistically significant findings for the non-work pedestrian model runs most likely reflects the higher difficulty we have found in predicting non-work trip mode choice.

### *Person Age Results*

Consistent with our theoretical assumptions and the pedestrian work trip model runs, walking to non-work activities appears to be primarily for the young. In all three city groupings' model runs, dummy variables representing people ages 40 years and older were statistically significant (with the exception of ages 40 to 59 in the Oakland & Berkeley model), and all age variables possessed negative signs. These findings suggest that in general, people aged 19 to 39 years are more likely to walk to non-work activities than are those who are older.

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### *Gender Results*

Results for the Gender (Male) dummy variable from all three models were statistically insignificant, indicating that gender does not play an important role in influencing pedestrian mode choice in these city groupings.

### *Householder Status*

This variable was statistically insignificant for all three city groupings/model runs, suggesting that this variable is not useful for predicting the mode choice of non-work trips.

### *Race Variable Results*

Results for this variable for the Oakland & Berkeley and Suburbs Only non-work pedestrian model runs were statistically insignificant, but highly significant (at the  $p < .01$  level) and positive for the San Francisco Only model. This finding suggests that survey participants who identified themselves as “White” were more likely than people who described themselves as members of some Non-White category to walk to non-work activities in San Francisco.

### *Employment Status Variable Results*

Results for this variable were statistically insignificant for all pedestrian non-work trip model runs.

### *Urban Form & Transit Accessibility Factor Score Variable Results*

Consistent with our theoretical assumptions, the higher the urban form/accessibility variable score, the more likely a household member is to walk to non-work activities from the Oakland & Berkeley and Suburbs city groupings/model runs. This suggests that neighborhoods with a high density of population and employment, with a traditional grid street network (with a high density of four-legged intersections), and with high transit accessibility tend to increase the probability that a resident will walk to work. The fact that the San Francisco model did not produce a statistically significant finding for this factor variable may be explained by the relatively high levels of density and transit accessibility throughout that city. As a result, there is not enough meaningful variation in this factor variable to explain the differences in mode choice there.

### *Neighborhood Crime Rate Variable Results*

Neighborhood crime variables were selected for each model run based on performance in preliminary modeling exercises and on theoretical considerations. For all pedestrian model runs, crime variables calculated as the number of crimes per TAZ resident/population tended to yield statistically significant results consistent with our theoretical expectations more than those calculated as the number of crimes per TAZ resident/population plus the number of TAZ employees. For the San Francisco Only and Oakland & Berkeley Only model runs, property crime rates were found to yield the best results whereas for the Suburbs Only model run, violent crime rates worked best.

Of the three non-work model runs, the crime variables were statistically significant only for the San Francisco model and, contrary to our assumptions, possessed a positive sign indicating that higher property crime rates are associated with a higher probability of selecting transit for non-work trips. There are two major interpretations of this finding that we can offer. First, the variation of crime rates within a San Francisco TAZ may be high due to the very dense urban fabric in that city. The tendency of crimes to cluster into “hot spots” may mean that the calculation of crime rates using TAZ boundaries (which are drawn for the purposes of analyzing travel behavior and not crime patterns) is inappropriate for very dense urban environments. This dynamic leads to an “ecological fallacy” that might have resulted in a counter-intuitive sign for the crime variable.

A second explanation for this result is that it is due to residential self-selection. In general, there is a tendency of crimes to cluster in neighborhoods and along arterial streets with high transit accessibility. Often these neighborhoods and arterials have liquor stores and other uses that have a tendency to attract crimes, increasing their crime rates. While these higher crime rates would ordinarily dissuade residents from walking and using transit, in San Francisco most residents have chosen to live in this dense urban environment despite the high crime rates, possibly in part because they value the walkable neighborhoods and high levels of transit service. Therefore, people who live in San Francisco already have “discounted” the high crime rates in their neighborhoods and have decided that they will not be dissuaded from walking in them. As a result, neighborhoods in San Francisco with high crime rates also have high levels of pedestrian activities for non-work purposes, but the relationship does not appear to be causal.

### Work and Non-Work Bicycle Trip Logistic Regression Analysis

Overall, of the modes of travel recorded in the BATS 2000 dataset, bicycle trips had the fewest records. Because our study cities comprised only seven of the over one hundred city and county jurisdictions in the nine-county San Francisco Bay Area, the number of bicycle trip records was scarce. Accordingly, to ensure that we had an adequate number of bicycle trip records for the binary logistic regression model runs, we reasoned it necessary to group all study cities together into a single analysis pool. In addition, to maximize the number of bicycle trip records at our disposal to analyze, we reasoned that most bicycle trips are typically less than 5 miles in length. Trip records were selected for all bicycle mode choice analysis model runs 5 miles in length or shorter, regardless of the mode of travel reported.

**Table 31 Binomial Logistic Regression Results for Bicycle Trips—All Cities Work and Non-Work**

Variable	Work	Non-Work
<b>Household income</b>		
Under \$15,000	0.1681	1.3296**
\$15,000–49,999	1.0185***	0.5465*
\$50,000–74,999	0.5940**	0.9292***
Over \$75,000	Referent	Referent

**Table 31 Binomial Logistic Regression Results for Bicycle Trips—All Cities Work and Non-Work**

Variable	Work	Non-Work
Household vehicles per licensed driver	-1.1858** *	-1.0566** *
Household bicycles	0.6252***	0.4158
<b>Age</b>		
19–39 years	Referent	Referent
40–59 years	-0.7910** *	-1.0797
Over 59 years	-1.7768**	-2.3648** *
Gender (1 = Male, 0 = Female)	1.1912***	0.8114***
Householder (HHR) (1 = HHR, 0 = non-HHR)	-0.0883	-0.2730
Race (1 = White, 0 = Non-White)	06.881**	0.5788*
Employed (1 = Yes, 0 = No)	N/A	-0.2949
Urban Form & Transit Accessibility Factor Score	0.1894*	0.3017***
Property crimes per person	2.5631	4.0898
Constant	-4.6227	-4.3991** *
N	2323	4433
-2 Log likelihood	727.10	725.95
Nagelkerke R Square	0.262	0.241

Notes:

\* =  $p < 0.10$ \*\* =  $p < 0.05$ \*\*\* =  $p < 0.01$ 

N/A = Not Applicable

N/D = No Data

### *Goodness of Fit*

Nagelkerke R2 results for the work and non-work bicycle trip purpose logistic model runs indicate their predictive power is somewhat low compared to that found for the pedestrian work trip model runs and somewhat high compared to the pedestrian non-work runs. The work trip model run explained roughly 26 percent of the variation in the dataset whereas the non-work trip model run explained between 9 and 24 percent.

### *Household Income Results*

While the income dummy variables included in all the logistic model runs were generally statistically insignificant for the pedestrian model runs, they were virtually all statistically significant in the work and non-work bicycle trips models; the only insignificant finding was for the \$15,000 to \$49,000 income category in the work trip model. The signs for all the income category variables in these two models were positive, indicating that those persons from households earning less than \$75,000 a year are more likely to ride a bicycle for work and

non-work purposes than is a person from a higher income household. This suggests that people partially choose to ride a bicycle to save on travel costs.

### *Household Vehicle and Bicycle Availability Results*

Consistent with our theoretical assumptions and the findings from the work trip pedestrian models, the higher the number of vehicles per licensed driver in the household, the less likely a household member will choose to bicycle for work and non-work purposes. However, while all the work trip pedestrian models had negative signs for these two variables—consistent with our expectations—the positive sign for the Household Bicycles variable suggests that the more bicycles available to the household, the more likely a household member will choose to bicycle. However, because this variable was statistically significant only for the bicycle work trips model, we can only confirm this relationship for work trips.

### *Person Age Results*

Consistent with our theoretical assumptions and the pedestrian work and non-work trip model runs, people aged 19 to 39 years are more likely to choose riding a bicycle for both work and non-work trips than are people from older age groups. In both bicycle work and non-work trip models, dummy variables representing people 40 years and older were statistically significant and all age group dummy variables possessed negative signs. These findings suggest that in general, people 19 to 39 years of age are more likely to bicycle for all trip purposes than are those who are older.

### *Gender Results*

Results for the Gender (Male) dummy variable from both bicycle models were statistically significant at the  $p < .01$  level, indicating that males are more likely to ride bicycles for both work and non-work purposes than are females.

### *Householder Status*

This variable was statistically insignificant for both work and non-work bicycle model runs, suggesting that this variable is not useful for predicting the mode choice of bicycle trips.

### *Race Variable Results*

Results for this variable for both work and non-work bicycle model runs were highly significant (at the  $p < .01$  level) and positive. This finding suggests that survey participants who identified themselves as “White” were more likely than people who described themselves as members of some Non-White category to bicycle to both work and non-work activities in the study cities.

### *Employment Status Variable Results*

Results for this variable were statistically insignificant for the bicycle transit non-work trip model run.

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### *Urban Form & Transit Accessibility Factor Score Variable Results*

Consistent with our theoretical assumptions, the higher the urban form/accessibility variable score, the more likely a household member is to bicycle to both work and non-work activities in the study cities. These results suggest that neighborhoods with a high density of population and employment, with a traditional grid street network (with a high density of four-legged intersections), and with high transit accessibility tend to increase the probability that a resident will choose to bicycle.

### *Neighborhood Crime Rate Variable Results*

Neighborhood crime variables were selected for each model run based on performance in preliminary modeling exercises and on theoretical considerations. For all bicycle model runs, crime variables calculated as the number of crimes per TAZ resident/population tended to yield statistically significant results consistent with our theoretical expectations more than those calculated as the number of crimes per TAZ resident/population plus the number of TAZ employees. For the All Cities bicycle mode choice model runs, property crime rates were found to yield the best results. Of the work and non-work bicycle model runs, the crime variables were statistically insignificant.

## **SUMMARY AND CONCLUSIONS**

In general, this study found substantiation for the proposition that neighborhood crime rates have an influence on the propensity to choose non-automotive modes of transportation for home-based trips. Specifically, high Vice and Vagrancy crime rates were associated with a lowered probability of choosing transit in Walnut Creek, Concord, and Santa Clara for both work and non-work trips, high Part 1 Property crime rates were associated with a lower probability of walking for work trips in Oakland and Berkeley, high Part 1 Violent crime rates were associated with a lower probability of walking for work trips in the four suburban study cities, and higher Part 1 Property crime rates in San Francisco were associated with an increased probability of walking for non-work trips.

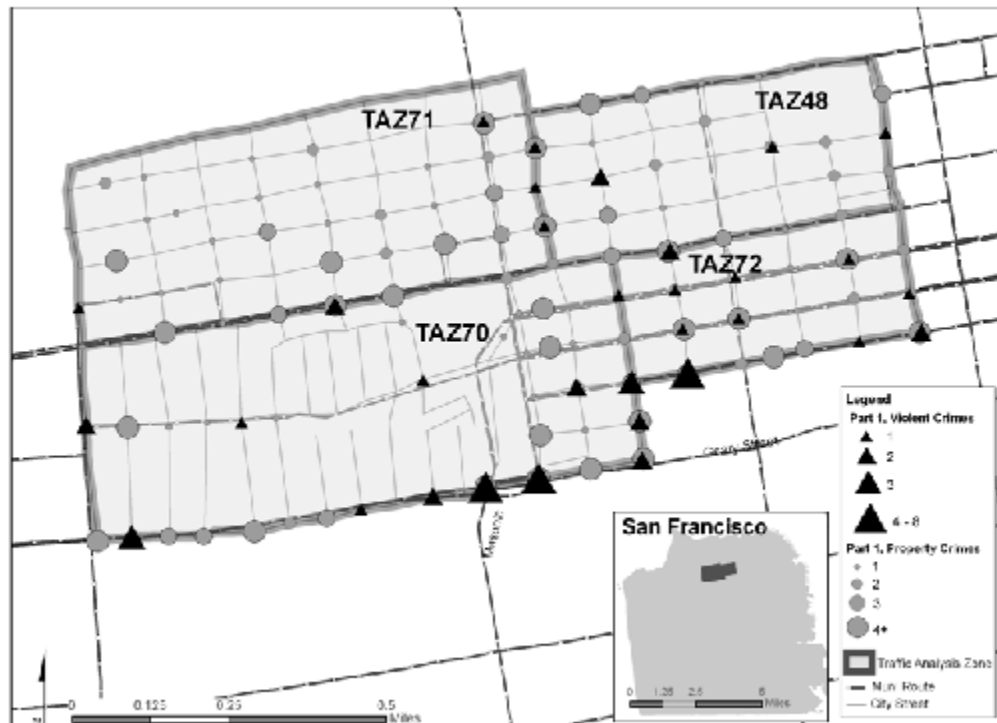
While the signs of these significant relationships conformed to our expectations (i.e., that high crime rates would tend to reduce the probability of people to choose non-automotive modes of travel), we did not find statistically significant relationships for all city/trip type model runs, suggesting that these relationships differ depending on the urban form and trip type contexts. This conclusion is further substantiated by the finding that different crime types were better predictive variables for certain city/trip type model runs, and by the positive, statistically significant relationship found for San Francisco non-work pedestrian trips. This San Francisco finding in particular challenged our assumptions about the nature of the relationship between neighborhood crime rates and mode choice. To fully understand this finding within the context of the other significant findings, which generally conformed to our expectations, will require additional and more focused research. However, we suspect that this finding is related to the very high densities of San Francisco coupled with the correlation between dense,

transit-rich neighborhoods, and high crime rates. In particular, we hypothesize that these urban transit neighborhoods in San Francisco attract residents who are aware of the crime challenges in these environments and, to some extent, have discounted these concerns for personal security. They have explicitly chosen to live in neighborhoods where they can enjoy the benefits of walkable, transit-rich, dense urban environments and have learned to live with or disregard the high crime rates in these areas. This spatial correlation is particularly pronounced with regard to violent crimes and is detectable in a visual examination of Figure 3. Violent Crimes, shown with black triangles, tend to cluster on or near main arterials, which also tend to carry transit service, shown with dashed lines. While significantly more dispersed, the gray circles, showing property crimes, tend to cluster near the transit lines as well, suggesting that blocks with high transit accessibility tend to also have a high incidence of crimes.

The difference between the distribution of crimes in these San Francisco TAZs and the distribution of crimes in four Oakland TAZs is detectable through comparison of [Figure 4](#) and [Figure 5](#).

In Oakland, there appears to be a greater distribution of both violent and property crimes throughout the city's TAZs, with only a slight spatial correlation between violent crimes and transit lines, and no detectable relationship between property crimes and transit lines.

Therefore, we suggest that our travel data sample for San Francisco suffers from a certain degree of self-selection bias in that a high proportion of this city's residents prefer non-auto modes of travel and choose to live in San Francisco—despite the challenges of its higher crime rates—to enjoy its high-quality transit and pedestrian-oriented environments. This would explain the counter-intuitive finding of a significant, positive relationship between crime rates and the probability of walking to non-work activities in San Francisco.

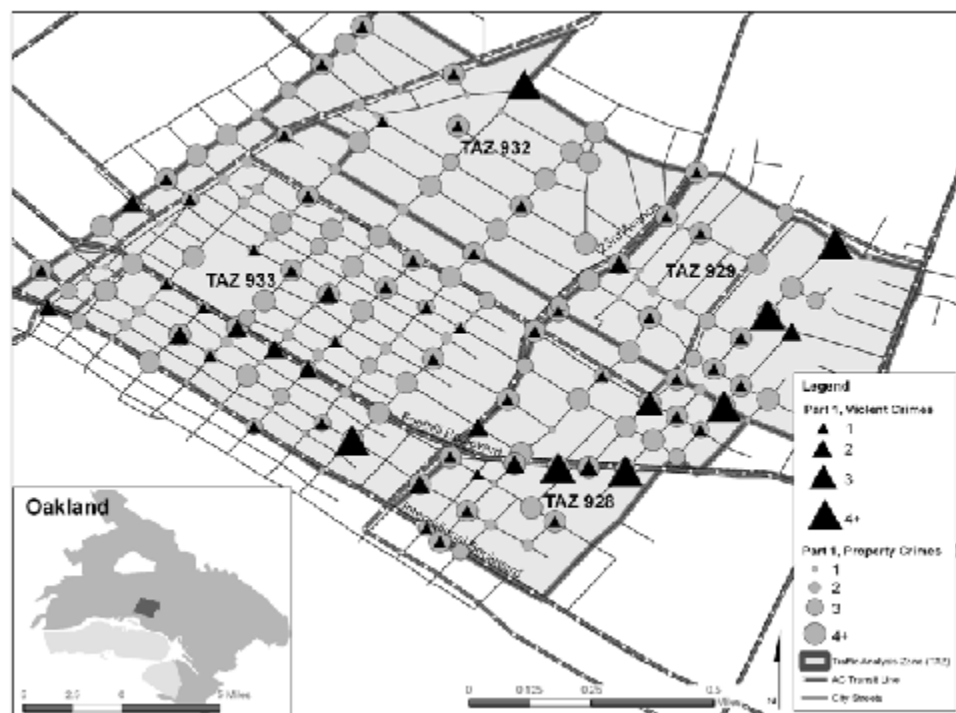


**Figure 4 Distribution of Part 1 Violent and Property Crimes in Four San Francisco TAZs**

In Oakland, there appears to be a greater distribution of both violent and property crimes throughout the city's TAZs, with only a slight spatial correlation between violent crimes and transit lines, and no detectable relationship between property crimes and transit lines.

Therefore, we suggest that our travel data sample for San Francisco suffers from a certain degree of self-selection bias in that a high proportion of this city's residents prefer non-auto modes of travel and choose to live in San Francisco—despite the challenges of its higher crime rates—to enjoy its high-quality transit and pedestrian-oriented environments. This would explain the counter-intuitive finding of a significant, positive relationship between crime rates and the probability of walking to non-work activities in San Francisco.





**Figure 5 Distribution of Part 1 Violent and Property Crimes in Four Oakland TAZs**

In addition to the possibility of self-selection bias, we also hypothesized that there may be difficulties associated with the measurement of crime rates using TAZs, particularly in dense, urban, transit-rich environments such as San Francisco. Due to the tendency of crimes to cluster along transit lines and where TAZ borders also tend to be drawn, crime “hot spots” may fall into zones where transit levels are high because the neighborhood overall has fewer crimes in its core residential areas. Because TAZs were drawn to describe travel behavior and not with reference to crime rates or distributions, the possibility exists that using TAZs to aggregate crimes is an “ecological fallacy,” where it is erroneously assumed that members of a group (e.g., individuals who live in a TAZ) exhibit the characteristics of the group at large (e.g., those represented by an aggregation of individuals in a TAZ).

This study has verified a statistically significant influence of neighborhood crime on the propensity to walk and ride transit. In three model runs, we found confirmation of our hypothesis that high crime rates are associated with a reduced propensity to walk or ride transit. In the San Francisco non-work trip model, we found a positive relationship between the propensity to walk and property crime rates—a finding for which we have proposed two hypothetical explanations. First, this could be the result of a self-selection bias in the BATS 2000 data in San Francisco, where those more likely to use transit and walk will cluster in neighborhoods with high transit accessibility and densities—the same neighborhoods where

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crime clusters or “hot spots” will occur. The second explanation is that there is an ecological fallacy at work in our use of TAZs to aggregate crime data because TAZs were not drawn to explain the spatial distribution of crimes.

Our analysis of the availability of crime data for use in transportation planning and policy research found that while the data collection and storage practices are improving, they are inconsistent and “spotty,” with considerable differences in data management and dissemination practices between jurisdictions. As discussed earlier, we strongly recommend that a national- or state-level policy be developed that would (perhaps as a supplement to the UCR system) encourage local police departments to digitally store historical crimes data. To encourage these activities, we see considerable opportunities for pilot-testing and joint funding of crime database improvements by research institutions, universities, non-profit organizations, and government agencies in cooperation with individual police departments and the criminal justice agencies within state and federal governments.

While the statistical results of this study show a significant effect of neighborhood crime rates on travel behavior, the difficulties in obtaining crime data from jurisdictions as well as some of the remaining questions we have that will require further study mean that at this time, we do not believe crime data should be routinely incorporated into travel demand modeling practices. Our recommendations for further research include a more disaggregated approach to measuring crimes, where crime hot spots are identified and the distances from these hot spots to the residences of each survey household are measured. More precise household locations may be available from MTC for BATS 2000 data—GIS locations that could provide a more precise measurement of a survey household’s distance to a crime hot spot. We further recommend investigation of the potential for a self-selection bias in San Francisco households. Additional survey work that collects travel, demographic, and attitudinal data could provide insights into whether San Francisco residents tend to be predisposed to travel by walking or transit, irrespective of the high crime conditions they may experience in their neighborhoods.

Finally, we recommend extending the analytic techniques explored here beyond home-based trips to include those with origins outside the home and developing crime, urban form, and transit accessibility variables for trip destinations as well as for trip origins. Such follow-up studies would improve the predictive strength of the models because it is likely that people choose modes of travel based on their perceived safety from crime at their trip’s destinations as well as their origins.



## APPENDIX A CRIME CATEGORIES

Table 32 Crime Categories

Part I Crimes	P1V	P1P	P2V	P2P	Broken Window	Vice, Vagrancy	Not Affect Walkability
Criminal homicide	X						
Forcible rape	X						
Robbery	X						
Aggravated assault	X						
Burglary		X					
Larceny-theft		X					
Motor vehicle theft		X					
Arson		X					
Part II Crimes	P1V	P1P	P2V	P2P	Broken Window	Vice, Vagrancy	Not Affect Walkability
Assault and battery			X				
Carjacking			X				
Injury by culpable negligence			X				
Kidnapping			X				
Minor assault			X				
Resisting or obstructing an officer			X				
Sex offenses			X				
Simple assault			X				
Unlawful use, possession, etc. of explosives			X				
Stolen property; Buying, receiving, possessing				X			
Vandalism					X		
Coercion						X	
Curfew and loitering laws						X	
Disorderly conduct						X	
Drug abuse violations						X	
Drunkenness						X	
Hazing						X	
Intimidation						X	
Prostitution						X	
Stalking						X	
Vagrancy						X	
Weapons: Carrying, possessing						X	
DUI							X
Embezzlement							X
Forgery and counterfeiting							X
Fraud							X

**Table 32 Crime Categories**

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<b>Gambling</b>	X
<b>Liquor laws</b>	X
<b>Offenses against the family and children</b>	X
<b>Runaways</b>	X
<b>Suspicion</b>	X
<b>Trespass</b>	X

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## APPENDIX B CITY PROFILES

### CITY OF BERKELEY

The city of Berkeley is described in the Census 2000 as having a population of 102,743, making it the fifth-largest city of the eight cities in this study. However, it ranks second in terms of population density after San Francisco, with a density of 9,823.2 persons per square mile. Its land area is 10.46 square miles. A summary of household incomes in Berkeley is shown in [Table 33](#).

**Table 33 Berkeley Household Income**

Household Income in 1999	Percent
Less than \$14,999	21.2
\$15,000–49,000	32.6
\$50,000–74,999	15.8
\$75,000 or more	30.4
Median household income (dollars)	44,485
Total households	45,007

Source: Census 2000

The Census 2000 data regarding Journey to Work for Berkeley reflects the commute patterns we would expect for a “university town.” It has the highest percentage of the eight cities of people who walk to work (14.9 percent) and bike to work (5.6 percent). Journey to Work Census data for Berkeley are summarized in [Table 34](#).

**Table 34 Berkeley Journey to Work Mode Share**

Mode	Percent
Car, truck, van or motorcycle	63.3
Public transportation	18.6
Bicycle	5.6
Walked	14.9
Other means	0.7
Worked at home	6.8

Source: Census 2000

A description of the density of intersections for Berkeley is provided in [Table 35](#). To measure the degree to which a city or neighborhood has a fine-grained, gridiron, walkable street network, we counted all the four-legged intersections within the study city boundaries. These counts were then divided by the total acreage of the city. In general, the density of

intersections for a city was related to the density of population per square mile—with high population density areas also having high density of four-legged intersections—though there were exceptions. Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings for all study cities. Berkeley is the second-most-dense study city, both in terms of population and intersections.

**Table 35 Berkeley Density of Intersections and Populations**

	4-legged intersections/ acre	4-legged intersections/ sq. mile	Density persons/acre	Density persons/sq. mile
Berkeley	0.1108	70.8823	15.35	9,823.20

Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000

The Berkeley Police Department (BPD) provided 12,818 records of crimes for the year 2000. Of these, 9,306 were used in the final analysis after the records were categorized and geocoded. A total of 5,798 Part 1 crimes and 3,508 Part 2 crimes were used for this study. A description of the types of crimes submitted by BPD is provided in [Table 36](#).

**Table 36 Berkeley Breakdown of Crimes by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
Berkeley # crimes	133	5,665	901	50	1,006	810	741
Berkeley # crimes/1000	1.2945	55.1376	8.7695	0.4867	9.7914	7.8837	7.2122
All cities # Crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471

Source: Crime data provided by Berkeley Police Department

\* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect propensity for biking and walking

\*\* Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.

Using our seven crime categories, only 8 percent of the data received from the City of Berkeley fell into the category we assumed would not affect the propensity to walk, bicycle, or use transit (i.e., “NOTAFFEC”)—the lowest of the eight cities in the study—well below the typical study city rate of 18.5 percent. Of these, at least 500 were either a liquor law violation, such as carrying an open container, or fraud including identity theft or forgery.

Berkeley records also showed the highest rate (60.8 percent) for Part 1 Property crimes (P1P) of the eight study cities. The P1P-type crimes which had the highest frequencies are shown in [Table 37](#).

**Table 37 Berkeley Part 1 Property Crimes with Highest Frequencies**

Description of crimes provided by Berkeley Police Department	Frequency
Theft (includes auto theft, grand theft, stolen vehicle)	3,141
Burglary (includes auto burglary)	2,099
Robbery	148

Source: Berkeley Police Department Crime Data 2000

Note: Figures aggregated from 12 Part I

Crime data received from the Berkeley Police Department also had the highest rate of Broken Window crimes at 11 percent. Of the 1,006 Broken Window crimes, 987 were for vandalism. No other study cities reported such a high percentage of crimes of vandalism. For example, Oakland reported that only 6 percent of its total reported crimes were Broken Window crimes.

## CITY OF CONCORD

The city of Concord is described in the Census 2000 as having a population of 121,780, making it the fourth-largest city of the eight cities in this study. This suburban city has a density of 4,041 persons per square mile, the third lowest of the study cities. The land area is 30.14 square miles. A summary of household incomes in Concord is shown in [Table 38](#).

**Table 38 Concord Household Incomes**

Household Income in 1999	Percent
Less than \$14,999	9.6
\$15,000–49,999	34.1
\$50,000–74,000	23.4
\$75,000 or more	32.9
Median household income (dollars)	55,597
Total households	44,111

Source: Census 2000

The Census 2000 data describing Journey to Work for Concord are summarized in [Table 39](#). As expected, Concord and the other suburban cities show high percentages for car travel and low percentages of travel by public transportation, walking, and bicycling.

**Table 39 Concord Journey to Work Mode Share**

Mode	Percent
Car, truck, van or motorcycle	83.4
Public transportation	9.6
Bicycle	1.0



**Table 39 Concord Journey to Work Mode Share**

Mode	Percent
Walked	1.7
Other means	1.0
Worked at home	3.2

Source: Census 2000

A description of the density of intersections for Concord is provided in [Table 40](#). Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings. Concord, a suburban city, has relatively low density with respect to population and intersections.

**Table 40 Concord Density of Intersections and Populations**

	4-legged intersections/acre	4-legged intersections/sq.mile	Density person/acre	Density persons/mile
Concord	0.013	8.33	6.31	4,041.00

Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000

The Concord Police Department provided 22,528 records of crimes and police activity for the year 2000. After records were removed which showed addresses for incidents outside of the city of Concord and the data were geocoded, 19,204 records remained. A total of 5,146 were Part 1 crimes, and 14,058 were Part 2 Crimes. A description of the types of crimes submitted by Concord Police is provided in [Table 41](#).

**Table 41 Concord Breakdown of Crimes by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
Concord # crimes	274	4,872	1,692	344	1,306	1,415	9,301
Concord # crimes/1000	2.2556	40.1062	13.9285	2.8318	10.751	11.6482	76.5656
All cities # crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471

Source: Crime Data provided by Concord Police Department

\* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect proponents for biking and walking

\*\* Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.

## CITY OF OAKLAND

The city of Oakland is the largest city in this study that provided both Part 1 and Part 2 crime data. Oakland provided the largest amount of data overall.

According to the 2000 Census, Oakland's population was 399,484 with a population density of 7,126.6 persons per square mile. It is the second-largest city of the eight cities with respect to population, but is surpassed in density by the city of Berkeley. The land area for Oakland is 56.06 square miles.

A summary of household incomes in Oakland is shown in [Table 42](#).

**Table 42 Oakland Household Income**

Household Income in 1999	Percent
Less than \$14,999	19.8
\$15,000–49,999	39.7
\$50,–74,999	16.8
\$75,000 or more	23.8
Median household income (dollars)	40,055
Total households	150,971

Source: Census 2000

Census 2000 data for Journey to Work for Oakland show 72.4 percent for use of car, truck, van, or motorcycle. This figure is comparable to that of Walnut Creek, a suburban city. Oakland's Journey to Work Census data are summarized in [Table 43](#).

**Table 43 Oakland Journey to Work Mode Share**

Mode	Percent
Car, truck, van or motorcycle	72.4
Public transportation	17.4
Bicycle	1.2
Walked	3.7
Other means	1.2
Worked at home	4.1

Source: Census 2000

A description of the density of intersections for Oakland is provided in [Table 44](#). To determine these numbers, four-legged intersections within the city boundaries were counted. These counts were then divided by the total acreage of the city. In general, the density of urban form, or density of intersections, was related to the density of population per square mile, though there were exceptions. Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings.

Oakland is surpassed by Santa Clara regarding density of intersections—a surprising fact because it is the third most dense study city after San Francisco and Berkeley regarding population, yet it is only the fifth most dense study city regarding density of intersections. Large sections of Oakland are hilly, lower density areas, which may explain this statistic.

**Table 44 Oakland Density of Intersections and Population**

	4-legged intersections/acre	4-legged intersections/sq. mile	Density persons/acre	Density persons/sq. mile
Oakland	0.0321	20.5494	1.11	7,126.60
Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000				

When compared to the other cities that submitted Part 1 and Part 2 crime data, the data provided by the City of Oakland Police Department were detailed and extensive. The initial file contained 193,131 “records” or lines of information, although this included supplemental data for crimes and records that were unusable when addresses were listed as “Unknown.” After geocoding, 68,513 records remained for the purposes of this study. These data were for the year 2000 and contained 22,552 Part 1 crimes and 45,961 Part 2 crimes. A description of the types of crimes submitted by Oakland Police is provided in [Table 45](#).

**Table 45 Oakland Breakdown of Crimes by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
Oakland # crimes	3,000	19,554	5,935	487	4,302	10,643	24,594
Oakland # crimes/1000	7.5098	48.944	14.8569	1.2191	10.7691	26.6423	61.5655
All Cities # crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471

Source: Crime data provided by Oakland Police Department

\* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect proponents for biking and walking

\*\* Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.

A total of 35.9 percent of the data received (n = 24,594 records) fell into the category of crimes considered to not affect the propensity of biking or walking (“NOTAFFEC”). Of the five cities that contributed Part 1 and Part 2 crimes, this is the second-lowest percentage after Berkeley’s eight percent. In contrast, Walnut Creek’s percentage of “NOTAFFEC” crimes is 83.6 percent. [Table 46](#) describes 11 of the 305 kinds of crimes we placed in the “NOTAFFEC” category in Oakland.

**Table 46 Oakland NOTAFFEC Crimes with Highest Frequencies**

Description	Frequency
Incidents of towed vehicles (including but not limited to driveway blocked, towaway zone, abandoned vehicle, etc.)	11,211
Towed vehicle (registration expired over 1 year)	5,919
Missing person	1,670
Missing parts needed to operate public street	1,4551
Annoying phone calls: repeated, threatening or obscene	1,427

**Table 46 Oakland NOTAFFEC Crimes with Highest Frequencies**

Description	Frequency
Runaway	918
Lost property	787
Found property	618
Hazard to traffic	509
Unexplained death	399
Forgery	305

Source: Oakland Police Department

Roughly 15 percent of the data received for Oakland (n = 10,643 records) were categorized as Vice and Vagrancy crimes (“VICEVAG”)—the highest of all the study cities. [Table 47](#) lists the top 15 highest frequency crimes from Oakland of the one hundred crimes placed in the “VICEVAG” category.

**Table 47 Oakland VICEVAG Crimes with Highest Frequencies**

Description	Frequency
Mental illness hold	3,187
Possess narcotic controlled substance	1,772
Disturb the peace	788
Use/under the influence of controlled substance	563
Possess/etc. base/rock cocaine for sale	552
Transport/sell narcotic controlled substance	516
Possess marijuana/hashish for sale	494
Possess controlled substance paraphernalia	466
Disorderly conduct: prostitution	422
Sell/furnish/etc. marijuana/hashish	278
Threaten crime with intent to terrorize	259
Possession or purchase for sale controlled substances	197
Possess marijuana 28.5 grams or less w/prior	158
Felon/addict/etc. possess firearm	131
Exhibit firearm	127
Exhibit deadly weapon: not firearm	102

Source: Oakland Police Department Crime Data 2000

Compare this list of crimes and frequencies to the fifteen highest frequency “VICEVAG” crimes from Walnut Creek (See [Table 65](#): “Walnut Creek VICEVAG Crimes with highest frequencies”). For Oakland, the count of “VICEVAG” crimes per 1,000 residents, 26.6423, is the highest of all the cities.

## CITY OF SAN FRANCISCO

The city of San Francisco, the largest city in this study, is described in the 2000 Census as having a population of 776,733. It also has the highest density with 16,634.4 persons per square mile. San Francisco's land area is 46.69 square miles.

A summary of household incomes in San Francisco is shown in [Table 48](#).

**Table 48 San Francisco Household Income**

Household Income in 1999	Percent
Less than \$14,999	14.8
\$15,00–49,999	30.8
\$50,000–74,999	17.7
\$75,000 or more	36.7
Median household income (dollars)	55,221
Total households	329,850

Source: Census 2000

For San Francisco, Census 2000 data regarding Journey to Work are strikingly different from any of the other cities, as is to be expected given its density and extensive public transportation system. It has the highest rate for use of public transportation for commuting (31.3 percent), and the lowest rate for use of car, truck, van, or motorcycle (52.2 percent). A total of 9.4 percent walk to work, which is the second-highest percentage for this category after Berkeley with 14.9 percent. Journey to Work Census data for San Francisco are summarized in [Table 49](#).

**Table 49 San Francisco Journey to Work Mode Share**

Mode	Percent
Car, truck, van or motorcycle	52.2
Public transportation	31.1
Bicycle	2.0
Walked	9.4
Other means	0.7
Worked at home	4.6

Source: Census 2000

A description of the density of intersections for San Francisco is provided in [Table 50](#). Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings. Of the eight study cities, San Francisco has the highest average population and intersection densities.

**Table 50 San Francisco Density of Intersections and Populations**

	4-legged intersections/acre	4-legged intersections/sq. mile	Density persons/acre	Density persons/sq. mile
San Francisco	0.1274	81.5485	25.99	16,634.40

Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000

The San Francisco Police Department (SFPD) provided 22,419 crime records for Part 1 crimes only. These data were for the year 2001 because year 2000 data were not available. San Francisco and Santa Clara were the only cities to provide 2001 data. Of the original data, 19,169 records were successfully geocoded and used for this study. A description of the types of crimes submitted by the SFPD is provided in [Table 51](#).

**Table 51 San Francisco Breakdown of Crimes by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
San Francisco # crimes	4,995	14,174	N/A	N/A	N/A	N/A	N/A
San Francisco # crimes/1000	6.4308	18.2462					
All cities # crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471

Source: Crime data provided by San Francisco Police Department

\* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect propensity for biking and walking

\*\* Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.

As we would expect for this older urban city, San Francisco, along with Oakland, has a higher than average P1P crime rate when compared to that of other cities in the study.

## CITY OF SANTA CLARA

The city of Santa Clara, a Silicon Valley suburb, is described in the 2000 Census as having a population of 102,361. While it is almost the size of the city of Berkeley in population, its density (5,566.2 persons per square mile) is roughly half that of Berkeley's. The land area for Santa Clara is 18.39 square miles. A summary of household incomes in Santa Clara is shown in [Table 52](#).

**Table 52 Santa Clara Household Income**

Household income in 1999	Percent
Less than \$14,999	8.4
\$15,000–49,999	25.4
\$50,000–74,999	20.4

**Table 52 Santa Clara Household Income**

Household income in 1999	Percent
\$75,000 or more	45.9
Median household income (dollars)	69,466
Total households	38,564

Source: Census 2000

Journey to Work Census data for Santa Clara shows the auto-dependent nature of this suburb. It has the highest percentage for car, truck, van, or motorcycle journey to work mode, next to its neighboring city, Sunnyvale, with 91 percent. Journey to Work data for Santa Clara are summarized in [Table 53](#).

**Table 53 Santa Clara Journey to Work Mode Share**

Mode	Percent
Car, truck, van or motorcycle	89.9
Public Transportation	2.9
Bicycle	1.4
Walked	3.2
Other means	0.3
Worked at home	2.3

Source: Census 2000

A description of the density of intersections for Santa Clara is provided in [Table 54](#). Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings. Santa Clara, although considered a suburban city, has the third-highest intersection density, surpassing Oakland, which has a higher population density.

**Table 54 Santa Clara Density of Intersections and Populations**

	4-legged intersections/acre	4-legged intersections/sq. mile	Density persons/acre	Density persons/sq. mile
Santa Clara	0.0328	20.9625	8.7	5,566.20

Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000

The Santa Clara Police Department provided 15,634 records of Part 1 and Part 2 crimes. These crimes were for the year 2001. After geocoding, 11,771 records were used for this study. There were 2,813 records of Part 1 crimes, and 8,958 records of Part 2 crimes. A description of the types of crimes submitted by the Santa Clara Police Department is provided in [Table 55](#).

**Table 55 Santa Clara Breakdown of Crime by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
Santa Clara # crimes	134	2,679	626	11	858	1,320	6,143
Santa Clara # crimes/1000	1.3091	26.1721	6.1156	0.1075	8.3821	12.8955	60.0131

**Table 55 Santa Clara Breakdown of Crime by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
All cities # crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471

Source: Crime data provided by Santa Clara Police Department

\* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect propensity for biking and walking

\*\* Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.

Santa Clara's crime patterns follow the typical suburban pattern. Figures for crimes per 1,000 residents for all categories are lower than the average for all cities. There is a university in this city, and a significant number of crimes, which were categorized as "NOTAFFEC" and were related to noise abatement around the campus.

## CITY OF SUNNYVALE

The city of Sunnyvale, a Silicon Valley suburb and neighbor to another study city, Santa Clara, is described in the Census 2000 as having a population of 131,760, the third-most-populated city in this study. With its density of 6,006 persons per square mile, it is the most densely populated city of the suburban cities in this study. The land area for Sunnyvale is 21.94 square miles.

A summary of household incomes in Sunnyvale is shown in [Table 56](#). Sunnyvale's median income was the highest of the study cities. The other Silicon Valley city studied, Santa Clara, had the next-highest median income.

**Table 56 Sunnyvale Household Income**

Household Income in 1999	Percent
Less than \$14,999	6.7
\$15,000–49,999	23.8
\$50,000–74,999	19.9
\$75,000 or more	49.6
Median household income (dollars)	74,409
Total households	52,610

Source: Census 2000

The Journey to Work information from Census 2000 shows Sunnyvale to be the highest auto-dependent study city. These data are summarized in [Table 57](#).



**Table 57 Sunnyvale Journey to Work Mode Share**

Mode	Percent
Car, truck, van or motorcycle	91.0
Public transportation	3.8
Bicycle	0.7
Walked	1.5
Other means	.0.4
Worked at home	2.6

Source: Census 2000

A description of the density of intersections for Sunnyvale is provided in [Table 58](#). Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings.

Sunnyvale follows Oakland in terms of population density. However, its density of intersections—typical of a suburban city—is low at roughly fourteen four-legged intersections per square mile, which ranks sixth of the seven study cities in this regard.

**Table 58 Sunnyvale Density of Intersections and Populations**

	4-legged intersections/acre	4-legged intersections/sq. mile	Density persons/acre	Density persons/sq. mile
Sunnyvale	0.0213	13.6281	5.17	3,309.50

Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000

The Sunnyvale Police Department provided 2,123 Part 1 crime records for the year 2000—the smallest number of records provided by any of the study city police departments. Of the data provided, all records were categorized, geocoded, and used for this study. A description of the types of crimes submitted by the Sunnyvale Police Department is provided in [Table 59](#).

**Table 59 Sunnyvale Breakdown of Crimes by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
Sunnyvale # crimes	152	1,968	N/A	N/A	N/A	N/A	N/A
Sunnyvale # crimes/1000	1.1536	14.9362					
All cities # crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471

Source; Crime date provided by Sunnyvale Police Department

\* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect propensity for biking and walking

\*\* Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.

## CITY OF WALNUT CREEK

The city of Walnut Creek is adjacent to the city of Concord, another study city. According to the 2000 Census, it is the smallest study city with a population of 64,296. It also is the lowest-density study city with 3,229.6 persons per square mile. The land area of Walnut Creek is 19.91 square miles.

A summary of household incomes in Walnut Creek is shown in [Table 60](#).

**Table 60 Walnut Creek Household Income**

Household Income in 1999	Percent
Less than \$14,999	7.5
\$15,000–49,000	31.5
\$50,000–74,999	19.6
\$75,000 and above	41.4
Median household income (dollars)	63,238
Total households	30,515

Source: Census 2000

The Census 2000 Journey to Work data for Walnut Creek are summarized in [Table 61](#).

**Table 61 Walnut Creek Journey to Work Mode Share**

Mode	Percent
Car, truck or motorcycle	77.3
Public transportation	13.8
Bicycle	0.6
Walked	2.0
Other means	0.5
Worked at home	5.7

Source: Census 2000

A description of the density of intersections for Walnut Creek is provided in [Table 62](#). Summary tables ([Table 2](#) and [Table 3](#)) are provided to show overall statistics and rankings. Walnut Creek, a suburban city, is the least-dense study city regarding population and intersection counts.

**Table 62 Walnut Creek Density of Intersections and Populations**

	4-legged intersections/acre	4-legged intersections/sq. mile	Density persons/acre	Density persons/sq. mile
Walnut Creek	0.0075	4.7715	5.05	3,229.60

Source: Metropolitan Transportation Commission 2000 Travel Analysis Zones (1454), Census 2000

The Walnut Creek Police Department provided 33,981 records of crimes for the year 2000. Of these, 25,023 were used in the final analysis after the records were categorized and geocoded. The amount of data provided by Walnut Creek was the largest amount after Oakland,

although Walnut Creek is the smallest study city in population. Of this relatively large amount of data, 84 percent turned out to be crimes which were considered to not affect the propensity of biking or walking (“NOTAFFEC”). A total of 2,013 records were categorized as Part 1 crimes, and 23,010 records were categorized as Part 2 crimes. A description of the types of crimes submitted by the Walnut Creek Police Department is provided in [Table 63](#).

**Table 63 Walnut Creek Breakdown of Crimes by Type\***

	P1V	P1P	P2V	P2P	BROKWIN	VICEVAG	NOTAFFEC
Walnut Creek # crimes	60	1,953	398	585	687	410	20,930
Walnut Creek # crimes/1000	0.9332	30.3751	6.1901	9.0985	10.685	6.3768	325.5257
All cities # crimes/1000**	5.4193	31.8894	12.081	1.8681	10.3192	18.463	78.0471
Source; Crime data provided by Walnut Creek Police Department							
* P1V = Part 1 crimes, P1P = Part 1 Property crimes, P2V = Part 2 Violent crimes, P2P = Part 2 Property crimes, BROKWIN = Broken Window-type crimes, VICEVAG = Vice and Vagrancy-type crimes, NOTAFFEC = Crimes that do not affect propensity for biking and walking							
** Eight cities submitted Part 1 crimes. Five of the eight cities submitted Part I and Part II crimes.							

For Walnut Creek, all statistics concerning population density, urban form, and crime describe a typical suburb. It has the lowest figures for population density and density of urban form of the study cities. Crimes per 1,000 residents were lower than the average of all the study cities. Regarding its ethnic makeup, with a rate of 86.8 percent, it had the highest percentage of white residents of all the study cities.

Crime data received from the Walnut Creek Police Department were extensive, although it included a high percentage of “NOTAFFEC” crimes (84 percent). Crimes per 1,000 residents in this category are 325.5, well above the average for all the cities. To describe these crimes more specifically, [Table 64](#) lists the crimes with greatest frequencies placed in the “NOTAFFEC” category.

**Table 64 Walnut Creek NOTAFFEC Crimes with Highest Frequencies**

Description	NOTAFFEC
Public service	4,516
Response to alarm	3,146
911 hang up	3,005
Suspicious circumstances	2,095
Miscellaneous traffic	916
Alarm—false	753
Other parking	682
Noise abatement	627
Assist other agency	539
Parking on private property	499
Civil matter	483
Supplement	342

**Table 64 Walnut Creek NOTAFFEC Crimes with Highest Frequencies**

Description	NOTAFFEC
Lost property	289

Source: Walnut Creek Police Department Crime Data 2000

The total number of “VICEVAG” crimes for Walnut Creek was 410, or 6.38 incidents per 1,000 residents. For purposes of comparison, in contrast to this, the amount of data received in this category for Oakland was 10,634, or 26.64 incidents per 1,000 residents. Specific crimes reported in this category are listed in [Table 65](#).

**Table 65 Walnut Creek VICEVAG Crimes with Highest Frequencies**

Description	Frequency
Drunkenness	
Disturbing the peace	
Under the influence of drug	
Possession of marijuana 1 oz.	
Driving under the influence	
Amphetamines possession	
Possession drug for sale	
Prowler/vagrant	
Curfew violation/loitering	
Display/use deadly weapon	
Possession drug paraphernalia	
Deadly weapon	
Marijuana sale	
Prohibited weapons	

Source: Walnut Creek Police Department Crime Data 2000



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## APPENDIX C

### COVER LETTER TO AGENCIES

April 11th, 2006

Mr./Ms. XXXX XXXXX

Crime Analysis

XXXX Police Department

XXX XXXXX Street

XXXXX, California 9XXXX

Greetings, Mr./Ms. XXXX:

I am a Research Assistant with the Mineta Transportation Institute (MTI), and I am writing to request data on behalf of a study on Neighborhood Crime and Travel Behavior. This project primarily seeks to measure how neighborhood crime affects people's choice of travel modes (e.g., walking, bicycling, transit, automobile, etc.). To measure this dynamic, we are looking to obtain electronic crime incident database records from Bay Area police departments, which we intend to analyze in tandem with travel behavior surveys (gathered from other sources).

MTI was created by Congress through the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) and established in the California State University system at the San José State University College of Business. This federally-funded research project is headed by Christopher Ferrell, Senior Transportation Planner with Dowling Associates, Inc. along with Professor Shishir Mathur of San José State University.

Our aim is to collect crime data from as many cities as possible around the Bay Area. To that end, we are requesting three kinds of data.

First and most importantly, we are looking for incident crime data (where each database record represents an individual reported crime) for the entire year of 2000 (to match the dates of our travel behavior survey data) with the following data fields:

1. Report Number
2. Date
3. Zip code
4. Beat
5. Reporting District
6. Crime Type
7. Address of Incident

Our research requires that we are able to identify as accurately as possible the location of each reported crime incident. That is why we are requesting that the address of each reported incident be included in this database file as well (see item #7). We understand that the department does not typically release data with this level of detail. However, since we will not be releasing these addresses for public viewing or use (and since we are not requesting any data that will reveal the identities of the crime victims or perpetrators), we hope that you will be willing to release these data to us with the goal of furthering our knowledge and understanding of the effects of crime on our communities. If it would be helpful, we would be happy to sign a Declaration of Intent.

Second, we are also interested in measuring the potential effects of police department resource distributions on crime and how people change their travel behavior as a result. To develop a very “broad brush” indicator of how your department distributes its resources, we would appreciate any data you have that would tell us the number of officers deployed to each city district. If these deployments are tracked by year, then we would like to request a list of the number of officers by district for the year 2000.

Finally, if you have maps or Geographic Information System (GIS) files that show the boundary lines of your reporting districts and beats, these would be very helpful as well.

While data from the year 2000 is ideal, it is understandable if this data is no longer accessible. We will gladly accept data from either 1998, 1999, 2001, or 2002 as a substitute. The closer to 2000 the better.

We understand that this is an enormous and somewhat irregular request. Please know that we greatly appreciate any and all efforts you can make on this project. As part of a federally-funded study, your department’s data will aide governments and communities alike in future urban planning. To ensure enough time for analysis, we will need to receive the data by the first or second week of May.

If you have any questions, feel free to contact me by phone at (802) 989-1911, or you can address any concerns to the study’s Principal Investigator, Chris Ferrell, at (510) 839-1742 x106.

Thank you for your time,

Charlie Chapin, Research Assistant

Mineta Transportation Institute

SJSU Research Center; 210 N. Fourth St., 4th Fl.; San José, CA 95112

Tel: (802) 989-1911

E-mail: [charliechapin@gmail.com](mailto:charliechapin@gmail.com)

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## ENDNOTES

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  39. Spatially, we can expect more dense concentrations of crimes in dense urban environments, but this may not be true in terms of population. Greater urban density may not increase the number of crimes per person.
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## ABBREVIATIONS AND ACRONYMS

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<b>ABAG</b>	Association of Bay Area Governments
<b>BATS</b>	Bay Area Travel Survey
<b>CPTED</b>	Crime Prevention Through Environmental Design
<b>FBI</b>	Federal Bureau of Investigation
<b>GIS</b>	Geographic Information Systems
<b>MTC</b>	Metropolitan Transportation Commission
<b>TAZs</b>	Travel Analysis Zones
<b>UCR</b>	Uniform Crime Records or Uniform Crime Recording

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## PEER REVIEW

San José State University, of the California State University system, and the MTI Board of Trustees have agreed upon a peer view process to ensure that the results presented are based upon a professionally acceptable research protocol.

Research projects begin with the approval of a scope of work by the sponsoring entities, with in-process reviews by the MTI research director and the project sponsor. Periodic progress reports are provided to the MTI research director and the Research Associates Policy Oversight Committee (RAPOC). Review of the draft research product is conducted by the Research Committee of the board of trustees and may include invited critiques from other professionals in the subject field. The review is based on the professional propriety of the research methodology.



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