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Neighborhood Crime and Travel Behavior: An Investigation of the Influence of Neighborhood Crime Rates on Mode Choice – Phase II

MTI Report 11-04

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NEIGHBORHOOD CRIME AND TRAVEL BEHAVIOR: AN INVESTIGATION OF THE INFLUENCE OF NEIGHBORHOOD CRIME RATES ON MODE CHOICE – PHASE II

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16. Abstract

There are considerable environmental and public health benefits if people choose to walk, bicycle, or ride transit, instead of drive. However, little work has been done on the effects of neighborhood crimes on mode choice. Instinctively, we understand that the threats posed by possible criminal activity in one's neighborhood can play a major role in the decision to drive, take transit, walk or ride a bicycle, but so far little empirical evidence supports this notion, let alone guides public infrastructure investments, land use planning, or the allocation of police services. This report--describing Phase 2 of a research study conducted for the Mineta Transportation Institute on crime and travel behavior--finds that high crime neighborhoods tend to discourage residents from walking or riding a bicycle. When comparing a high crime to a lower crime neighborhood the odds of walking over choosing auto decrease by 17.25 percent for work trips and 61 percent for non-work trips. For transit access to work trips, the odds of choosing walk/bike to a transit station over auto decrease by 48.1 percent. Transit trips, on the other hand, are affected by neighborhood crime levels in a similar way to auto trips, wherein high crime neighborhoods appear to encourage transit mode choice. The odds of taking transit over choosing auto increase by 17.25 percent for work trips and 164 percent for non-work trips. Surprised by this last finding, the research team tested two possible explanations for why high levels of neighborhood crime would increase transit use: 1) the mode choice models do not adequately account for the effects and interplay between urban form and crime levels and mode choice; and 2) people who ride in cars or take transit may feel more protected when riding in a vehicle (termed here, the "neighborhood exposure hypothesis"). To investigate the first explanation, the researchers tested a number of alternative urban form and crime interaction variables to no effect. Digging deeper into the second hypothesis, the researchers tested whether the access portion of transit trips (walking, bicycling, or driving to a transit stop) is sensitive to neighborhood crimes as well, wherein high crime neighborhoods discourage walking and bicycling and encourage driving to transit stations. The report provides evidence that high crime neighborhoods encourage driving to transit stops and discourage walking or bicycling, lending support to the neighborhood exposure hypothesis.

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EXECUTIVE SUMMARY

OVERVIEW

This study is a continuation (Phase 2) of the Mineta Transportation Institute-funded 2008 study titled, “Neighborhood Crime and Travel Behavior: An Investigation of the Influence of Neighborhood Crime Rates on Mode Choice”[1] (hereafter referred to as “Phase 1”) that empirically estimated the impact of neighborhood-level crime on mode choice for seven San Francisco Bay Area cities. Phase 1 studied seven San Francisco Bay Area cities, 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. Key findings from the Phase 1 study were:

- High vice and vagrancy crime rates were associated with a lower 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 cities and inner-ring suburban cities.
- High violent crime rates were associated with a lower probability of walking for work trips in suburban study cities.
- Higher property crime rates in San Francisco were associated with a higher probability of walking for non-work trips.

Several of these findings seem at odds with one another and with our theoretical assumptions. Foremost among these was the finding that higher crime rates were associated with higher probability of walking in San Francisco. The research team believed that these inconsistencies may have been a result of methodological shortcomings of the research design. As a result, the team was hesitant to offer insights into the policy implications of these findings but rather, put their attention on improving the measurement methods employed in Phase 1.

RATIONALE FOR THE SECOND PHASE

The reasons for undertaking this Phase 2 research were based primarily on the perceived shortcomings of the Phase 1 work. These shortcomings include the questionable validity of our Phase 1 crime variable measures, and the use of binary logit modeling rather than a more widely accepted multinomial logit modeling technique.

While the Phase 1 research produced interesting results, the crime variables tested yielded inconsistent, and at times, counter-intuitive results. We hypothesized that the calculation method used for these measures—where the number of crimes in a traffic analysis zone (TAZ) were summed and divided by the TAZ’s population—may have been the cause. However, as discussed in the Phase 1 report, TAZs were drawn to describe travel behavior and not with reference to crime rates or distributions. Therefore, using TAZs to aggregate crimes may result in an “ecological fallacy,” where it is erroneously assumed that members of a group (such as individuals who live in a TAZ) exhibit the characteristics of the group at large (such as those represented by an aggregation of individuals in a TAZ).

To address this problem, in Phase 2 we developed a new, more fine-grained set of crime measures that are specific to the crime conditions of the immediate environments of each trip origin in our travel data set (BATS 2000). To evaluate the performance of these new crime measures, we re-ran the original binary logistic regression models developed for Phase 1, replacing the Phase 1 crime variables with the new Phase 2 variables.

Following our estimation and analysis of these binary logit models with the new crime variables, this study analyzed the impact of crime on an individual's mode choices using a discrete choice modeling approach, the multinomial logit (MNL) model. The MNL model estimated the propensity of a traveler choosing non-auto modes—transit (bus or rail), walking or biking—over car for the primary trip.

While these methodological improvements increased the consistency and validity of the findings, we were still faced with findings that were difficult to explain. Prominent among these, we found that transit and pedestrian mode choice behaviors respond differently to neighborhood crime levels. Specifically, crimes were positively correlated to the transit mode and negatively correlated to the pedestrian mode. We had expected all non-auto trips to be negatively correlated with crime levels, so the positive correlation with transit mode choice was puzzling. To explain this difference in behavior, we proposed the "Neighborhood Exposure Hypothesis," where enclosed, motorized modes of travel (transit and automobiles) tend to confer a higher level of personal safety and control over one's travel environment than non-motorized mode (bicycling and walking). If true, then we hypothesized that a similar effect should be seen for transit access trips.

To test this hypothesis, we developed a set of binary logit models that predicted mode choice for the access portion of the trip to the transit stop or station for transit riders. Every transit trip requires an access trip (unless the bus stops right at the travelers front door step). These access trips are generally car, walking, or bicycle trips. These models use a similar structure used to predict mode choice for the primary mode, but have been refined to the needs and requirements of predicting transit access mode choice. We hypothesized that in high-crime areas, more people would access transit by car compared to biking or walking.

SPECIFIC RESEARCH QUESTIONS

The specific research questions explored by this study are as follows:

1. How does the new neighborhood crime measure perform compared to the old measure?

2. How does the multinomial model result compare to the binary model results?

3. Is there a unique effect of crime on mode choice in San Francisco (self-selection bias)?

4. How might neighborhood crime and access to transit combine to affect mode choice?

STUDY RESULTS

The results are summarized below in three groups. Group 1 model results are obtained by re-estimating the Phase 1 binary logit models using the new crime variables. The Group 2 model results are obtained by running the MNL models to identify the impact of crime on the four mode choices—auto, transit, walking and biking. Finally, the Group 3 model results summarize the impact of crime on transit access mode choice.

Group 1 Model Results

Comparisons of binary logistic mode choice model runs using Phase 1 and Phase 2 crime variables suggest that our Phase 2 variables provide significant, but modest improvements over our Phase 1 crime variables. We hoped that these improved crime measures would yield two benefits: more consistent and powerful statistical significance across all model runs, and relationships (signs) that are more consistent with our theoretical expectations (for example, more neighborhood crimes lead to less non-auto and more auto mode choice).

These comparisons produced a wider variety of statistically significant results, providing the research team with a host of crime variables to choose from and suggesting that the Phase 2 crime measures represent an important improvement over the Phase 1 measures. However, the fact that (like our findings in Phase 1) many statistically significant Phase 2 crime variables had counter-intuitive, positive signs also suggests that our Phase 1 methods of measuring crimes—in particular, the methods that relied on calculating crime rates for entire neighborhoods (TAZs)—are not the cause of these counter-intuitive results.

Group 2 Model Results

Critiques of our Phase 1 research pointed out that binary logit models are not capable of distinguishing between multimodal options. MNL models are capable of identifying the subtle neighborhood crime conditions that affect the selection of specific modes simultaneously, much as a person actually evaluates modal choices in reality, and not sequentially as one mode compared to an indistinguishable block of all other modal choices together.

While MNL modeling did not eliminate the somewhat inconsistent and counter-intuitive binary logit model results found in Phase 1, comparison and analysis of the findings of Phases 1 and 2 suggest that it yielded significant if somewhat modest improvements. First, while Phase 1 binary logit model results suggested that under certain conditions, higher crime levels might encourage walking, Phase 2 MNL model results did not confirm these findings. In fact, it found that for both work and non-work trips, high-crime neighborhoods tend to encourage transit and discourage pedestrian mode choice. The fact that these findings were more consistent and robust across multiple exploratory model runs suggests to us that MNL modeling methods have helped disentangle the complex relationships between neighborhood crime, urban form and mode choice. However, Phase 2 MNL model results also found statistically significant positive relationships between high-crime neighborhoods and transit mode choice. These counter-intuitive findings led the research team to test the “Neighborhood Exposure Hypothesis” using the Group 3 models.

Group 3 Model Results

Every transit trips requires an access trip (unless the bus stops right at the travelers front doorstep). A set of binary logit models were developed to predict mode choice (driving versus walking or biking to access transit) for the access portion of the trip to the transit stop or station for transit riders. The research team hypothesized that if the Neighborhood Exposure Hypothesis is correct, then even transit trips that were hitherto found to have a positive relationship with high-crime neighborhoods (for instance, the more neighborhood crimes, the more likely people are to choose transit) have trip links prior to reaching the transit stop (transit access trip links) where travelers must choose between cars, walking, and bicycling. Thus, when broken down into its component segments, transit trips will have links where non-auto modes will be negatively affected by high-crime neighborhoods.

Violent crime variables worked best for the work and non-work models, yielding the expected signs, and in the case of work trips, a statistically significant result. Therefore, it appears that violent crimes near a transit rider’s home will deter them from walking or riding a bicycle and encourage them to drive instead. Thus, while transit mode choice model results continue to give counter-intuitive results—where people who live in high-crime neighborhoods are more likely to take transit than drive—travelers in high-crime neighborhoods are less likely to walk or ride their bicycles to a transit stop than drive. We hypothesized that this was due to the fact that while driving and transit, to some extent, offer some level of protection from neighborhood crimes, walkers and cyclists feel more exposed in these same neighborhoods.

IMPLICATIONS FOR PRACTICE

While the results of this study thus far require confirmation through follow-up research, particularly with respect to the Neighborhood Exposure Hypothesis, we can identify several implications for planning and law enforcement practice.

First, the analysis of home-based mode choice shows that high levels of neighborhood violent crime increases automobile use. When aiming to reduce auto emissions, suburban sprawl, obesity rates, and other societal ills that come with auto dependency, planners and policy-makers need to look at a range of interventions. While the arguments in favor of reducing auto dependency through land use and urban design interventions have attracted serious attention in recent years, these changes take place over the course of decades, as will their anticipated benefits. Improved crime intervention strategies that can reduce the safety concerns of residents living in high-crime neighborhoods hold promise for more immediate benefits and should be considered as part of a larger package of both short-term and long-term measures to reduce auto dependency.

Second—and much to our surprise—high-crime neighborhoods also favor transit use. A simplistic assessment of these findings may lead to the conclusion that we may be able to increase transit use by providing additional transit services to high-crime neighborhoods.

However, the Neighborhood Exposure Hypothesis and our findings that high-crime neighborhoods also encourage residents to drive instead of walking or biking to transit, suggest that transit oriented development plans that do not address the safety concerns of residents and visitors will fall short in reducing auto trips.

I. LITERATURE REVIEW

INTRODUCTION

This literature review updates the literature review conducted for the Phase 1 report, and is comprised of four parts. It describes the rationale for expecting to find an impact of crime on mode choice, reviews the literature on the determinants of crime both around transit stations and elsewhere in the built environment, provides support for the MNL modeling and crime counting methods employed in this report, and finally discusses potential methodological concerns with respect to endogeneity of crime and urban form, and the potential for omitted variables bias. The sections below argue that the reasons for expecting to find an impact of crime on mode choice are numerous, and the support for MNL modeling and crime-counting methods are also sound.

EVIDENCE FOR IMPACT OF CRIME ON MODE CHOICE

Research on the impact of crime on travel behavior distinguishes tangible impact from intangible impact. Dolan and Peasgood describe these two categories, noting that tangible impacts would include direct costs for medical losses and additional security while an intangible impact would relate to the psychological impact of crime-related trauma.[2] Within this framework, they argue that changes in different types of behavior (for instance, travel behavior) can be influenced by the perceived and anticipated costs of crime as ex-victims and members of the public anticipate potential costs associated with crime (*for instance*, people believe they will incur a cost if they do not change their behavior to avoid crime). Though not mentioned specifically by Dolan and Peasgood, changes in mode choice could be thought of within their framework as a tangible cost of crime, which the traveler could place a value on, if asked. The following sections describe research showing that crime not only impacts mode choice, but also reduces levels of physical activity and home sale prices.

Mode Choice

Two recent studies use disaggregate choice models and find an impact of crime on urban travel behavior. Kim, Ulfarsson, and Hennessy describe use data from St. Louis, Missouri, to measure how crime affects station access mode choice of light rail riders.[3] The authors built a MNL regression model to compare the likelihood of riders to drive and park, compared to three other modes: taking the bus, walking, or being dropped off at the station. The study shows that crime at the station is likely to lead more female riders to be picked up and dropped off at the station compared to the other three modes.

Likewise, Ferrell, Mathur, and Mendoza (in Phase 1 of this study) uncover a relationship between crime and mode choice.[4] They built a binary logit model to analyze the impact of crime on the likelihood that a traveler will use public transit, compared to the likelihood of other modes. They used crime data from seven San Francisco Bay Area cities, aggregated to the level of the Traffic Analysis Zone (TAZ), and merged it with travel data from the Bay Area Travel Survey. They also included in their model a set of variables measuring urban form, transit accessibility, and traveler's socio-demographic characteristics. Their study results vary by the crime type, the mode of travel and the city type analyzed, and suggest that for work and non-work trips, higher vice and vagrancy crime rates are associated with a lower probability of transit usage in the suburban cities (for example, Concord and Santa Clara). Both of these studies, the one by Kim, Ulfarsson, and Hennessy, and the other by Ferrell, Mathur, and Mendoza, provide support for the proposition that the distribution of crime can affect mode choice under certain conditions.

Further support for crime's impact on mode choice comes from studies that suggest that crime significantly deters people from riding public transit. One study by Wachs argues that the presence of crime, or of the perception of crime, is a significant deterrent against public transit usage in the Los Angeles area.[5] Wachs notes that ridership surveys single out crime as the most significant deterrent against riding buses. Meanwhile, Needle and Cobb document the effect that crime and the perceptions of crime have on transit ridership.[6] They argue that in the presence of crime, ridership and revenues fall, and they provide numerous case studies to illustrate the point.

Ingalls, Hartgen, and Owens note that concerns for personal safety affect people's propensity to ride transit in small city environments, and their results suggest that our culture's perceptions of urban environments play a key role in determining our sense of personal safety and our willingness to use transit.[7] They surveyed both residents and bus riders in Greensboro, North Carolina, and found that the city's residents rarely used transit (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 group was specifically concerned for the safety of the transit system itself, but rather were more concerned for their safety in their communities as a whole. The authors conclude 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 conclude that this fear of crime is a major impediment to transit ridership growth.

Finally, a study of American public transit systems over the 1990s found empirical support for Needle and Cobb's argument. Taylor and others studied the factors that contributed to the nation-wide gains in transit ridership seen during the economic boom times of the 1990s.[8] They built a model to explain changes in ridership and found that, among other factors, a reduction in crime around public transit stations contributed to increased ridership.

Taken together, the above reviewed studies suggest that crime plays a key role in driving down transit usage, and hence, is likely to play a role in mode choice.

LEVELS OF PHYSICAL ACTIVITY

A meta-analysis of the extant literature conducted by Seefeldt, Malina, and Clark finds strong evidence that high crime rates and fears for personal safety significantly reduce levels of physical activity, especially among ethnic minorities.[9] But not all studies find a relationship between crime levels and physical activity, and this section summarizes this disagreement in the literature. This section also reviews studies on both sides of the argument that street lighting influences physical activity levels through its affect on crime.

The concept of *self-efficacy* explains why researchers expect to find a relationship between crime levels and physical activity. Hofstetter, Hovell, and Sallis argue that *self-efficacy*, which is defined as the sense of confidence that one has in performing an activity, is a major determinant of a young person's decision to be physically active.[10] They note that factors such as the "safety and ease of exercising in [one's] own neighborhood" can greatly influence one's *self-efficacy*, and in turn affect the likelihood that one will repeat the activity.

Evidence on crime's negative affect on physical activity is substantial. For example, McDonald studied the affect of crime on the number of walk trips taken by minority populations in Oakland, California.[11] Using a negative binary regression model with the number of crimes per 1,000 block-group population as the independent variable, the study finds that a reduction in violent crimes significantly increases the number of minutes walked. However, property or quality of life crimes (for example, weapon offenses, prostitution, drug arrest, and disorderly conduct) do not produce a measurable effect on walk trips. Booth and others provide further support for the argument that the presence of crime discourages physical activity.[12] In a survey of older (60+) Australian adults' self-reported physical activity and perceived physical activity, a strong connection between perceived safety and walking activity is evident. This is clear through bivariate relationships, where people who said they were physically inactive were unable to find crime-safe footpaths. Also a logistic regression analysis showed that a respondent's inability to find safe footpaths negatively impacted his physical activity level.

The question of whether crime influences physical activity has been addressed by other studies as well, including King and others,[13] Gordon-Larsen, McMurray, and Popkin,[14] Humpel, Owen, and Leslie,[15] and Eyler and others.[16] The conclusions from these studies are mixed: gender, age and race seem to combine to form an intricate web of causality underlying how neighborhood crime levels affect the propensity to exercise.

To give an example of the complexity of these findings, we review Wilcox and others.[17] The study finds that, among other factors, the key environmental barriers to leisure time physical activities for urban women are high crime and several other factors including a lack of sidewalks and streetlights, a lack of access to exercise facilities, and infrequent sighting of others exercising in the neighborhood. The study reports that women are significantly more likely than men to report the presence of unattended dogs as an important impediment the physical activity. While these univariate statistical findings point to crime as one key factor correlated with physical activity levels, multivariate analyses do not find crime to be a significant determinant of a sedentary lifestyle for either rural or urban women. Therefore, while in general crime is often correlated with levels of physical activity, the relationship is not consistently apparent.

Evidence of Street Lighting's Affect on Crime and Physical Activity

Several studies reveal a link between crime and physical activity by looking specifically at the impact of street lighting on crime. Street lighting is often seen as a crime deterrent. Farrington and Welsh offer two reasons why improved street lighting would reduce crime levels.[18] First, improved lighting encourages surveillance of potential offenders on the street, both through improved visibility and an increased number of people on the street. Second, improved lighting sends a signal to potential criminals and the community that the neighborhood is improving and that there will be increased community pride, cohesiveness, and informal social controls. Farrington and Welsh performed a meta-analysis of 16 studies examining the affects of street lighting on crime. Their analysis reveals that about half of the studies find that improved street lighting has a significant affect on crime, while the other half do not. While Farrington and Welsh found no clear reasons for these differing results, they point out that studies that found a significant effect were more likely to have measured the crime levels during both the daytime and nighttime periods. This suggests that the beneficial effects of street lighting may be related to the authors' theory about how street lighting sends a signal that the area is improving.

Two studies find evidence that street lighting influences travel behavior through its impact on crime, or on perception of crime. Wallace and others studied the effects of transit safety measures, including improved lighting in transit facilities and vehicles on passenger levels of perceived safety.[19] Their study finds that increased police presence and improved lighting are two of the most highly visible interventions studied and the most effective in terms of reducing the safety concerns of transit patrons. In addition, Painter conducted surveys of residents in two neighborhoods in London before and after street lighting improvements were made.[20] Her research shows that incidents of crime and disorder, as well as the general fear of crime, dropped markedly, while after-dark pedestrian activity in the study area increased significantly after lighting improvements. These results suggest that without adequate street lighting, travel behavior might be affected either by real or perceived fear of crime.

It is noteworthy that not all studies examining the impact of street lighting on crime come to the same conclusion as Painter. Atkins, Husain, and Storey, studying the effects of street lighting on neighborhood crime levels and perceptions of crime in the London borough of Wandsworth,[21] found no detectable changes in travel behavior among neighborhood residents. The residents seemed to engage in the same patterns of avoiding certain streets and places after street lighting improved. This, in spite of the fact that poor lighting fell from the most frequently cited reason for avoiding these areas, to a minor ranking among reasons listed. These results suggest that improved street lighting might not be significant enough to reduce residents' fear of crime.

Depressed Home Values

The price of a house is an indicator of its utility to current and future residents. Crime has been show to depress home values in several empirical studies. For example, Lynch and Rasmussen built a hedonic price model of home sales in Jacksonville, Florida, in which the level of crime in the home's police beat is used as an independent variable.[22] While overall the affect of crime on home prices is insignificant, the study finds that houses in very high crime police beats are discounted significantly below their counterparts in areas with fewer crimes. The paper suggests that there is some threshold at which high crime begins to negatively impact people's preferences. Gibbons also studied the impact of property crime in London on local house prices, and his study shows a significant and negative correlation between crime levels and home values.[23]

These examples from studies of home values, physical activity, and mode choice all add support to the theory that individuals are perceptive of crime patterns in observable ways.

How Transit and Built Environment Affect Crime

The existing literature suggests that people associate crime with public transportation. When the reasons for the decline in transit use in the United States are examined, explanations often point to people's associations of transit with dense, often crime-ridden, urban areas.[24] With the growth of the suburbs came the commonly held perception of these new neighborhoods as sanctuaries from the inner city crime.[25] Furthermore, the lack of transit in suburbs often leads people to associate transit with crime as well. The expansion of transit lines into wealthy, suburban areas is often fought by locals fearing transit services will import crime into their neighborhood.[26]

The sections below look first at whether the perceived association between transit and crime is accurate. To do so, we look at research on how the presence of transit stations affects the pattern of crime around them. Then, we examine whether crime around transit can be reduced by exploring the factors that have been observed to differentiate between high- and low-crime transit hubs. Finally, we identify strategies from the literature, mainly related to environmental design, which have been proposed as crime reducing techniques. The purpose of these sections is to explore the drivers behind association of crime with mode choice, and to begin to think about how policies could make non-auto modes more popular.

Do Transit Systems Themselves Encourage Crime?

Research on this subject provides somewhat conflicting evidence on causal link between transit and crime. Liggett and others studied the effects of the introduction of light rail service along the Los Angeles Green Line on crime levels in the surrounding neighborhoods.[27] This line passes through low-income, high-crime areas and terminates in the affluent areas of West Los Angeles. This study analyzes five years of crime data in the neighborhoods surrounding the Green line, before and after the line's introduction. The study shows that the transit line did not significantly affect crime trends or location in the station areas, and did not transport crimes from high-crime areas to low-crime areas.

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, their study shows a concentration of street robberies near 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.[28] 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.

Taken together, these two studies suggest that while the introduction of transit may not drive crime upward in a neighborhood, one might find observable differences between stations in the way that crime clusters around them.

What Factors Affect Crime Levels Around Transit?

Studies that seek to identify the determinants of transit crime often look at what high-crime bus stops have in common with each other. Loukaitou-Sideris researched crime at the ten most dangerous and crime-ridden bus stops in Los Angeles. Her study lists “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.[29] Most of these ten bus stops are located in downtown commercial areas, at the intersections of multi-lane streets, and are often not visible from nearby shops and lack adequate lighting, pubic phones, or a nearby police presence. Many are located near vacant lots, abandoned buildings, with easy escape routes for criminals in alleys and mid-block connections, and generally dilapidated conditions.

Cozens and others used virtual reality walkthrough scenes to test people’s fear of crime in the British rail system environs.[30] They found that rail station designs that provided high levels of visibility for passengers were perceived as offering high levels of safety, and conclude that station designs that provide high visibility are good examples of effective crime prevention through environmental design.

Meanwhile, a study by Loukaitou-Sideris, Liggett, and Hiseki speaks directly to the influences of the social environment on crime and focus specifically on neighborhoods surrounding transit stations.[31] This study finds that there were more crimes against people at stations within low-income neighborhoods, with more persons per household and higher concentrations of youth, than comparison neighborhoods. The researchers also found a strong correlation between station crime and the presence of liquor stores in the station neighborhood. Further, the busiest stations (those with the highest transit ridership) tended to concentrate the most serious crimes. Less serious crimes, such as vandalism, tended to be concentrated at stations in dense neighborhoods with a high percentage of people with less than 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.

How the Built Environment can Discourage Crime

We turn now to crime reduction strategies that have been proposed, beyond the realm of transit stations. For example, research by Doran and Lees draws 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 property damage found, was most spatially correlated with concentrations of crime.[32]

Beyond reduction of graffiti, researchers have identified other 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.[33] More specifically, any theory of crime should explain and describe the interactions between the propensity for criminal behavior (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 lists four different objectives to reduce crime opportunities. These are:

- to increase the perceived difficulty of crime
- to increase the perceived risks of crime
- to reduce the anticipated rewards of crime
- to remove excuses for crime

Among the first researchers to articulate the relationships between crime and environment, Mayhew and others[34] and Jeffery[35] proposed that crime prevention should be approached from the perspective of reducing the opportunities for crime rather than on enforcement and sentencing. Crime prevention was therefore a matter of redesigning our urban physical spaces to reduce the opportunities for crime. This approach is known as “Crime Prevention Through Environmental Design,” or CPTED. Since the early 1970s, a number of crime researchers and practitioners have articulated and refined 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.[36] Defensible space theory maintains that people feel safe from crime in environments that allow them to mark out and protect their territory, and where people feel they can easily see and monitor all surrounding non-private spaces. Initially focusing 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 low-rise buildings. He proposed that apartment blocks should be designed to maximize the amount of public space that was under public surveillance at all times. He 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 neighborhood.

Geason and Wilson place emphasis on physical design changes to residences and neighborhoods as opposed to increased police activities as an important and effective means to reduce crime.[37] They note that traditionally, increasing criminal activities have been met with increased policing and tougher sentencing to punish criminals after the crimes have taken place. They list a number of physical design elements that are potentially effective at reducing neighborhood crime, including: houses and their entrances 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; off-street parking that is visible from the owner's house; use of cul-de-sacs to control access to homes; residences designed with "defensible space" by providing adequate building setbacks; clustered houses, where the intended use of space is clear, and adequate recreational space is provided for social cohesion.

Newman and Franck used path analysis to identify a number of factors influencing crime and instability in housing sites in urban areas across the U.S. including socioeconomic characteristics, management effectiveness, quality of city police and security services, and form of ownership.[38] Supporting the CPTED perspective of Newman's earlier work, they found that physical (built environment) and social factors largely accounted for the 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.

Newman also reported on the results of an effort to reduce crime in the Dayton, Ohio neighborhood of Five Oaks.[39] 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 while allowing pedestrian access. One year after implementation, the city observed 67 percent reduction in cut-through traffic and 40 percent reduction in traffic accidents. Reported crime in the neighborhood declined 26 percent and violent crimes declined 50 percent, while citywide crime went up one percent. Fears of crime displacement from the study area to surrounding neighborhoods were also 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 of residents thought there was less crime and 45 percent felt safer, suggesting that neighborhood design can play an important role in crime prevention.

Further support for the CPTED principles comes from Carter, Carter, and Dannenberg.[40] They studied the effects of zoning, physical design changes as well as 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, 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 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 nine-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 for the city. Finally, the number of prostitution police reports during the study period fell in the North Trail area while it rose in the city as a whole.

This section of the literature review has highlighted ways of reducing crime not just around transit, but also by looking more broadly at the benefits of environmental design in cities.

SUPPORT FOR MODELING APPROACH

From a methodological perspective, this paper builds on Ferrell, Mathur, and Mendoza (Phase 1 study) in two ways: by using a MNL model, and by disaggregating crime data to reflect conditions at individual points, rather than presenting aggregated statistics at the neighborhood level.[41] There is broad support for both methodological improvements in the literature.

Basis for MNL

MNL model has been commonly used as a technique for explaining or predicting mode choice since the 1970s. It is widely used in the field of transportation planning to illustrate travel demand model by focusing on the factors influencing an individual’s travel decisions.

McFadden first defined the discrete choice framework for studying travel demand.[42] His theories state that mode choice fits into a decision tree wherein people decide first that they want to make a trip and where the destination will be, before deciding which mode to take. McFadden fits the mode choice decision into choice theory, from the field of psychology. People, the theory holds, are guided by wants and drives, and the more that a certain activity lowers their sense of deprivation of such wants, the more likely the activity is to be learned, reinforced, and repeated.

Later, Ben-Akiva and Lerman further defined the method for estimating a MNL model by producing a list of alternatives.[43] Their paper argues that any mode choice model should consider the following elements: a decision-maker, a set of alternatives, attributes of those alternatives, and a decision rule. Alternatives should include only those that are physically available and feasible given a set of financial and time constraints, but they acknowledge "what constitutes a feasible alternative for any particular individual may be difficult of the analyst to determine." Analysts who devise MNL mode choice models, they say, should "make informed judgments about...the *choice set generation process*."[44] This means that people who use MNL models must think carefully about which alternatives to include in the model.

Operationalizing MNL Models

There are literally hundreds of examples of the use of MNL models in travel behavior research. Accordingly, we only list a few here as examples to illustrate the theory and practice of MNL modeling.

A good overview of mode choice theory and its practical applications can be found in the 2002 study by Cervero. Cervero calls mode choice theory an "application of consumer choice theory" in which agents make decisions among competing alternatives so as to maximize either personal utility or net benefit.[45] Elaborating on the typology of variables to include in mode choice models, he argues that capturing the full picture of the traveler's net benefit should take into account both attributes of the trip and attributes of the traveler. Attributes of the trip would include travel times, monetary costs, and other attributes of the modes that are being considered. Attributes of the traveler would include such variables as automobile access and other demographic information about the traveler. Further variables of importance include land use around the trip origination and destination, including the density (population plus employment totals within a given area) and diversity (a measure of the evenness of population and employment totals within a given area) of land uses, and the ratio of sidewalk miles to road miles in the area.

As mode choice modeling has progressed, the affects of urban form on travel behavior have received increased attention. Schwanen and Mokhtarian used MNL model to analyze the affect of urban form on mode choice.[46] The four modes that they include in their model are personal vehicles, bus, rail, and *slow*, which is their term for bicycling, walking and jogging. Schwanen and Mokhtarian apply a similar specification to Cervero in that a combination of attributes about the trip, the traveler, and the neighborhoods on both end of the trip are included.[47]

Increasingly, researchers have delved into the mode choice behaviors for trip components, using MNL models to understand the factors that influence mode choice for transit station access trip links. For example, Loutzenheiser examined the importance of different factors in encouraging or discouraging walking as a mode choice between home and Bay Area Rapid Transit (BART) stations.[48] His goal was to identify the factors that encourage walking to and from BART stations so that station area land use planning and urban design can more precisely target improvements that will produce a pedestrian-friendly environment. The logit models compared the likelihood of walking relative to driving, taking transit, and non-walk trips (including a small number of people who did not walk, drive, or take transit). Loutzenheiser included variables related to trip purpose, availability of other modes, traveler characteristics, trip distance, and station area characteristics.

Finally, the influences of transit station crimes on station access and egress mode choice have been modeled by Kim and others using MNL modeling techniques. They found that station crimes increased the likelihood that female transit riders would choose to be picked up or dropped off at stations, as opposed to other access modes.[49]

All four of the above reviewed studies are recent examples of applications of MNL to mode choice, demonstrating the model specifications that are common in literature. These studies provide support for the mode choice models specified in this report.

Neighborhood Crime Counting Methods

This report has disaggregated crime to a lower level than what was used in Ferrell, Mathur, and Mendoza (Phase 1 study) to test the hypothesis that aggregating crime counts to the neighborhood level (*for example*, the number of crimes within a traffic analysis zone) may have led to aggregation bias.[50] Research in other areas have dealt similarly with the issue of moving from data aggregation at the neighborhood, or census tract-level, to disaggregated measures, which measure observations within a specified radii from a particular point.

Gibbons analyzes the impact of property crime on residential home sales in London.[51] Using geo-coded crime data, he counted crimes within 250 meters of each property, and also the squared number of crimes within a kilometer of the property.

Other Examples of Radius Counts from Transportation Literature

A number of studies do not count crimes, but are nevertheless noteworthy because they count various phenomena that are analogous to crimes within specified radii. This method provides a geographically fine-grained measure of count data, and potentially, a set of variables that are sensitive to spatial patterns and variation in what that data represents. Unfortunately, not all spatial data are recorded with sufficient spatial accuracy to create a radius count measure. Census data, for instance, is typically summarized at the census tract or block group levels, and does not lend itself to radius count summarization unless the radius is sufficiently large to capture many tracts. Therefore, radius counts are a useful tool for summarizing its density and distribution when spatially accurate point-level data is available.

Cervero and Duncan obtain many variables by counting within different radii of properties.[52] They build a hedonic pricing model based on home sales in Santa Clara County, California, and include, for example, the mean household income of homes within a one-mile radius of the parcels, and the proportion of African-Americans living within one mile of the parcel. Such counting is widespread in studies of the obesity epidemic, a phenomenon that is heavily investigated in the public health and health economics fields. Many such studies have used arbitrarily defined regions like census tracts to describe the food landscape (for instance, prevalence of fast food restaurants, among other things) in the person's vicinity. This effectively led them to make fallacious assumptions; for example, that people were not buying food outside their census tracts, even if they lived on the edge of a census tract. To deal with this problem, Chen, Florax, and Snyder counted the number of different food establishments within a half-mile radius of an individual's home in a study of people in Indianapolis.[53] In a regression in which body mass index (BMI) is the dependent variable, they include a variety of independent variables such as the number of fast food establishments, large grocery stores, and serious crimes within a half-mile radius of the subject's home.

Currie and others performed a similar distance-based analysis on ninth graders in California public schools over a multi-year period.[54] They find that the presence of a fast food restaurant within one-tenth of a mile from a child's school is tied to a 5% increase in the obesity rate.

METHODOLOGY CONCERNS

There are two potential issues that we see with the models employed in this report: the potential endogeneity between urban form and crime variables, and the omission of variables related to the perception of crime.

Endogeneity

We explore three types of potential endogeneity. One section below looks at whether the crime variables and the urban form and transit accessibility might be correlated. Another looks at whether there might be a relationship between the different types of crime variables, specifically between the broken windows crime variable and the rest. Finally, we explore the link between the income variable and the crime variables.

Urban Form/Land Use and Crime

Urban form might be correlated with crime. In this report, urban form/land use is operationalized by counting: a) the number of four-legged intersections in the vicinity of the trip end, a proxy for compactness of an urban area; b) the number of attractions in the area (*for instance*, retail establishments, shopping centers, and other non-work uses); and c) density (both employment and residential) at the trip origin and destination.

Four studies look at the complex relationship between crime and urban form or land use. Matthews and others, using spatial poison regression under a Bayesian analytical framework, write that several built environment variables impact the number of property crime incidents in Seattle, Washington.[55] For example, the study finds that the presence of highways and bars in a census tract leads to an increase in the incidence of crime. Presence of schools in a census tract is correlated with arson, and the presence of parks is correlated with theft. Crime was measured as the number of crime incidents per 100,000 people, or as the number of crime incidents per census tract.

Meanwhile, Stucky and Ottensmann estimated the impact of several land use variables on violent crimes in Indianapolis, Indiana. The land use variables include the proportion of area under residential, commercial and industrial use, proportion of area under water bodies, and the presence or absence of land uses such as parks, cemeteries, hospitals and schools.[56] They use a moving 1,000 feet by 1,000 feet grid as the unit of analysis. A negative binary regression model is used, with the number of violent crime in each 1,000 feet by 1,000 feet cell being the dependent variable. The study finds that the presence of high-density development and cemeteries, the length of major streets, as well as the proportion of area under commercial, industrial, and water are positively correlated with violent crime, while the presence of parks, schools, hospitals, and the percentage of vacant land did not have an impact. These two studies provide some empirical evidence that land use is correlated with crime.

Meanwhile, Cozens and Hillier take a meta-analysis approach to analyze this question.[57] They compare the cul-de-sac to more traditional urban form, symbolized by the grid, and find that while there are many advantages to the traditional pattern, crime prevention is not one of them. They argue that *permeable* street layouts generally exhibit higher levels of crimes than cul-de-sacs. One reason for this, they argue, is that rear alleys provide both access and escape routes for criminals.

Finally, Bowes looks specifically at the complex relationship between retail uses and the distribution of crime.[58] He examines claims that high crime discourages retail development, and that retail development attracts crime. He disentangles these processes by building a two-stage least squares regression model using panel data from 206 census tracts in Atlanta, Georgia, over a three-year period in the 1990s. In one model, retail development in a census tract is a function of crime levels and a set of neighborhood characteristics. In another model, crime levels in a census tract are a function of retail development and a different set of neighborhood characteristics. His results provide support for the assertion that there are endogenous relationships between crime and retail development, and all four of these papers suggest that the crime variables in this study could be endogenously related to the urban form and transit accessibility score.

Broken Windows and Other Types of Crime

Several studies suggest that there might be a relationship between the broken windows variable used in this report and other crime variables. Wilson and Kelling were the first to propose the now famous “broken windows” theory of neighborhood deterioration and crime.[59] They suggested that neighborhoods that provide a space where 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 unrepaired, 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. 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 the 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 the sharp decline in crime seen in New York City in the 1990s.[60] They found that these declines were not due to the improving economy, an aging population, and declining crack cocaine use, as has been suggested, but rather they found that laws against minor crimes, known as “broken windows” policing, was a statistically significant cause of the decline in violent crime.

Income and Crime

Several papers provide evidence that there may be endogeneity between the income variable and crime variables used in the report. Social and economic conditions of the neighborhood are important determinants of crime, more significant even than perceptions of neighborhood disorder. For example, Sampson and Raudenbush performed a longitudinal study of crime and neighborhood disorder in 1,966 Chicago neighborhoods.[61] 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. 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.

Studies suggest that perceptions of neighborhoods and their relative safety from crime are determined both by the characteristics of the perceiver and the characteristics of the neighborhood. For example, Taylor conducted a longitudinal study of the links between social disorder, physical disorder, fear of crime and incidence of crime.[62] He found that in neighborhoods with high property values, property crimes decreased faster or increased more slowly than 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 the study neighborhoods; rather the economic status of the neighborhoods appeared to play a more important role in the levels of fear of crime.

Omission of Perceived Crime Variable

Meanwhile, there is a concern that perceptions of crime may be equally important as crime, or even more important than crime, in determining mode choice. Eyler and others is one of many studies that uses perceptions of crime, rather than real crime, as a variable that influences travel behavior.[63] In addition, Seefeldt, Malina, and Clark argue that perceptions of crime may be a more important determinant of travel behavior than reported crime levels.[64] If this is true, the crime variables used in the models developed for the current research project are best thought of as proxy indicators of perceived crime levels.

II. RESEARCH METHODS

This chapter provides an overview of the rationale for the Phase 2 research, states the research objectives, provides an overview of the data sources, and describes the modeling techniques employed to analyze the data.

RESEARCH OBJECTIVES

Our research questions and expectations can be summarized as follows:

- How do the new neighborhood crime measures perform compared with the Phase 1 measures?
- How do the MNL model results compare with the binary logit model results?
- Is there a unique effect of crime on mode choice in highly urban environments (self-selection bias)?
- How might neighborhood crime and access to transit combine to affect mode choice?

Crime Measures Performance Comparison

The crime variables tested in Phase 1[65] were found to yield inconsistent, and at times, counter-intuitive results. We hypothesized that the calculation method used for these measures may have been the cause. The Phase 1 crime variables were calculated by summing the number of crimes in the traffic analysis zone (TAZ) of the origin of each Bay Area Travel Survey (BATS 2000) trip. This total number of crimes was then normalized by dividing by the population of the TAZ. This yielded an estimate of the total crimes per capita in each TAZ. However, as discussed in the Phase 1 report, since 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 (such as individuals who live in a TAZ) exhibit the characteristics of the group at large (such as those represented by an aggregation of individuals in a TAZ).

To address this problem, in Phase 2 we developed a new, more fine-grained set of crime measures that are specific to the crime conditions of the immediate environments of each trip origin in the BATS data set. Crimes within ⅛-, ¼- and ½-mile buffers around each trip origin were counted using a geographic information system (GIS) software tool (ArcGIS). To evaluate the performance of these new crime measures, we re-ran the original binary logistic regression models developed for Phase 1, replacing the Phase 1 crime variables with the new Phase 2 variables.

How does the MNL Model Result Compare with the Binary Logit Model Results?

After estimating binary logit model with the new crime variables, this study analyzed the impact of crime on an individual's mode choices using a discrete choice modeling approach, the MNL model. MNL models estimate the propensity of a traveler choosing non-auto modes—transit (bus or rail), walking, or biking—over car for the primary trip. MNL models (as opposed to the binary logit models used in Phase 1) are capable of identifying the subtle neighborhood crime conditions that affect the selection of specific modes simultaneously, much as a person actually evaluates modal choices in reality, and not sequentially as one mode compared to an indistinguishable block of all other modal choices together. This misrepresentation of individual mode choice also affects the interpretation of the influence of neighborhood crimes and other independent variables on mode choice. For example, a neighborhood's crime conditions may affect transit and pedestrian mode choice differently, but since a binary logit model lumps these modes together as a single alternative to choosing an automobile, these distinctions may be masked or distorted. As a result, the influence of our model's independent variables on mode choice will be more realistically represented by a MNL model than a binary logit model.

Is There a Unique Affect of Crime on Mode Choice in Highly Urban Environments (Self-Selection Bias)?

Attitudes towards 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 from enjoying their transit-oriented lifestyles by high crime rates. 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 like San Francisco, Oakland and Berkeley, we may actually find a positive correlation between crime rates and non-automotive mode share.

How Might Neighborhood Crime and Access to Transit Combine to Affect Mode Choice?

Contingent on our success at meeting the first two objectives (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.

DATA SOURCES

Crime Data

The objectives listed above served to guide our efforts at identifying and collecting the appropriate data sources for this project. Accordingly, this research first focused on developing binary 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 geo-coded to specific street addresses. Starting in January 2006, the police departments of thirty-six cities in the San Francisco Bay Area were contacted via email or letter requesting crime data for the year 2000. Of the thirty-six cities contacted, seven cities (Berkeley, Concord, Oakland, Santa Clara, Walnut Creek, San Francisco, and Sunnyvale) ultimately shared their data.

Crime Categories

The Uniform Crime Reporting (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 I and II.

Crime Categories – Part I

Part I crimes are considered the more serious crimes and are, therefore, most likely to be reported by law enforcement agencies.[66] Part I crimes 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 I crimes were broken down into two categories:

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

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

Crime Categories – Part II

As Part II crimes are described as all other crimes outside of Part I 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 II crimes.

The five Part II categories were determined as follows:

1. Part II, Violent Crimes: The UCR Handbook describes crimes such as simple assault, and assault and battery as Part II crimes. These crimes were considered for this study as P2V, or Part II violent crimes. Other violent crimes that fell into this category included sexual offense crimes, kidnapping and carjacking.
2. Part II, Crimes Against Property: Crimes involving stolen property are put into the P2P category.
3. Broken Window Crimes: This category captures Part II 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 affect 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 II-type crimes, which were put into the Broken Window category. In the City of Oakland, it must be noted that data was available regarding abandoned cars. For this city, this data was included in the Broken Window category. This category is abbreviated as BROKWIN.
4. Vice and Vagrancy Crimes: An important group of Part II crimes to be captured by this study were crimes such as prostitution, and drug- and weapon-related offenses. These activities are expected to affect walkability. These crimes describe criminal activity as opposed to the Broken Window type crimes, which refer to the environment or appearance of the neighborhood. The abbreviation used for this category is VICEVAG.
5. Crimes that do not Affect Walkability: Many Part II-type crimes were determined to not impact whether or not residents will walk, bike or take public transportation. Crime data collected for this 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 those involving major or minor injuries. These crimes or records of police activity were considered inconsequential on whether residents would walk, bike or take public transportation. The abbreviation used for this category is NOTAFFEC.

Final List of Crime Categories

Thus seven crime categories were developed altogether to group Part I and Part II type crimes. The seven categories and their abbreviations are:

1. Part I, Violent Crimes (P1V)
2. Part I Crimes Against Property (P1P)
3. Part II, Violent Crimes (P2V)

4. Part II, Crimes Against Property (P2P)
5. Broken Window Crimes (BROKWIN)
6. Vice and Vagrancy Crimes (VICEVAG)
7. Crimes that do not affect pedestrians' mode choice (NOTAFFEC)

A detailed list of these crime categories and their constituent crime types is provided in Table 25 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. Since we requested crime data from San Francisco Bay Area police departments, we needed a 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. There were two primary reasons why we ultimately selected the BATS 2000 dataset. First, since journey-to-work data is provided in aggregate form, it is not suitable for a disaggregate mode choice model. Second, it is a distinct possibility that neighborhood crime rates may have different effects on different trip purposes. Since Census data only reports commute trips, and BATS 2000 data surveys and reports the full spectrum of trip types, we felt our research would benefit from a wider range of trip purposes.

The BATS 2000 dataset provides detailed activity diary records for 14,563 households, which represents roughly 0.6 percent of the 2,429,257 total San Francisco Bay Area households in 1998. The surveyors utilized a geographically stratified sample, with the stratification based on counties and MTC's pre-defined 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 for these counties at 600 each. The other seven counties were randomly sampled according to the stratification method mentioned above.

These data are used by MTC to calibrate the regional travel demand model. Since it contains detailed activity records for each individual—including travel purpose, 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

Three measures of urban form were developed to determine the influence of urban form on transit, pedestrian and bicycle mode choice. The measures are: 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 1 comparing street patterns in a nine-square mile area of San Francisco and Walnut Creek.

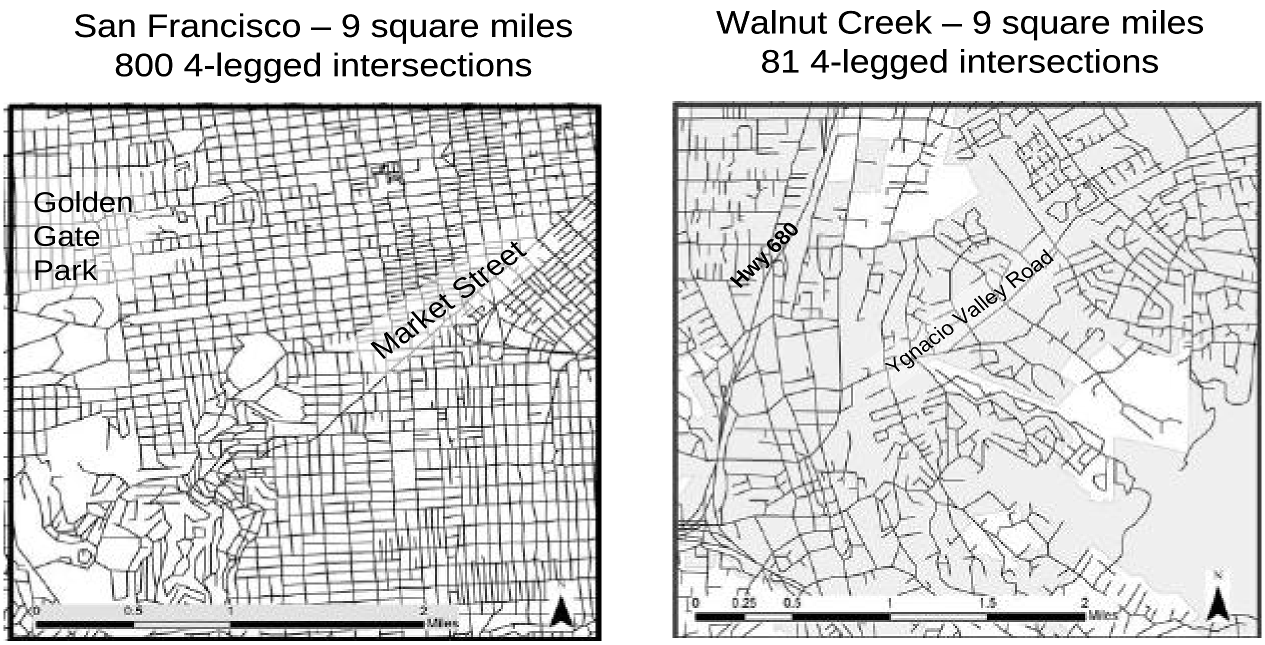

Figure 1. Gridiron vs. Suburban Street Network Patterns

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

Both the residential, and the residential and 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 was obtained from the MTC and the employment population data was obtained from the Association of Bay Area Governments (ABAG) in census tract form. Using census tract to TAZ correspondence tables also provided by the MTC, the employment per census tract estimates was 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 (for example, shopping centers, central business districts, and so on) for each survey respondent in the BATS 2000 dataset was developed. Data on the geographical distribution of shopping opportunities was obtained from the Association of Bay Area Governments (ABAG), which provides estimates of employees at the Travel Analysis Zone (TAZ) level for the Bay Area.[67]

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:

$$A_i = \Sigma_j [Jobs_j * F_{ij}]$$

Where:

F_{ij} = $Time_{ij}^{-v}$
Jobs = # of jobs in TAZ
Time = network travel times
i = residential zone
j = employment zone
-v = an empirically calculated friction factor using BATS 2000 data

DATASET PREPARATION

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

1. **Household File:** Contains coded data descriptions of each household that participated in the survey. Household data includes household income, the number of household vehicles, the number of persons in the household, the type of dwelling, the location of the household (city and TAZ) and other variables that describe the household.

2. **Person File:** Contains coded data descriptions of each person in each household that participated in the survey. Person data includes 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 two-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/Gov't
11 = Social Activities
12 = Relaxing/Resting
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
996 = Other
998 = Don't Know
999 = Refused

Source: MTC BATS 2000 Activity Survey File.

The location of each activity is also identified by a TAZ number, and if an activity is a trip, the origin and destination TAZs as well as the mode used for each trip are also 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 above, 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 above, with only trip data records. This file also identifies 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 Metropolitan Transportation Commission. This process is explained in greater detail in "Trip Linking Procedures" working paper.[68]

The first step was to create data tables that combined data from the various files described above. Mode choice analysis is typically done at a disaggregated level, meaning that each data record in the analysis table 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.

Since the largest share of trips taken by a person during a typical travel day are home-based and since 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 affect 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 since home-based transit trips are under-represented in the Unlinked Trips file. Since 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 (for instance, 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 since these modes are most likely to be used directly from the home.

Crime Data Coding

Five cities used in this study provided both Part I and Part II crime data. The cities of Berkeley, Concord, Oakland and Walnut Creek provided both Part I and Part II data for the year 2000. The city of Santa Clara provided Part I and Part II data for the year 2001.

The cities of San Francisco and Sunnyvale were only able to provide Part I data. Details regarding the coding process for these cities are given below.

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. 9,306 of the records provided (or 72.6%) were successfully geo-coded 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 geo-coding was done, 19,216 records, 85.3%, remained that were successfully geo-coded with sufficient descriptive information for each record for the purposes of categorizing. All records had unique case numbers.

Oakland

The city of Oakland provided the most comprehensive dataset. We received 193,131 records of Part I and Part II crimes and incidents for the year 2000. However, these records included entries with either follow-up information on crimes that 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 the crime description was left blank, 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 this data. Consequently, these records were also removed from the dataset.

The remaining records were categorized and geo-coded. 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 geo-coded and included in this study for the city of Oakland was 68,513 (or 35.5%).

Santa Clara

The city of Santa Clara provided 15,634 records of Part I and Part II crimes for the year 2001. Since this was the earliest year for which data was 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 this 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%) were geo-coded successfully.

Walnut Creek

The city of Walnut Creek provided 33,981 records of Part I and Part II crimes for the year 2000. Of these records, 25,023, or 73.7 percent, geo-coded successfully and fell within the bounds of the city limits.

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

Sunnyvale

2,123 Part I 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—and therefore, we were not able to geo-code 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 geo-code a total of 2,120 records, or 99.9 percent of the original dataset provided.

San Francisco

22,429 Part 1 crime records were provided by the city of San Francisco 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.

In order to geo-code 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.

III. MODELING APPROACH

DISAGGREGATE CRIME VARIABLES

The crime variables tested in Phase 1 were found to yield inconsistent, and at times, counter-intuitive results. We hypothesized that the calculation method used for these measures may have been the cause. The Phase 1 crime variables were aggregate measures, calculated by summing the number of crimes in the traffic analysis zone (TAZ) of the origin of each BATS 2000 survey trip. This total number of crimes value was then normalized by dividing by the population of the TAZ. This yielded an estimate of the total crimes per capita in each TAZ, and as such the TAZ was this measure's unit of analysis. However, as discussed in the Phase 1 report, since 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 erroneously assumes that members of a group (such as individuals who live in a TAZ) exhibit the characteristics of the group at large (such as those represented by an aggregation of individuals in a TAZ). Furthermore, discrete choice analysis (the method widely used in mode choice analysis today) is performed at the person-level, or disaggregate-level of analysis.

To address these problems, we developed a new, more fine-grained set of crime measures that are specific to the crime conditions of the immediate environments of each trip origin in the BATS data set, and thereby more appropriate to the disaggregate measures used in discrete choice analysis methods. Crimes within ⅛-, ¼- and ½-mile buffers around each trip origin were counted using a geographic information system (GIS) software tool (ArcGIS). Since population estimates for these buffers were not available, these crime variables could not be normalized. However, we assumed that the improvements in locational specificity gained by using this method would outweigh the reductions in comparability between crime estimates at trip origins that may have occurred due to using un-normalized data. To evaluate the performance of these new crime measures, we re-ran the original binary logistic regression models developed for Phase 1, replacing the Phase 1 crime variables with the new Phase 2 variables.

As mentioned previously, only Part 1 crime data was available for San Francisco and Sunnyvale while both Part 1 and Part 2 crime data was available for Berkeley, Oakland, Walnut Creek, Santa Clara and Concord. Hence a separate set of models, examining the impacts of both Part 1 and Part 2 crimes, were run for Berkeley, Oakland, Walnut Creek, Santa Clara and Concord.

THE MNL MODEL

After estimating binary logit model with the new crime variables, this study analyzed the impact of crime on an individual's mode choices using the MNL modeling technique, with the individual traveler as the unit of analysis.

While the binary logit model employed in the Phase 1 report could group the mode choices into two categories (for example, transit, and all modes other than transit), MNL allows separate estimation of the probability (Pr) of an individual (i) choosing a specific mode choice out of several "j" choices. The choice set in this report included traveling by car, taking transit, walking and biking. The MNL model assumes that each individual selects the mode that maximizes her utility. As mentioned earlier, MNL models are very commonly used in transportation planning, especially in travel demand forecasting.

$$\Pr(y_i = j) = \frac{\exp(X_i\beta_j)}{1 + \sum_{j=1}^{J}\exp(X_i\beta_j)}$$

NEW INDEPENDENT VARIABLES

Several new independent variables were created to reduce the probability of omitted variable bias. For example, the new land use/urban design variables include those measuring the relative mix of land uses, and variables measuring accessibility to jobs by car and transit during both peak and off-peak periods. Further, several new socio-demographic variables were created such as the race/ethnicity and income at the census tract-level. Finally, while the Phase 1 report only controlled for the urban design and socio-demographic conditions at the trip origin, the Phase 2 study hypothesized that an individual's choice of mode at the start of the trip would not only be impacted by the conditions at the place of trip origin, but also at the trip destination. For example, if John needs to walk a fair bit from the transit stop to his office, his choice of choosing transit would be impacted by the urban form at the trip destination. Hence the urban form/land use, socio-demographic, and crime variables were created for both the trip origin and trip destination (although the destination crime variable was not used since it restricted the number of trip observations we could use in the MNL model).

MODELING TRANSIT ACCESS TO TEST THE NEIGHBORHOOD EXPOSURE HYPOTHESIS

The MNL models measuring the impact of crime on mode choice found that transit and pedestrian mode choice behaviors respond differently to neighborhood crime levels. The crimes seemed to be positively correlated to the transit mode and negatively correlated to the pedestrian mode. To explain this difference in behavior, the research team outlined what they termed the "Neighborhood Exposure Hypothesis," where enclosed, motorized modes of travel (transit and automobiles) tend to confer a higher level of personal safety and control over one's environment when traveling than non-motorized mode (bicycling and walking). If true, then we hypothesized that a similar effect should be seen for transit access trips.

To test this hypothesis, we developed a new set of binary logit models that predicted mode choice for the access portion of the trip to the transit stop/station for transit riders. Every transit trip requires an access trip (unless the bus stops right at the travelers front doorstep). These access trips are generally car, walk, or bicycle trips. These models use a similar structure used to predict mode choice for the primary mode, but have been refined to the needs and requirements of predicting transit access mode choice. It is hypothesized that in high-crime areas more people would access transit by car, compared to biking or walking.

IV. MODELING RESULTS

THE NEW CRIME MEASURE: HOW WELL DOES IT WORK?

The crime variables tested in Phase 1 were found to yield inconsistent, and at times, counter-intuitive results. We hypothesized that the calculation method used for these measures may have been the cause. To address this problem, we developed a new, more "fine-grained" set of crime measures. Crimes within ⅛-, ¼- and ½-mile buffers around each trip origin were counted using a geographic information system (GIS) software tool (ArcGIS). To evaluate the performance of these new crime measures, we re-ran the original binary logistic regression models developed for Phase 1, replacing the Phase 1 crime variables with the new Phase 2 variables.

Comparison of Crime Variable Results for the Transit Binary Logistic Models

Table 2 compares the binary logistic regression results for Phase 1 and 2 crime variables for San Francisco transit work trips.

Table 2. Binary Logistic Results for Transit Work Trips – San Francisco

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	2.714		0.001		-0.001		0.000	
p1v	-		0.009	**	0.003	**	0.001	***

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

While the number of property crimes per capita in the TAZ of each trip origin was not statistically significant for work trips in San Francisco, Phase 2 binary logistic regression runs found that violent crime count variables for all three buffer sizes were statistically significant, suggesting the new crime measures are better at capturing the affects of neighborhood crimes on travel behavior. However, the signs of these relationships are all positive, indicating that more crimes lead to more transit mode choice—a counter-intuitive set of results that are inconsistent with our theoretical expectations.

Table 3 compares the binary logistic regression results for Phase 1 and 2 crime variables for San Francisco transit non-work trips.

Table 3. Binary Logistic Results for Transit Non-Work Trips – San Francisco

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	5.293		0.008	*	0.002		0.000	
p1v	-	-	0.004		0.001		0.001	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

As seen above for San Francisco transit work trips, the per capita (Phase 1) crime variable was not statistically significant for transit non-work trips. The only statistically significant Phase 2 crime variable was the number of Part 1 property crimes within a ⅛-mile buffer of each trip origin, and similar to work trips, the sign of this relationship is positive and counter-intuitive.

Table 4 compares the binary logistic regression results for Phase 1 and 2 crime variables for Berkeley and Oakland transit work trips.

Table 4. Binary Logistic Results for Transit Work Trips – Berkeley & Oakland

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	1.075		-0.001		-0.002		0.000	
p1v	-	-	0.021		0.003		0.002	
p2p	-	-	0.001		0.001		0.001	
p2v	-	-	0.095		0.046		0.014	
bw	-	-	-0.011		-0.003		0.001	
vv	-	-	0.003		-0.001		0.000	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

Consistent with the results from Phase 1, none of the Phase 2 crime variables were statistically significant.

Table 5 compares the binary logistic regression results for Phase 1 and 2 crime variables for Berkeley and Oakland transit non-work trips.

Table 5. Binary Logistic Results for Transit Non-Work Trips – Berkeley & Oakland

Crime Type	Phase 1 Per Capita in TAZ *B*	Phase 1 Per Capita in TAZ Sig.	Phase 2 1/8 mi *B*	Phase 2 1/8 mi Sig.	Phase 2 1/4 mi *B*	Phase 2 1/4 mi Sig.	Phase 2 1/2 mi *B*	Phase 2 1/2 mi Sig.
p1p	-3.051		0.004		0.002		0.001	*
p1v	-	-	0.089	***	0.037	***	0.009	***
p2p	-	-	0.035	**	0.026	***	0.008	***
p2v	-	-	-0.030		0.051		0.003	
bw	-	-	0.027	***	0.017	***	0.008	***
vv	-	-	0.015	**	0.007	***	0.002	**

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

In contrast to the transit work trip models developed for these cities, more than half the Phase 2 crime variable variants were statistically significant for non-work transit trips, while the per capita (Phase 1) crime variable was not statistically significant. This suggests the new crime calculation methods are a substantial improvement over the Phase 1 method for non-work transit trips in Berkeley and Oakland. However, as mentioned above, all of these statistically significant results have a positive sign, suggesting that people choose transit in high-crime neighborhoods—a counter-intuitive set of results.

Table 6 compares the binary logistic regression results for Phase 1 and 2 crime variables for Suburban transit work trips.

Table 6. Binary Logistic Results for Transit Work Trips – Suburbs (Concord, Walnut Creek & Santa Clara)

Crime Type	Phase 1 Per Capita in TAZ *B*	Phase 1 Per Capita in TAZ Sig.	Phase 2 1/8 mi *B*	Phase 2 1/8 mi Sig.	Phase 2 1/4 mi *B*	Phase 2 1/4 mi Sig.	Phase 2 1/2 mi *B*	Phase 2 1/2 mi Sig.
p1p	-	-	0.000		0.003		0.002	**
p1v	-	-	0.156		0.040		0.013	
p2p	-	-	-0.001		-0.001		0.004	
p2v	-	-	0.143	***	0.028	**	0.011	***
bw	-	-	0.031		0.003		0.010	**
vv	-51.252	*	-0.054		-0.030	*	-0.003	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

The best performing crime variable in Phase 1's suburban work transit mode choice model runs was the number of vice and vagrancy crimes per capita—a variable that also had a negative sign making it consistent with our theoretical expectations. Echoing this Phase 1 finding, the Phase 2 model runs found that the higher the number of vice and vagrancy crimes within a ¼-mile of trip origins, the less likely these travelers were to choose transit. However, this was the only variable that yielded a statistically significant, negative sign. The five other statistically significant crime variables all had positive signs.

Table 7 compares the binary logistic regression results for Phase 1 and 2 crime variables for Suburban transit non-work trips.

Table 7. Binary Logistic Results for Transit Non-Work Trips – Suburbs (Concord, Walnut Creek & Santa Clara)

Crime Type	Phase 1 Per Capita in TAZ		Phase 2 1/8 mi		Phase 2 1/4 mi		Phase 2 1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	-	-	-0.004		-0.003		0.001	
p1v	-	-	-0.077		-0.047		-0.006	
p2p	-	-	-0.021		-0.005		0.000	
p2v	-	-	0.136	**	0.006		0.011	**
bw	-	-	-0.006		0.005		0.006	
vv	-87.433	*	-0.112		-0.019		-0.001	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

Similar to Suburban work trips, the best performing Phase 1 suburban transit non-work crime variable was the number of vice and vagrancy crimes per capita. This variable also had the expected negative sign. Phase 2 model runs for suburban non-work trips did not find any statistically significant variables with the expected negative signs, and no statistically significant finding for the vice and vagrancy variables.

Comparison of Crime Variable Results for the Pedestrian Binary Logistic Models

Table 8 compares the binary logistic regression results for Phase 1 and 2 crime variables for San Francisco pedestrian work trips.

Table 8. Binary Logistic Results for Pedestrian Work Trips – San Francisco

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	-21.433		0.024		0.008	*	0.003	**
p1v	-	-	0.030		0.012		0.006	**

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

While the number of property crimes per capita in the TAZ of each trip origin was not statistically significant for pedestrian work trips in San Francisco, Phase 2 pedestrian binary logistic regression runs found that both property and violent crime count variables were statistically significant at the half- and quarter-mile levels. However, similar to the transit work mode choice models discussed above, the signs of these relationships are all positive.

Table 9 compares the binary logistic regression results for Phase 1 and 2 crime variables for San Francisco pedestrian non-work trips.

Table 9. Binary Logistic Results for Pedestrian Non-Work Trips – San Francisco

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	31.483	**	0.012	**	0.004	**	0.001	***
p1v	-	-	0.020	*	0.003		0.002	**

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

The Phase 1 model runs found that the best performing crime variable was the number of property crimes per capita. However, the sign of this variable was positive—a counter-intuitive result. Phase 2 model runs found all but one of the tested crime variables were statistically significant and all of these had counter-intuitive (positive) signs as well.

Table 10 compares the binary logistic regression results for Phase 1 and 2 crime variables for Berkeley and Oakland pedestrian work trips.

Table 10. Binary Logistic Results for Pedestrian Work Trips – Berkeley & Oakland

Crime Type	Phase 1 Per Capita in TAZ *B*	Sig.	Phase 2 1/8 mi *B*	Sig.	1/4 mi *B*	Sig.	1/2 mi *B*	Sig.
p1p	-12.073	**	-0.003		-0.003		-0.001	*
p1v	-	-	-0.056		-0.016		-0.005	
p2p	-	-	-0.026		-0.023	**	-0.009	**
p2v	-	-	-0.685	**	-0.384	***	-0.015	
bw	-	-	-0.038		-0.009		-0.006	**
vv	-	-	-0.025	*	-0.008	*	-0.002	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

The best-performing Phase 1 crime variable for this model was the number of property crimes per capita—a variable that also had a negative sign that was consistent with our theoretical expectations. Consistent with the results from Phase 1, all Phase 2 pedestrian work model runs had the expected (negative) sign, and roughly half of the crime variables were statistically significant.

Table 11 compares the binary logistic regression results for Phase 1 and 2 crime variables for Berkeley and Oakland pedestrian non-work trips.

Table 11. Binary Logistic Results for Pedestrian Non-Work Trips – Berkeley & Oakland

Crime Type	Phase 1 Per Capita in TAZ *B*	Sig.	Phase 2 1/8 mi *B*	Sig.	1/4 mi *B*	Sig.	1/2 mi *B*	Sig.
p1p	-2.784		0.011	**	0.003		-0.001	
p1v	-	-	-0.017		0.002		-0.001	
p2p	-	-	-0.030		-0.011		-0.005	**
p2v	-	-	0.041		-0.041		-0.014	
bw	-	-	0.051	**	0.015	**	-0.001	
vv	-	-	-0.004		0.000		0.000	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

While the best Phase 1 crime variable for these model runs was not statistically significant, there were four statistically significant Phase 2 crime variables. Of these, three had counter-intuitive signs (positive) while one (P2P half-mile) had a negative sign consistent with our theoretical expectations.

Table 12 compares the binary logistic regression results for Phase 1 and 2 crime variables for Suburban pedestrian work trips.

Table 12. Binary Logistic Results for Pedestrian Work Trips – Suburbs

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	-	-	0.031		0.007		0.001	
p1v	-277.312	*	0.315		0.074		0.049	*
p2p	-	-	0.088		0.022		0.010	
p2v	-	-	0.158		-0.025		-0.004	
bw	-	-	0.005		0.008		0.006	
vv	-	-	0.304	***	0.040	**	0.015	**

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

Here, the best Phase 1 crime variable (P1V—violent crimes per capita) for these model runs was statistically significant and had a negative sign consistent with our expectations. However, of the four statistically significant Phase 2 crime variables, all had counter-intuitive signs (positive).

Table 13 compares the binary logistic regression results for Phase 1 and 2 crime variables for Suburban pedestrian non-work trips.

Table 13. Binary Logistic Results for Pedestrian Non-Work Trips – Suburbs

Crime Type	Phase 1		Phase 2					
	Per Capita in TAZ		1/8 mi		1/4 mi		1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	-	-	0.002		0.007	*	0.002	
p1v	-57.898		0.119		0.094	*	0.018	
p2p	-	-	0.066	*	0.033	***	0.006	
p2v	-	-	0.075		0.055	**	0.013	**
bw	-	-	0.040		0.024	*	0.010	*
vv	-	-	0.033		0.024	***	0.008	**

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

In Phase 1, no statistically significant crime variable was found for these model runs. However, a total of eight crime variables were significant in the Phase 2 model runs. All of these significant Phase 2 variables had counter-intuitive, positive signs.

Comparison of Crime Variable Results for the Bicycle Binary Logistic Models

Since the BATS 2000 dataset for the study cities contained a relatively small amount of bicycle trip records, we chose to analyze all cities together. Table 14 compares the binary logistic regression results for Phase 1 and 2 crime variables for All Cities bicycle work trips.

Table 14. Binary Logistic Results for Bicycle Work Trips – All Cities

Crime Type	Phase 1 Per Capita in TAZ		Phase 2 1/8 mi		Phase 2 1/4 mi		Phase 2 1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	2.563		-0.007		-0.001		0.000	
p1v	-	-	-0.009		-0.004		-0.001	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

In both Phases 1 and 2, no statistically significant crime variables were found for bicycle work trip model runs.

Table 15 compares the binary logistic regression results for Phase 1 and 2 crime variables for All Cities bicycle non-work trips.

Table 15. Binary Logistic Results for Bicycle Non-Work Trips – All Cities

Crime Type	Phase 1 Per Capita in TAZ		Phase 2 1/8 mi		Phase 2 1/4 mi		Phase 2 1/2 mi	
	B	Sig.	*B*	Sig.	*B*	Sig.	*B*	Sig.
p1p	4.090		0.002		0.003		0.001	
p1v	-	-	-0.003		-0.001		0.001	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01

In both Phases 1 and 2, no statistically significant crime variables were found for bicycle non-work trip model runs.

Analysis and Conclusions

Comparisons and analysis of binary logistic mode choice model runs using Phase 1 and Phase 2 variables suggests that our Phase 2 variables provide significant, but still modest improvements over our Phase 1 crime variables. We hoped that these improved crime measures would yield two benefits: more consistent and powerful statistical significance across all model runs, and relationships (signs) that are more consistent with our theoretical expectations (for example, more neighborhood crimes lead to less non-auto and more auto mode choice).

These comparisons produced a wider variety of statistically significant results, providing the research team with a host of crime variables to choose from and suggesting that the Phase 2 crime measures represent an important improvement over the Phase 1 measures. However, the fact that (like our findings in Phase 1) many statistically significant Phase 2 crime variables had positive signs (contrary to our theoretical expectations) also suggests that our Phase 1 methods of measuring crimes—in particular, the methods that relied on calculating crime rates for entire neighborhoods (TAZs)—are not the cause of these counter-intuitive results. To further investigate the possible reasons for these curious findings, we also tested and analyzed a variety of modified crime measures that selectively identify the highest crime neighborhoods.

WHAT TYPE OF CRIME VARIABLE WORKS BEST?

Additional efforts to identify a refined set of crime variables that would improve the consistency of our analytic results included the analysis of crime binary or “dummy” variables. A variety of dummy variables were created with the hypothesis that the effect of the number of neighborhood crimes on travel behavior might not be continuous and linear. In other words, the likelihood of choosing to walk might not increase at the same rate when the number of neighborhood crimes decreases from 10 to 5 as it does from 100 to 95. Therefore, the continuous variable measuring the number of crimes in our study neighborhoods may not be appropriate or comparable for all neighborhoods.

We constructed a number of “dummy” variables where values of “1” were given to high-crime neighborhoods and a “0” to moderate–and low-crime–neighborhoods. A variety of definitions for what constitutes a high-crime neighborhood were constructed and tested. For each model run (work, non-work, and so on) the home neighborhood of each trip case was classified according to its percentile ranking in terms of the number of reported crimes. Thus, dummy crime variables were created that coded the neighborhood crime levels of each home-based trip in the BATS 2000 data set where each trip record would receive a “1” if it was in the 99th, 98th, 97th, 96th, 95th, 90th, and 80th percentile rankings of neighborhood crimes. These variables were then run in each of our MNL models in place of the continuous crime counts variables described above and evaluated for performance.

Table 16 compares the multinomial logistic regression results for the all cities work model using the best-performing continuous crime variable and the results for the best-performing dummy crime variable.

Table 16. Key Model Performance Results Comparing Continuous and Dummy Crime Variables – All Cities Work Model

Variable	Nagelkerke R Square	Transit		Walk		Bicycle	
		B	Sig.	*B*	Sig.	*B*	Sig.
Violent Crimes (P1V) w/in 1/8-Mile of Home	0.433	0.015	***	-0.015	*	-0.014	
Violent Crimes (P1V) w/in 1/8-Mile of Home (Top 2%)	0.431	0.878	**	-0.827		-0.869	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

In terms of overall model goodness of fit (as measured with the Nagelkerke R Square method), the continuous crime variable performed slightly better than the dummy variable in the All Cities Work model. In terms of individual mode choice results, the continuous variable performed better as well, with a statistically significant affect on walking mode choice while the dummy crime variable did not have a statistically significant affect on walking or bicycling mode choice.

Table 17 compares the MNL regression results for the All Cities non-work model using the best-performing continuous crime variable and the results for the best-performing dummy crime variable.

Table 17. Key Model Performance Results Comparing Continuous and Dummy Crime Variables – All Cities Non-Work Model

Variable	Nagelkerke R Square	Transit		Walk		Bicycle	
		B	Sig.	*B*	Sig.	*B*	Sig.
Violent Crimes (P1V) w/in 1/8-Mile of Home	0.479	-0.004		-0.022	*	0.052	
Violent Crimes (P1V) w/in 1/8-Mile of Home (Top 20%)	0.487	0.972	***	-0.934	**	0.151	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

In terms of overall model goodness of fit (as measured with the Nagelkerke R Square method), the All Cities non-work model with the dummy crime variable performed slightly better than the continuous variable model. In terms of individual mode choice results, the dummy variable performed better as well, with a statistically significant affect on transit mode choice (although the positive sign is counter-intuitive and inconsistent with our theoretical expectations) while the dummy crime variable did not have a statistically significant affect on transit or bicycling mode choice.

Analysis and Conclusions for Continuous Versus "Dummy" Crime Variable Comparisons

Tests of a variety of dummy and continuous crime variables found that the continuous violent crime variables seems to work best in terms of model goodness of fit as well as in terms of their ability to influence the choice of individual modes for work trips, while the dummy variable representing the neighborhoods with violent crimes in the 80th percentile ranking seems to work best for non-work trips. However, these findings continue to be somewhat inconsistent with our theoretical expectations, since for both model runs, transit mode choice is more attractive to both work and non-work travelers in high-crime neighborhoods. Nevertheless, as we analyzed these results, we noticed that with these improved crime variables we began to see some consistency emerge, with transit mode choice associated with high-crime neighborhoods while high-crime areas tend to discourage pedestrian mode choice.

HOW DOES CRIME AFFECT DIFFERENT TRIP PURPOSES?

Once the research team identified the best Phase 2 crime measures to use for MNL mode choice modeling purposes, we ran the best-performing work and non-work models for analysis of how crimes might influence mode choice.

Work Trips

Table 18 provides the detailed MNL regression results for the All Cities work model using the best-performing crime variable.

Table 18. Multinomial Logistic Regression Results for Work Trip Mode Choice

Variable	Transit	Walk	Bicycle
Person Variables			
Race (White=1, Non-White=0)	-0.0780	1.0370 ***	0.7370 **
Age Categories			
1=under 19	N/D	N/D	N/D
2=19-39	Referent	Referent	Referent
3=40-59	-1.0050 ***	-0.1940	-0.9740
4=above 59	-0.4960 *	0.2320	-0.4510
Gender (2=Male, 1=Female)	0.1480	-0.0660	1.0260 ***
Household Variables			
Household Income (<$50k=0, >$50k=1)	0.2230 *	-0.2290	-0.1390
Tenure (Own Home=2, Don't Own Home=1)	0.0940	-0.2100	-0.6420 **
Home in San Francisco (1=yes, 0=no)	0.2830	0.2920	0.6480
Number of HH Bicycles	-0.0970 ***	-0.0640	0.5590 ***
Household Vehicles per Licensed Driver	-1.5120 ***	-1.4340 ***	-1.8310 ***
Trip Characteristics			
Total Trip Distance (1/100th-Mile)	-0.0010 ***	-0.0050 ***	-0.0008 ***
Trip Start Time (1= peak, 0=non-peak)	1.0390 ***	-0.0210	-0.4100 *
Neighborhood Variables			
Home TAZ Transit Accessibility Score	1.39E-07	1.58E-07	1.40E-06 ***
Home TAZ Population Density	-0.0030	0.0090	-0.0010
Home TAZ Mixed Use (Jobs-Housing Balance)	-0.6650 **	0.5390	-0.1770
Home TAZ # 4-Legged Intersections/Acre	0.8260	3.8300 ***	1.9790
Home TAZ Median Income	-6.07E-06 *	-5.82E-06	-1.05E-05
Home TAZ Percent White	1.1910 ***	0.5230	0.8980
Destination TAZ Population Density	8.70E-06 **	-4.26E-06	-1.72E-05 *
Destination TAZ Mixed Use (Jobs-Housing Balance)	-1.0330 ***	-0.4830	-0.1970
Destination TAZ Median Income	-1.52E-05 ***	-1.39E-05 ***	-6.91E-06
Violent Crimes (P1V) w/in 1/8-Mile of Home	0.0150 ***	-0.0150 *	-0.0140
Constant	1.4100 **	-0.0100	-6.4150 ***
Model Fit			
N			3630
-2 Log likelihood			4117.00
Nagelkerke R Square			0.433

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

Goodness of Fit

Nagelkerke R-Square results for the work logistic model runs indicate the model explains roughly 43 percent of the variation in the dataset.

Person Variable Results

While race was not a statistically significant variable determining work trip mode choice, caucasian respondents were more likely to choose to walk or bicycle than drive or ride in a car. On the other hand, the older a person was, the less likely they were to choose to ride transit, though age did not play a role in determining the propensity to walk or ride a bike. Finally, gender played an important role in determining bicycle mode choice (with men more likely to bicycle to work than women) while it did not have a statistically significant influence determining transit or pedestrian mode choice.

Household Variable Results

Somewhat surprisingly, household income did not have a consistent, statistically significant affect on work trip mode choice. Households earning more than $50,000 a year were more likely to choose transit over driving, but had no measureable effect on pedestrian or bicycling mode choice.

Home ownership (tenure) might also capture some of the affects of income on mode choice, thereby helping to explain why the household income variable did not play a more important role in these work trip model runs. However, tenure only had a statistically significant impact on the propensity to bicycle to work, suggesting that those who own their homes are less likely to choose this mode and more likely to drive or ride in a car instead.

Household location (San Francisco or not San Francisco) was not a statistically significant determinant of any mode choice for work trips.

Consistent with our theoretical assumptions, the higher the number of vehicles per licensed driver within a household, the less likely a household member will choose to ride transit, walk or bicycle for work trips. Similarly, the number of bicycles per household was a statistically significant determinant for riding transit or bicycling, with more bicycles in a household leading to a lower likelihood of taking transit and a higher likelihood of bicycling to work.

Trip Characteristics Results

We had hypothesized that trip length would be negatively associated with the propensity to take transit, walk or ride a bicycle. This hypothesis was confirmed with the findings that for work trips, the longer the trip length, the more likely a traveler will choose to drive or ride in a car.

The start time for the trip played a statistically significant role in determining work transit and bicycle mode choice, with a trip started during the peak period leading to a greater likelihood of riding transit. This is consistent with our expectations since most transit services are designed to serve peak-period traffic.

Neighborhood Variable Results

Overall, statistically significant results for the urban form variables included in the work model were somewhat spotty. The Home TAZ Transit Accessibility Score was not significantly related with the propensity to ride transit (contrary to our expectations) and to walk, while it was a highly statistically significant determinant of bicycling mode choice, with higher accessibility scores leading to a greater propensity to cycle to work.

Results for the Home TAZ Population Density variable were statistically insignificant across all three non-automotive modes. We interpret these inconclusive findings as suggesting that the focus in urban form and travel behavior research in the past on population (or housing) density may be misguided (at least for the trip origin neighborhood), particularly when it comes to work trips. While higher population densities would reasonably lead to a higher aggregate level of transit ridership in a neighborhood, higher population densities would not affect any individual’s decision to walk, bicycle or ride transit.

A curious result for the Home TAZ Mixed Use variable suggests that the more balanced jobs and housing are within a neighborhood, the less likely a person will be to choose transit, and the more likely they will choose to drive or ride in a car. We suspect that resident-rich and job-poor neighborhoods—and vice-versa—may reflect the distribution of BART stations in the Bay Area since a large share of these stations are located in suburban, residential neighborhoods or in downtown, jobs-rich areas.

The Home TAZ # 4-Legged Intersections/Acre variable represents the degree to which a person’s neighborhood is designed in a pedestrian or auto-oriented fashion. The more 4-legged intersections in a neighborhood, the more grid-like the street network is and the more pedestrian friendly it will feel to its residents. The statistically significant, positive sign for this variable for pedestrian work trip mode choice suggests that the more pedestrian-oriented a neighborhood’s urban design qualities, the more likely a person will be to choose to walk rather than drive.

The socio-demographic characteristics of the home neighborhood also play an important role for work trip transit mode choice, but do not seem to play a role determining work pedestrian or bicycle mode choice. For work trips, the higher the neighborhood’s median income and the higher the share of Caucasions, the greater the likelihood that a person will choose to take transit. Therefore, wealthier, white commuters may be more willing to take transit when they see that many of their neighbors are doing the same.

This model also included a number of variables to measure the urban form characteristics of the destination neighborhoods of each BATS 2000 trip. Interestingly, population densities at the destination TAZ were positively correlated with the propensity to choose transit or walk. This is particularly interesting when compared to the lack of statistically significant findings for the Home TAZ Population Density variable. We speculate that population density variables might be serving as a stand-in for transit service quality, since transit services are often more plentiful and have higher quality of service in dense urban neighborhoods than in low-density areas.

Reflecting the curious result for the Home TAZ Mixed Use variable, the Destination TAZ Mixed Use variable finding suggests that the more balanced jobs and housing are within a destination's neighborhood, the less likely a person will be to choose transit and the more likely he or she will choose to drive or ride in a car. Our suspicion that the BART over-sample in the BATS 2000 dataset is skewing our results applies to this finding as well.

The economic characteristics of the destination neighborhood play an important role for work trip transit and pedestrian mode choice. For work trips, the higher the neighborhood's median income and the higher the share of Caucasions, the greater the likelihood a person will choose to take transit. As suggested above, this may be the result of the BART over-sample, as well as the tendency for wealthier neighborhoods to be insulated from high levels of traffic and crimes.

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 the work model, the continuous/count variable for the number of violent crimes within ⅛th of a mile of each trip origin worked best.

For work trips the number of crimes within ⅛ th mile of a survey respondent's home was positively related to transit mode choice—a counter-intuitive result. Specifically, the crime coefficient (0.015) for the transit mode choice indicates that every unit increase in crime increases the odds of transit mode choice over auto by 1.5 percent [exp(0.015) = 1.015. Odds = 1.015-1 = 0.015, or 1.5 percent increase]. For residential areas one standard deviation (11.5 crime incidents) higher than the mean crime areas, this translates into 17.25 percent increase in odds. However, more crimes were also correlated with a lower propensity to walk with high crime neighborhoods decreasing the odds of walking over choosing auto decrease by 17.25 percent for work trips. Specifically, the crime coefficient (-0.0150) for the walk mode choice indicates that every unit increase in crime decreases the odds of walk mode choice over auto by 1.5 percent [exp(-0.015)=0.985. Odds = 0.985-1 = -0.015, or 1.5 percent decrease]. For areas one standard deviation (11.5 crime incidents) higher than the mean crime areas, this translates into 17.25 percent decrease in odds.

The counter-intuitive finding for transit mode choice may be due to a number of factors, including still-inadequate measures of urban form, the potential for a residential self-selection bias for San Francisco residents (as discussed in the Phase 1 report and in the Research Methods section of this report) and the affects of the mode of access transit riders use to get to their bus or train stop.

Nevertheless, the negative and statistically significant sign for crimes on pedestrian mode choice support our theoretical assumptions that high neighborhood crimes tend to depress pedestrian mode choice and encourage auto use for work trips. We further suspect that transit riders may feel safe from crimes in a way similar to car riders, particularly when a car is used to access the transit stop or station, while high neighborhood crimes would depress walking and bicycling mode choice to reach a stop or station. Therefore, it is possible that neighborhood crimes primarily affect people's perception of safety when they are most exposed to their neighborhood environments—for instance, when they are not protected by a vehicle and they are walking or bicycling.

Non-Work Trips

Table 19 provides the detailed MNL regression results for the All Cities non-work model using the best-performing crime variable.

Table 19. Multinomial Logistic Regression Results for Non-Work Trip Mode Choice

Variable	Transit	Walk	Bicycle
Person Variables			
Race (1=White, 0=Non-White)	-0.4700	-0.5900	0.7350
Age Categories			
1=under 19	N/D	N/D	N/D
2=19-39	Referent	Referent	Referent
3=40-59	-0.3820	-0.9740 **	0.3240
4=above 59	0.4000	-0.0170	1.2680
Gender (2=Male, 1=Female)	-0.7640 ***	-0.0070	-0.2970
Employment Status (1=Employed, 0=Unemployed)	-0.5730	-0.8290 ***	1.6890
Household Variables			
Household Income (0=$50k & under, 1=over $50k)	-0.2390	-0.1810	1.1530
Tenure (2=Own Home, 1=Don't Own Home)	-0.4920	-0.0050	-1.2140 *
Home in San Francisco (1=yes, 0=no)	0.0470	0.2290	-0.6110
Number of HH Bicycles	-0.1590	0.0360 ***	0.4830 ***
Household Vehicles per Licensed Driver	-2.2450 ***	-1.2960 ***	-1.6220 *
Trip Characteristics			
Total Trip Distance (1/100th-Mile)	0.0001	-0.0090 ***	-0.0030
Trip Start Time (1= peak, 0=non-peak)	1.2460 ***	-0.1600	0.9240
Neighborhood Variables			
Home TAZ Transit Accessibility Score	2.44E-07	-9.40E-08	1.32E-06
Home TAZ Population Density	0.0050	0.0360 ***	0.0220
Home TAZ Mixed Use (Jobs-Housing Balance)	-2.3040 ***	-0.9350	-1.4720
Home TAZ # 4-Legged Intersections/Acre	1.1250	-2.4430	11.4230 **
Home TAZ Median Income	4.89E-06	6.56E-06	1.09E-05
Home TAZ Percent White	0.4700	0.5900	-0.7350
Destination TAZ Population Density	1.67E-05 *	1.11E-05	-5.60E-05 *
Destination TAZ Mixed Use (Jobs-Housing Balance)	0.3260	0.9330	-1.4920
Destination TAZ Median Income	-1.29E-05 **	-1.85E-05 ***	1.49E-06
Violent Crimes (P1V) w/in 1/8-Mile of Home (Top 20%)	0.9720 ***	-0.9340 **	0.1510
Constant	0.4710	-1.0910	-4.7160
Model Fit			
N			1073
-2 Log likelihood			905.55
Nagelkerke R Square			0.487

Notes:

* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

Goodness of Fit

Nagelkerke R-Square results for non-work logistic model runs indicate the model explains roughly 49 percent of the variation in the dataset.

Person Variable Results

While race was not a statistically significant variable determining non-work trip mode choice, the older a person was, the less likely she was to choose to walk. However, age did not impact the propensity to ride transit or a bicycle. Gender influenced transit mode choice, with women more likely to ride transit to non-work activities than men, but not bicycle or pedestrian mode choice. Finally, employed persons were less likely to choose to walk to non-work trip destinations than to drive. However, employment status did not impact the likelihood of choosing to ride transit or a bicycle versus a car for a non-work trip.

Household Variable Results

Again, somewhat surprisingly, household income did not have a consistent, statistically significant effect on non-work trip mode choice. Home ownership (tenure) might also capture some of the affects of income on mode choice, thereby helping to explain why the household income variable did not play a more important role in these work trip model runs. However, tenure only had a statistically significant impact on the propensity to bicycle to non-work activities (just as was found for work trips), suggesting that those who own their homes are less likely to bike and more likely to drive or ride in a car instead.

Household location (San Francisco or not San Francisco) was not statistically significant determinant of any mode choice for non-work trips.

Consistent with our theoretical assumptions, the higher the number of vehicles per licensed driver within a household, the less likely is a household member to ride transit, walk or bicycle for non-work trips. Similarly, more bicycles in a household lower the likelihood of walking and increase the likelihood of bicycling to non-work destinations.

Trip Characteristics Results

We had hypothesized that the trip length would be negatively associated with the propensity to take transit, walk, or ride a bicycle. This hypothesis was confirmed for walking mode choice, with the finding that for non-work trips, the longer the trip length, the more likely a traveler will choose to drive or ride in a car.

The start time for the trip played a statistically significant role in determining non-work transit mode choice, with a trip started during the peak period leading to a greater likelihood of riding transit, consistent with our expectations since most transit services are designed to serve peak-period traffic. However, the trip start time did not impact pedestrian or bicycle mode choice.

Neighborhood Variable Results

Overall, statistically significant results for the urban form variables included in the non-work model were somewhat spotty. The Home TAZ Transit Accessibility Score did not impact the propensity to ride transit, a bicycle, or to walk to non-work trip destinations.

Results for the Home TAZ Population Density variable were statistically insignificant for bicycle and transit mode choice probabilities, but were statistically significant and with a positive sign for pedestrian mode choice. This finding suggests that people are more comfortable walking to non-work destinations when their home neighborhood has more “eyes on the street” as Jane Jacobs hypothesized, making people feel safer from crimes.

A curious result for the Home TAZ Mixed Use variable (identical to the findings for the work trip model) suggests that the more balanced jobs and housing are within a neighborhood, the less likely a person is to choose transit and the more likely she is to choose to drive or ride in a car. (See the discussion above in the Work Trip model results section.)

The Home TAZ Four-Legged Intersections/Acre variable represents the degree to which a person’s neighborhood is designed in a pedestrian or auto-oriented fashion. The more 4-legged intersections in a neighborhood, the more grid-like the street network is and the more pedestrian friendly it will feel to its residents. The statistically significant, positive sign for this variable for bicycle work trip mode choice suggests that the more pedestrian-oriented the neighborhood, the more likely a person is to choose to bicycle for non-work trips rather than drive.

The socio-demographic characteristics of the home neighborhood do not seem to play a role determining non-work mode choice. There were no statistically significant findings for either the Home TAZ Median Income or the Home TAZ Percent White variables.

This model also included a number of variables to measure the urban form characteristics of the destination neighborhoods of each trip. Interestingly, while population density at the destination TAZ was positively correlated with the propensity to ride transit, it was negatively correlated with the propensity to choose a bicycle. These findings suggest that people may feel less safe when bicycling to a dense urban destination.

There were no statistically significant findings for the Destination TAZ Mixed Use variable; however, the economic characteristics of the destination neighborhood play an important role for non-work trip transit and pedestrian mode choice. For these trips, the higher the neighborhood’s median income, the lower the likelihood a person will choose to take transit or walk.

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 the non-work model, the dummy variable for the 80th percentile of violent crimes within ⅛ th-mile of the traveler’s home location worked best.

For non-work trips, travelers who lived in neighborhoods in the 80th percentile of violent crimes within ⅛ th mile were less likely to choose to walk to their non-work destinations—a finding consistent with our theoretical assumptions that high neighborhood crimes tend to depress pedestrian mode choice and encourage auto use for work trips. Specifically, the crime dummy coefficient (-0.9340) for the walk mode choice indicates that when compared to an area where crime is lower than 80th percentile in violent crime (lower crime area), the odds of choosing to walk over driving decrease by 61 percent in a higher crime area (violent crimes are at or above 80th percentile) [exp(-0.9340) = 0.39. Odds = 0.39-1 = -0.61, or 61 percent decrease]. However, just as we found for work trips, residents of the highest violent crime neighborhoods were also more likely to choose to ride transit than to drive a car—a counter-intuitive result. Specifically, the crime dummy coefficient (0.9720) for the transit mode choice indicates that the odds of choosing transit mode choice over auto are 1.64 times, or 164 percent, higher in high crime area [exp(0.9720) = 2.64. Odds = 2.64-1 = 1.64, or 164 percent increase].

COMPARING BINARY TO MNL MODEL RESULTS

By modeling mode choice using MNL instead of binary logit modeling techniques (as were used in Phase 1), Phase 2 substantially improved the credibility and applicability to practice of our research findings. Critiques of our Phase 1 research pointed out that binary logit models are not capable of distinguishing between multimodal options—only the choice of one mode and all the others as another indistinguishable group. Therefore, MNL models are capable of identifying the subtle neighborhood crime conditions that affect the selection of specific modes simultaneously, much as a person actually evaluates modal choices in reality, and not sequentially as one mode compared to an indistinguishable block of all other modal choices together.

While MNL modeling methods did not magically eliminate the somewhat inconsistent and counter-intuitive binary model results found in Phase 1, comparison and analysis of the findings of Phases 1 and 2 suggest that they have yielded significant, if somewhat modest improvements. First, while Phase 1 binary model results suggested that under certain conditions, higher crime levels might encourage walking, Phase 2 multinomial model results did not confirm these findings, and in fact, found that for both work and non-work trips high-crime neighborhoods tend to encourage transit and discourage pedestrian mode choice. The fact that these findings were more consistent and robust across multiple model runs suggests to us that the MNL modeling methods have helped to disentangle the somewhat complex relationships between neighborhood crime, urban form, and mode choice.

Finally, the use of MNL modeling techniques enhances the potential for more direct applications of our findings to planning practice. MNL models are widely accepted as the preferred method for evaluating discrete choices and are nearly ubiquitous in travel demand modeling practice across the United States.

THE INFLUENCE OF RESIDENTIAL LOCATION ON NEIGHBORHOOD CRIMES AND MODE CHOICE

Results for MNL mode choice models suggest that while high crime levels reduce the propensity to walk, they tend to increase the likelihood of selecting transit. These results seem counter-intuitive, since riding transit often requires a person to expose him or herself to their high-crime neighborhoods when walking or bicycling to a transit stop or station. Since our Phase 1 research found similarly counter-intuitive results, we hypothesized that the large number of San Francisco trips in our study, and the high numbers of crimes in San Francisco neighborhoods compared with the rest of the Bay Area may be the cause of these curious findings. More specifically, we surmised that since the San Francisco residents have chosen to live in the most urbanized city in the Bay Area, they may discount concerns for their safety from crimes. In other words, San Francisco residents may have selected to live there explicitly to enjoy the benefits of its urban environment, which include walkable neighborhoods and high-quality transit services, and in choosing this lifestyle, they have already decided these benefits outweigh their fears of higher levels of crime.

To test this hypothesis, we divided our data set into San Francisco and non-San Francisco cases and ran work and non-work mode choice models for each. Table 20 reports the results for the San Francisco Only work trip mode choice logistic regression model.

Table 20. Multinomial Logistic Regression Results for Work Trip Mode Choice – San Francisco Only

Variable	Transit	Walk	Bicycle
Race (1=White, 0=Non-White)	-0.0690	0.8580 **	1.5140 **
Age (1=39 & Under, 2=Over 39)	0.7550 ***	-0.5250 *	-0.5240
Gender (2=Male, 1=Female)	-0.0780	0.0550	-0.6110
Household Variables			
Household Income (0=$50k & under, 1=over $50k)	0.3870 **	-0.1450	-0.3490
Tenure (2=Own Home, 1=Don't Own Home)	-0.0230	-0.2870	-1.1520 **
Number of HH Bicycles	-0.2240 ***	0.0140 *	0.8800 ***
Household Vehicles per Licensed Driver	-1.7020 ***	-1.6530 ***	-2.3130 ***
Trip Characteristics			
Total Trip Distance (1/100th-Mile)	-0.0010 ***	-0.0040 ***	-0.0007 **
Trip Start Time (1= peak, 0=non-peak)	0.7550 ***	0.5100 *	-1.0670 ***
Neighborhood Variables			
Home TAZ Transit Accessibility Score	-6.61E-08	1.42E-06 **	-7.13E-07
Home TAZ Population Density	0.0004	0.0140 *	-0.0110
Home TAZ Mixed Use (Jobs-Housing Balance)	-0.5180	2.0180 ***	0.0790
Home TAZ # 4-Legged Intersections/Acre	-0.0670	2.9400	6.4530 **
Home TAZ Median Income	-1.23E-05 *	-4.59E-07	-1.77E-05
Home TAZ Percent White	0.7970	-0.9100	1.1380
Destination TAZ Population Density	4.51E-06	2.60E-06	-3.11E-05 **
Destination TAZ Mixed Use (Jobs-Housing Balance)	-1.2010 ***	-1.3000 **	-0.4310
Destination TAZ Median Income	-1.29E-05 ***	8.63E-07	-1.32E-05 *
Violent Crimes (P1V) w/in 1/8-Mile of Home	0.0080	-0.0210 **	-0.0200
Constant	3.4020 ***	-3.8790 **	-1.4890
Model Fit			
N			1375
-2 Log likelihood			1872.00
Nagelkerke R Square			0.493

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

Table 21 reports the results for the non-San Francisco (Oakland, Berkeley, Walnut Creek, Concord, Sunnyvale and Santa Clara) work trip mode choice logistic regression model.

Table 21. Multinomial Logistic Regression Results for Work Trip Mode Choice – Not San Francisco

Variable	Transit	Walk	Bicycle
Person Variables			
Race (1=White, 0=Non-White)	-0.0960	2.2050 ***	0.3980
Age (1=39 & Under, 2=Over 39)	-0.7260 ***	-0.2720	-0.7060 **
Gender (2=Male, 1=Female)	-0.2530 *	0.4070	-1.3300 ***
Household Variables			
Household Income (0=$50k & under, 1=over $50k)	0.1920	-0.4090	-0.3000
Tenure (2=Own Home, 1=Don't Own Home)	0.1810	0.0740	-0.1600
Number of HH Bicycles	-0.0200	0.0400 *	0.4840 ***
Household Vehicles per Licensed Driver	-1.1870 ***	-1.3440 ***	-1.8010 ***
Trip Characteristics			
Total Trip Distance (1/100th-Mile)	-0.0010 ***	-0.0080 ***	-0.0008 ***
Trip Start Time (1= peak, 0=non-peak)	1.4170 ***	-0.8950 ***	-0.2330
Neighborhood Variables			
Home TAZ Transit Accessibility Score	2.42E-07	-1.67E-06 **	2.40E-06 ***
Home TAZ Population Density	-0.0210 **	0.0400 *	0.0080
Home TAZ Mixed Use (Jobs-Housing Balance)	-1.1990 **	-0.9870	-0.6330
Home TAZ # 4-Legged Intersections/Acre	2.7110 **	8.1890 ***	1.3510
Home TAZ Median Income	-7.46E-06	1.16E-06	-1.05E-05
Home TAZ Percent White	1.6470 ***	3.2060 *	1.9810
Destination TAZ Population Density	2.80E-05 ***	-4.53E-05	5.67E-06
Destination TAZ Mixed Use (Jobs-Housing Balance)	-0.4310	-0.6430	0.6300
Destination TAZ Median Income	-1.55E-05 ***	-4.21E-05 ***	1.19E-07
Violent Crimes (P1V) w/in 1/4-Mile of Home (Top 4%)	1.2960 ***	1.3820 *	0.7700
Constant	1.8140 *	5.0380 *	-10.0730 ***
Model Fit			
N			2255
-2 Log likelihood			2074.00
Nagelkerke R Square			0.402

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

Both work models (San Francisco Only and Not San Francisco) yielded acceptable goodness of fit measures (Nagelkerke R Square values of 0.49 and 0.402, respectively) and individual statistically significant variable coefficients largely consistent with the All Cities model and with each other.

Crime variable results, however, did not conform to our hypothesis. While we expected that San Francisco-based work trips would favor transit, pedestrian, and bicycle mode choices over automobiles in high-crime neighborhoods (and by expectation, highly transit-oriented neighborhoods as well), we found that in San Francisco, high crimes were not statistically correlated to transit or bicycle mode choice, and were negatively correlated with pedestrian mode choice.

Also in contrast to our initial hypothesis, non-San Francisco residents were found to favor transit and pedestrian mode choice for work trips when they live in high-crime neighborhoods while bicycle mode choice was not affected by crime levels.

Table 22 reports the results for the San Francisco Only non-work trip mode choice logistic regression model.

Table 22. Multinomial Logistic Regression Results for Non-Work Trip Mode Choice – San Francisco Only

Variable	Transit		Walk		Bicycle	
Person Variables						
Race (1=White, 0=Non-White)	-0.0460		0.7940	***	0.5570	
Age (1=39 & Under, 2=Over 39)	-0.4040	**	-0.3070		-2.0810	***
Gender (2=Male, 1=Female)	-0.4910	***	-0.3070	*	-0.7120	*
Household Variables						
Household Income (0=$50k & under, 1=over $50k)	-0.2820		0.0960		-0.4120	
Tenure (2=Own Home, 1=Don't Own Home)	-0.3760	*	-0.3730	*	-0.4660	
Number of HH Bicycles	-0.1620	**	0.0130	**	0.5470	***
Household Vehicles per Licensed Driver	-1.9270	***	-1.3720	***	-1.9040	***
Trip Characteristics						
Total Trip Distance (1/100th-Mile)	-0.0010	***	-0.0070	***	-0.0008	
Trip Start Time (1= peak, 0=non-peak)	1.0360	***	-0.1530		0.3040	
Neighborhood Variables						
Home TAZ Transit Accessibility Score	1.66E-07		1.25E-07		4.51E-07	
Home TAZ Population Density	0.0030		0.0130	**	0.0010	
Home TAZ Mixed Use (Jobs-Housing Balance)	-0.8990	*	-0.0740		-1.9160	
Home TAZ # 4-Legged Intersections/Acre	-1.0020		-1.2360		2.5450	
Home TAZ Median Income	-9.71E-06		-1.49E-05	*	-2.37E-05	
Home TAZ Percent White	0.6790		1.1020		0.1530	
Destination TAZ Population Density	1.39E-06		1.43E-05	***	1.14E-05	
Destination TAZ Mixed Use (Jobs-Housing Balance)	-0.6060		-0.3480		0.4430	
Destination TAZ Median Income	-2.52E-05	***	-5.50E-06		-1.51E-06	
Violent Crimes (P1V) w/in 1/8-Mile of Home (Top 10%)	0.3160		-1.0410	***	-0.5300	
Constant	2.7670	*	-0.3240		-4.4690	
Model Fit						
N					1446	
-2 Log likelihood					1948.00	
Nagelkerke R Square					0.484	

Notes:
* = p < 0.10
** = p < 0.05
*** = p < 0.01
N/A = Not Applicable.
N/D = No Data.

Table 23 reports the results for the non-San Francisco non-work trip mode choice logistic regression model.

Table 23. Multinomial Logistic Regression Results for Non-Work Trip Mode Choice – Not San Francisco

Variable	Transit	Walk	Bicycle
Race (1=White, 0=Non-White)	-0.3080	0.2670	0.7840 *
Age (1=39 & Under, 2=Over 39)	-0.3770	-0.2950	-0.7440 **
Gender (2=Male, 1=Female)	-0.0100	-0.3000 *	-0.6900 **
Household Variables			
Household Income (0=$50k & under, 1=over $50k)	-0.5430 **	0.2670	-0.4640
Tenure (2=Own Home, 1=Don't Own Home)	0.0970	-0.3980 **	-0.5040
Number of HH Bicycles	-0.2700 ***	0.0140	0.4060 ***
Household Vehicles per Licensed Driver	-1.9740 ***	-1.2800 ***	-1.5240 ***
Trip Characteristics			
Total Trip Distance (1/100th-Mile)	0.0002 *	-0.0070 ***	-0.0030 ***
Trip Start Time (1= peak, 0=non-peak)	1.6360 ***	-0.2270	0.6210 *
Neighborhood Variables			
Home TAZ Transit Accessibility Score	9.27E-07 **	3.78E-07	1.18E-06 *
Home TAZ Population Density	0.0130	0.0140	0.0400 **
Home TAZ Mixed Use (Jobs-Housing Balance)	-1.7090 **	1.4420 *	2.9940 **
Home TAZ # 4-Legged Intersections/Acre	-0.3070	3.2910 **	0.8490
Home TAZ Median Income	5.69E-06	2.01E-06	1.65E-05
Home TAZ Percent White	1.3220	-1.6080 **	-0.9890
Destination TAZ Population Density	1.55E-05	-3.64E-06	-3.56E-06
Destination TAZ Mixed Use (Jobs-Housing Balance)	0.8940	-0.9430	-1.5380
Destination TAZ Median Income	-1.39E-05 ***	-4.48E-06	-5.80E-06
Violent Crimes (P1V) w/in 1/8-Mile of Home	0.0640 *	-0.0930 **	-0.0290
Constant	-3.5650 **	-0.7800	-7.4420 ***
Model Fit			
N			3004
-2 Log likelihood			2165.00
Nagelkerke R Square			0.361

Notes:
* = $p < 0.10$
** = $p < 0.05$
*** = $p < 0.01$
N/A = Not Applicable.
N/D = No Data.

Both non-work models (San Francisco Only and Not San Francisco) yielded acceptable goodness of fit measures (Nagelkerke R Square values of 0.484 and 0.361, respectively) and individual statistically significant variable coefficients largely consistent with the All Cities model and each other.

Crime variable results for the non-work models were somewhat different from those generated by the work models above, but did not conform to our hypothesis, either. Again, while we expected that San Francisco-based non-work trips would favor transit, pedestrian, and bicycle mode choices over automobiles in high-crime neighborhoods (and by expectation, highly transit-oriented neighborhoods as well), we found that in San Francisco, high crimes were not statistically correlated to transit or bicycle mode choice, and were negatively correlated with pedestrian mode choice (findings that were consistent with the San Francisco Only Work model). However, while we found that non-San Francisco work trips were positively correlated with the propensity to choose transit and walking, high-crime neighborhoods tend to discourage non-San Francisco non-work trips in these same neighborhoods. Meanwhile, transit trips were positively correlated with the propensity to select transit for non-work trips in non-San Francisco neighborhoods.

Therefore, the fact that we found positive relationships between transit mode choice and high crime in non-San Francisco neighborhoods for both work and non-work trip mode choice suggests that crime levels may indeed be serving as a proxy for transit service levels in non-San Francisco cities, while crime levels only appear to serve as a proxy for pedestrian-oriented urban form characteristics in non-San Francisco neighborhoods for work trips.

HOW DOES NEIGHBORHOOD CRIME AFFECT ACCESS TO TRANSIT MODE CHOICE?

As discussed above, while the above findings suggest that neighborhood crimes reduce the propensity to choose walking, they also suggest that high-crime neighborhoods encourage transit ridership—a counter-intuitive finding. For those who choose to drive to a transit stop or station (park-and-ride or kiss-and-ride), transit may be a relatively safe alternative compared to driving for the whole trip, since high-crime neighborhoods can be safely traversed via car and the risks associated with driving due to collisions can be reduced by riding transit.

To understand why transit is favored over cars in higher crime neighborhoods, we developed a new set of models that predicted mode choice for the access portion of the trip to the transit stop/station for transit riders. Every transit trip requires an access trip (unless the bus stops right at the travelers front doorstep). These access trips are generally car, walk, or bicycle trips. These models use a similar structure as used to predict mode choice for the primary mode, but have been refined to the needs and requirements of predicting transit access mode choice.

Table 24 reports the results for the All Cities Work and Non-Work transit access trip mode choice logistic regression models.

Table 24. Logistic Regression Results for Transit Access Mode Choice

Variable	Work		Non-Work	
Person Variables				
Race (White=1, Non-White=0)	-0.0290		0.6340	
Age Categories				
1=under 19	Referent		Referent	
2=19-39	-0.7750		-1.1620	
3=40-59	-1.1960		-2.1500	**
4=above 59	N/D		N/D	
Gender (2=Male, 1=Female)	-0.1710		0.5610	
Household Variables				
Household Income (<$50k=0, >$50k=1)	-1.2780	***	-0.2110	
Tenure (Own Home=2, Don't Own Home=1)	-0.5610	*	-1.5190	**
Home in San Francisco (1=yes, 0=no)	2.6730	***	2.2730	**
Number of HH Bicycles	0.0760		0.1920	
Household Vehicles per Licensed Driver	-1.5380	***	-1.0820	*
Trip Characteristics				
Total Trip Distance (1/100th-Mile)	-0.0010	***	0.0000	*
Trip Start Time (1= peak, 0=non-peak)	-0.4450		-1.3010	**
Neighborhood Variables				
Home TAZ Transit Accessibility Score	0.0000	**	0.0000	**
Home TAZ Population Density	0.0070		-0.0340	
Home TAZ # 4-Legged Intersections/Acre	2.8350		10.5280	***
Home TAZ Median Income	0.0000	**	0.0000	
Home TAZ Percent White	2.0480	*	0.7750	
Destination TAZ Median Income	0.0000		0.0000	
Violent Crimes (P1V) w/in 1/8-Mile of Home	-0.0260	*	N/A	
Violent Crimes (P1V) w/in 1/2-Mile of Home	N/A		-0.0010	
Constant	-0.8830		-4.3930	
N	470		218	
-2 Log likelihood	345.84		148	
Nagelkerke R Square	0.624		0.571	

Notes:

* = $p < 0.10$

** = $p < 0.05$

*** = $p < 0.01$

N/A = Not Applicable.

N/D = No Data.

Goodness of Fit

Nagelkerke R-Square results for the work and non-work transit access logistic model runs indicate the models explain between 57 and 62 percent of the variation in the dataset.

Person Variable Results

While there were few statistically significant results in these model runs for person-level variables, almost all signs of these variables were consistent with our theoretical assumptions. The single statistically significant (and negative sign) result, for persons aged 40 to 59, suggests that walking and bicycling to transit for non-work trips are primarily for the young.

Results for the Race variable were statistically insignificant as were results for the Gender (Male) dummy variable, suggesting that both race and gender do not affect transit access mode choice in these city groupings.

Household Variable Results

While household income is generally thought to play an important role in determining mode choice, we found it was only statistically significant in determining the likelihood of choosing to walk or ride a bicycle to a transit stop for non-work trips. For both work and non-work transit access trips, the negative signs suggest that in general, high income people are more likely to drive than walk or cycle.

Home ownership (tenure) has a statistically significant influence on transit access mode choice, with home owners more likely to drive to a transit station rather than walk or bicycle.

Household location also plays an important role in determining transit access mode choice, with San Francisco residents more likely to walk or ride a bicycle to transit for both work and non-work trips. These findings are consistent with our theoretical assumption that San Francisco’s transit and pedestrian-oriented built environment tends to attract residents who want to live a more car-free lifestyle.

Consistent with our theoretical assumptions, the higher the number of vehicles per licensed driver within a household, the less likely a household member will choose to walk or bicycle to transit for both work and non-work trips. Somewhat surprisingly, the variable measuring the number of bicycles per household was not statistically significant for either transit mode access models. This may be due to the fact that very small shares of the total non-auto trips in these models were bicycle trips.

Trip Characteristics Results

In general, we assumed that the longer the total trip distance, the less likely a person would be to walk or ride a bicycle to a transit stop. When it comes to work trips, this is the case, with the Total Trip Distance variable showing a statistically significant negative sign. However, a counter-intuitive result was found for non-work trips, where the longer the total trip distance, the more likely it was that transit riders would walk or ride a bike to the transit stop.

The start time for the trip also played a statistically significant role in determining non-work transit access mode choice, but not for work trips. If the start time for the trip was during a peak travel period, people were less likely to choose walking or bicycling to reach their transit stop. This finding seems counter-intuitive, since it seems that the increased competition for park-and-ride spaces at transit stations during peak periods would influence people taking non-work trips to avoid driving. However, since carpooling to a transit station was included in the automobile mode choice category of the dependent variable, these non-work travelers may be taking advantage of a household member driving to work and leaving during the peak.

Neighborhood Variable Results

Of the three variables representing urban form (Home TAZ Transit Accessibility, Home TAZ Population Density, and Home TAZ 4-Legged Intersections/Acre), it is interesting to note that Transit Accessibility is highly statistically significant in both models while Population Density is not significant in either. This suggests that even when choosing transit access mode choice, which would presumably be more influenced by the urban form of one's immediate neighborhood and not the urban form of the larger region accessible by transit, the land uses accessible by transit is more important than the density of a person's home neighborhood. The positive signs for these variables suggest that the more employment accessible by transit (for instance, a short travel distance) from a person's home TAZ, more the likelihood that he or she will walk or ride a bicycle to the transit stop.

However, the findings for the urban design characteristics of the home neighborhood add to our understanding of how local versus regional urban form characteristics influence transit access mode choice. The Home TAZ Four-Legged Intersections/Acre variable represents the degree to which a person's neighborhood is designed in a pedestrian or auto-oriented fashion. The more 4-legged intersections in a neighborhood, the more grid-like the street network is and the more pedestrian friendly it will feel to its residents. The statistically significant, positive signs for this variable in both work and non-work models suggest that the more pedestrian-oriented a neighborhood, the more likely a person is to choose to walk or ride a bicycle to a transit stop rather than drive.

The socio-demographic characteristics of the home neighborhood also play an important role for work trip transit access mode choice, but do not seem to play a role determining non-work transit access trips. For work trips, both the higher the neighborhood's median income and the higher the share of Caucasions, the more likely a person will choose walking or bicycling to the transit stop over driving. The median income of the trip's destination TAZ was not a statistically significant factor determining transit station access mode choice.

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 the work and non-work models, violent crime variables worked best, yielding the expected signs and in the case of work trips, a statistically significant result. Therefore, it appears that violent crimes near a transit rider's home will deter them from walking or riding a bicycle, and encourage them to drive to a transit station instead. Specifically, the crime coefficient (-0.026) for the work trip model indicates that every unit increase in crime decreases the odds of biking or walking to transit station over auto mode choice by 2.6 percent [exp(-0.015)=0.974. Odds = 0.974-1 =-0.026, or 2.6 percent decrease]. For areas one standard deviation (18.5 crime incidents) higher than the mean crime areas, this translates into 48.1 percent decrease in odds.

V. SUMMARY AND CONCLUSIONS

This study (Phase 2) found additional substantiation for the proposition that neighborhood crime rates influence the propensity to choose non-motorized modes of transportation for home-based trips. While Phase 1 provided findings that supported this hypothesis, it also found several cases where high crime rates were associated with an increased likelihood of travelers choosing non-auto modes of travel. The methods and measures employed in Phase 2 were specifically designed to understand the reasons for these inconsistent and counter-intuitive Phase 1 results.

PHASE 1 IMPROVEMENTS

This Phase 2 research investigated the following possible explanations for the inconsistent and counter-intuitive Phase 1 results:

Geographically "Coarse" Crime Measures

We hypothesized that the calculation method used for crime measures may have been the cause. The Phase 1 crime variables were calculated by summing the number of crimes in the traffic analysis zone (TAZ) of the origin of each BATS 2000 survey trip. This total number of crimes number was then normalized by dividing by the population of the TAZ. This yielded an estimate of the total crimes per capita in each TAZ, however, since 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 (such as individuals who live in a TAZ) exhibit the characteristics of the group at large (such as those represented by an aggregation of individuals in a TAZ). To address this problem, we developed a new, more "fine-grained" set of crime measures that are specific to the crime conditions of the immediate environments of each trip origin in the BATS data set. Crimes within ⅛-, ¼- and ½-mile buffers around each trip origin were counted. Since population estimates for these buffers were not available, these crime variables could not be normalized. However, we assumed that the improvements in locational specificity gained by using this method would outweigh the reductions in comparability between crime estimates at trip origins that may have occurred due to using un-normalized data. To evaluate the performance of these new crime measures, we re-ran the original binary logistic regression models developed for Phase 1, replacing the Phase 1 crime variables with the new Phase 2 variables.

Comparisons and analysis of binary logistic mode choice model runs using Phase 1 and Phase 2 variables suggests that our Phase 2 variables provide significant, but still modest improvements over our Phase 1 crime variables. The Phase 2 crime variables produced a wider variety of statistically significant results, providing the research team with a host of crime variables to choose from and suggesting that the Phase 2 crime measures represent an important improvement over the Phase 1 measures. However, the fact that (like our findings in Phase 1) many statistically significant Phase 2 crime variables had counter-intuitive positive signs also suggests that our Phase 1 methods of measuring crimes—in particular, the methods that relied on calculating crime rates for entire neighborhoods (TAZs)—are not the primary cause of these counter-intuitive results.

Different Relationships Between Mode Choice and High and Low Crime Neighborhoods

Phase 2 tested and compared the performance of a variety of “dummy” and continuous crime variables in an effort to identify a set of crime variables that would improve the consistency and interpretability of our model results. A variety of dummy variables were created with the hypothesis that the effect of the number of neighborhood crimes on travel behavior might not be continuous and linear. In other words, the likelihood of choosing to walk might not increase at the same rate when the number of neighborhood crimes decreases from 10 to 5 as it does from 100 to 95. Therefore, the continuous variable measuring the number of crimes in our study neighborhoods may not be appropriate or comparable for all neighborhoods.

We constructed a number of “dummy” variables where values of “1” were given to high-crime neighborhoods and a “0” to moderate and low-crime neighborhoods. Thus, dummy crime variables were created where each home-based trip record would receive a “1” if it was in the 99^{th}, 98^{th}, 97^{th}, 96^{th}, 95^{th}, 90^{th}, and 80^{th} percentile rankings of neighborhood crimes. These variables were then included in each of our MNL models in place of the continuous crime counts variables.

These tests found that the continuous violent crime variables seem to work best (in terms of model goodness of fit as well as in terms of their ability to influence the choice of individual modes) for work trips, while the dummy variable representing the neighborhoods with violent crimes in the 80^{th} percentile ranking seems to work best for non-work trips. However, these findings continue to be somewhat inconsistent with our theoretical expectations, since for both model runs, transit mode choice is more attractive to both work and non-work travelers in high-crime neighborhoods. Nevertheless, as we analyzed these results, we noticed that with these improved crime variables we began to see some consistency emerge—high-crime areas tend to discourage pedestrian mode choice and encourage transit mode choice.

Binary Versus MNL Modeling Techniques

Phase 2 substantially improved the credibility and applicability to practice of our research findings by employing MNL modeling techniques. MNL models (as opposed to the binary logit models used in Phase 1) are capable of identifying the subtle neighborhood crime conditions that affect the selection of specific modes simultaneously, much as a person actually evaluates modal choices in reality, and not sequentially as one mode compared to an indistinguishable block of all other modal choices together.

Comparison and analysis of the findings of Phases 1 and 2 suggest that the MNL modeling technique has yielded significant if somewhat modest improvements. While Phase 1 binary model results suggested that under certain conditions, higher crime levels might encourage walking, Phase 2 MNL model results did not confirm these findings, and in fact, found that for both work and non-work trips high-crime neighborhoods tend to encourage transit and discourage pedestrian mode choice. The fact that these findings were more consistent and robust across multiple model runs suggests to us that the MNL modeling methods have helped to disentangle the somewhat complex relationships between neighborhood crime, urban form, and mode choice.

BEYOND PHASE 1 IMPROVEMENTS: NEW DEVELOPMENTS AND FINDINGS FROM PHASE 2

Once the improved Phase 2 methods and measures were developed and tested, the research team turned their attention to analyzing the model results to help us understand the relationships between neighborhood crimes and mode choice.

Transit and Pedestrian Mode Choice: Different Responses to Neighborhood Crimes

A comparison of model results for work and non-work trips (all cities) found that while the continuous/count variable for the number of violent crimes within ⅛ th of a mile of each trip origin performed best for work trips, the dummy 80th percentile of violent crimes within ⅛ th of a mile of each trip origin performed best for non-work trips.

For both work and non-work trip mode choice models, high-crime neighborhoods were positively associated with transit mode choice—a counter-intuitive result—and negatively associated with the propensity to walk. The counter-intuitive finding for transit mode choice may be due to a number of factors, including still-inadequate measures of urban form, the potential for a residential self-selection bias for San Francisco residents (as discussed in the Phase 1 report) and the effects of the mode transit riders use to get to their bus or train stop.

Residential Location, Neighborhood Crimes and Mode Choice

While the finding that high-crime neighborhoods tend to reduce the likelihood of a traveler choosing to walk, we also found to our surprise that the same neighborhoods also tend to increase the likelihood of selecting transit. In an effort to better understand these findings, we hypothesized that the large number of San Francisco trips in our study and the high numbers of crimes in San Francisco neighborhoods compared to the rest of the Bay Area may be the cause. More specifically, San Francisco residents may have chosen to live there specifically to enjoy the benefits of its urban environment, which include walkable neighborhoods and high-quality transit services, and in choosing this lifestyle, they have decided these benefits outweigh their fears of higher levels of crime.

To test this hypothesis, we divided our data set into San Francisco and non-San Francisco cases and ran work and non-work mode choice models for each. While we expected that San Francisco-based work trips would favor transit, pedestrian, and bicycle mode choices over automobiles in high-crime neighborhoods (and by expectation, highly transit-oriented neighborhoods as well), we found that in San Francisco, high crime rates were not statistically correlated to transit or bicycle mode choice, and were negatively correlated with pedestrian mode choice. However, while we found that non-San Francisco work trips were positively correlated with the likelihood of choosing transit and walking, high-crime neighborhoods tend to discourage non-San Francisco non-work walk trips. Meanwhile, crime was positively correlated with the propensity to select transit for non-work trips in non-San Francisco neighborhoods.

Transit Station Access Mode Choice and the Neighborhood Exposure Hypothesis

The research team outlined what they termed, the “Neighborhood Exposure Hypothesis” to understand why transit and pedestrian mode choice behaviors respond differently to neighborhood crime levels. We hypothesized that compared with non-motorized mode (bicycling and walking), enclosed, motorized modes of travel (transit and automobiles) tend to confer a higher level of personal safety and control over one’s environment. If true, we further hypothesized that a similar effect should be seen for transit access trips.

To test this hypothesis, we developed a new set of models that predicted mode choice for the access portion of the trip to the transit stop/station for transit riders. For the work and non-work models, violent crime variables worked best, yielding the expected sign, and in the case of work trips, a statistically significant result. Therefore, it appears that violent crimes near a transit rider’s home will deter them from walking or riding a bicycle and encourage them to drive instead. Thus, while transit mode choice model results continue to give counter-intuitive results—where people who live in high-crime neighborhoods are more likely to take transit than drive—travelers in high-crime neighborhoods are less likely to walk or ride their bicycles than drive. We attributed this finding to the fact that while driving and, to some extent, transit offer some level of protection from neighborhood crime, walkers and cyclists feel more exposed in these same neighborhoods. If true, then we thought we might find that the affect of crime on transit trips can be better understood within this context as well. Simply put, transit trips require an access trip link or “leg” where the person travels from his or her home to the transit stop or station. Mode choice for this transit access link should be similarly influenced by crime if our crime exposure hypothesis is correct—driving to the transit stop should be more attractive to people living in high-crime neighborhoods than walking or bicycling. Our analysis of transit access trips from the BATS 2000 dataset supports this hypothesis. We found that violent crimes were negatively associated with pedestrian and bicycling mode choices for transit access work trips. The fact that we did not find a statistically significant result for non-work trips may be the result of our small sample size (just over 200 cases for non-work trips versus 470 for work trips).

IMPLICATIONS FOR PRACTICE

While the results of this study thus far require confirmation through follow-up research (particularly with respect to the Neighborhood Exposure Hypothesis), there are several implications for planning and law enforcement practice that we can make.

First, the analysis of home-based mode choice shows that high levels of neighborhood violent crime increase automobile use. When aiming to reduce auto emissions, suburban sprawl, obesity rates, and other societal ills that come with auto dependency, planners and policy-makers need to look at a range of interventions. While the arguments in favor of reducing auto dependency through land use and urban design interventions have attracted serious attention in recent years, these changes take place over the course of decades, as will their anticipated benefits. Improved crime intervention strategies that can reduce the safety concerns of residents living in high-crime neighborhoods hold promise for more immediate benefits and should be considered as part of a larger package of both short-term and long-term measures to reduce auto dependency.

Second—and much to our surprise—high-crime neighborhoods also favor transit use. A simplistic assessment of these findings may lead to the conclusion that we may be able to increase transit use by adding additional transit services to high-crime neighborhoods. However, the Neighborhood Exposure Hypothesis and our findings that high-crime neighborhoods also encourage residents to drive instead of walk or ride a bike to transit, suggest that transit oriented development plans that do not address the safety concerns of residents will fall short in reducing auto trips.

BEYOND PHASE 2 IMPROVEMENTS: NEW RESEARCH DIRECTIONS

Based on the findings and analysis of Phases 1 and 2 of this research effort, we have a number of recommendations for further research.

First, while the evidence mounts that the neighborhood exposure hypothesis has merit, at least partially explaining the positive relationship between neighborhood crimes and transit mode choice, these counter-intuitive findings may still be due to the coarseness (for example, TAZ-level aggregation) of our urban form variables. Therefore, we recommend that subsequent research should develop an improved, fine-grained set of urban form measures.

Furthermore, a more rigorous analysis using a larger travel dataset should be done focused specifically on transit station access trips, to confirm and study in more detail the potential differences between transit mode choice and crimes for transit trip components, including the station access and egress trip links of a larger transit trip.

This analysis will provide insights into the following issues and questions: first, confirmation of the “neighborhood exposure” hypothesis; second, confirmation of the effects of neighborhood crime on mode choice using a new source of data; and third, improved analysis of the interplay between neighborhood crime and urban form mode choice behavior, particularly regarding the effects of crime and urban form patterns along the entire length of a trip path.

APPENDIX A: CRIME CATEGORIES

Table 25. List of Crime Categories

PART I CRIMES	**P1-V**	**P1-P**	**P2-V**	**P2-P**	**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	**P1-V**	**P1-P**	**P2-V**	**P2-P**	**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

Gambling	X
Liquor Laws	X
Offenses against the family and Children	X
Runaways	X
Suspicion	X
Trespass	X

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Justin Meek teaches at San Jose State University (SJSU) in the Urban and Regional Planning Department and works as an independent consultant for municipalities throughout the San Francisco and Monterey Bay Areas. Justin is presently co-teaching a community assessment planning course at SJSU course. He is also providing planning services to the City of Pacific Grove and City of Marina. Justin serves on the local APA Section Board as its Administrative Director and sits on the SJSU Urban and Regional Planning Department Alumni Committee.

Justin holds a Master of Urban Planning degree (2010) from San Jose State University where he was the recipient of the APA California Chapter Distinguished Leadership Award for a Student Planner and AICP Outstanding Graduating Student Award. Justin also has a Bachelor of Science degree in Earth Sciences (1999) and Bachelor of Arts degree in

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MATTHEW PIVEN

Matt is an urban planner interested in economic development. He holds a Master of Urban Planning degree with honors from San Jose State University, and a B.A. in Economics from Williams College. He has spent three years in public and private sector planning. In two consulting projects, Matt used a variety of metrics to assess the effectiveness of community development initiatives. His graduate thesis used GIS and quantitative modeling to explore the relationship between ethnolinguistic diversity and neighborhood revitalization.

Matt benefited from working on this project with the Mineta Transportation Institute, as it expanded his ability to conduct spatial and statistical analysis and to work with neighborhood indicators.

PEER REVIEW

San José State University, of the California State University system, and the MTI Board of Trustees have agreed upon a peer review process required for all research published by MTI. The purpose of the review process is to ensure that the results presented are based upon a professionally acceptable research protocol.

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