

Neighborhood Crime and Transit Station Access Mode Choice - Phase III of Neighborhood Crime and Travel Behavior



MTI Report 12-45



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REPORT 12-45

NEIGHBORHOOD CRIME AND TRANSIT STATION ACCESS MODE CHOICE - PHASE III OF NEIGHBORHOOD CRIME AND TRAVEL BEHAVIOR

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16. Abstract This report provides the findings from the third phase of a three-part study about the influences of neighborhood crimes on travel mode choice. While previous phases found evidence that high levels of neighborhood crime discourage people from choosing to walk, bicycle and ride transit, consistent with the authors' hypothesis, they also produced counterintuitive findings suggesting that in some cases, high crime neighborhoods encourage transit ridership at the expense of driving—the opposite of what common sense would suggest. Phase 3 tested possible explanations for these counterintuitive findings with a series of methodological improvements. These improvements were: - Improvement 1: Used the Bay Area Rapid Transit (BART) system's 2008 Station Profile Survey travel data set to replace the Bay Area Travel Survey (BATS) 2000 data used in previous phases. - Improvement 2: Separated drop-off and drive-alone modes in logit models. - Improvement 3: Variables at the corridor level replaced previous variables at the transportation analysis zone (TAZ) level. - Improvement 4: Average parcel size (APS) variable replaced the intersection density measure of urban design. - Improvement 5: Used nested logit modeling techniques. These yielded strong evidence supporting the hypothesis that high-crime neighborhoods encourage driving, and they generated none of the counterintuitive findings from previous phases.				
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EXECUTIVE SUMMARY

OVERVIEW

This study is a continuation (Phase 3) of “Neighborhood Crime and Travel Behavior: An Investigation of the Influence of Neighborhood Crime Rates on Mode Choice—Phase II”¹ (hereinafter referred to as “Phase 2”), which empirically estimated the impact of neighborhood-level crime on mode choice for seven San Francisco Bay Area cities. Phase 2, a follow-on project to Phase 1 of the same name, 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 activities and associated findings from the Phase 2 study were reported in the following three categories:

- Improved neighborhood-level crime metrics
- Multinomial logit (MNL) modeling improvements
- Preliminary testing of the Neighborhood Exposure Hypothesis (defined and explained below)

These Phase 2 activities and associated findings are summarized below.

IMPROVED NEIGHBORHOOD-LEVEL CRIME METRICS

Phase 2 employed an improved set of crime metrics that counted the number of crimes within a standard radius of each trip origin as compared with the Phase 1 crime metrics, which counted the number of crimes within each trip origin’s Transportation Analysis Zone (TAZ). These improved metrics were tested against the Phase 1 TAZ-level metrics using otherwise identical Phase 1 binary logistic models. Comparisons of binary logistic mode choice model runs using Phase 1 and Phase 2 crime variables suggest that the Phase 2 variables provide significant but modest improvements over Phase 1 crime variables. However, the fact that—similar to the findings in Phase 1—many statistically significant Phase 2 crime variables had counterintuitive, positive signs also suggests that the Phase 1 methods of measuring crimes—in particular, the methods that relied on calculating crime rates for entire neighborhoods (TAZs)—were not the main cause of these counterintuitive results, although they may play a role.

MULTINOMIAL LOGIT (MNL) MODELING IMPROVEMENTS

Critiques of the binary logistic modeling techniques used in Phase 1 suggested that MNL techniques could be more appropriate for measuring and predicting mode choice decisions. While Phase 2’s MNL modeling did not eliminate the inconsistent and counterintuitive binary logistic model results found in Phase 1, comparison and analysis of the findings of Phases 1 and 2 suggest that MNL yielded significant if somewhat modest improvements. The fact that these findings were more consistent and robust across multiple exploratory model runs suggested 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 counterintuitive findings led the research team to propose and preliminarily test the Neighborhood Exposure Hypothesis—wherein people seek respite from neighborhood crimes by traveling in enclosed vehicles such as transit or autos—in the final round of modeling improvements implemented in Phase 2.

PRELIMINARY TESTING OF THE NEIGHBORHOOD EXPOSURE HYPOTHESIS

Every transit trip requires an access trip “link,” in which the rider leaves his or her trip origin and travels to the nearest bus or train stop, unless the bus stops at the traveler’s front doorstep. A set of binary logit models were developed to predict mode choice (driving versus walking or biking) 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 (i.e., the more neighborhood crimes, the more likely people are to choose transit over auto travel) would have trip links prior to reaching the transit stop (transit access trip links) in which they would prefer to travel in an enclosed vehicle in high-crime neighborhoods. Analyzing mode choice for the transit access link trip effectively eliminated the transit mode choice from the analysis, thereby allowing the team to determine how robust the findings were for the influence of crimes on the remaining modes of travel. Therefore, when broken down into its component segments, transit trips should have links in which non-auto modes are negatively affected by high-crime neighborhoods.

Both the work and non-work transit access trip models yielded the expected signs, and in the case of work trips, a statistically significant result. Therefore, it appeared that violent crimes near a transit rider’s home deter them from walking or riding a bicycle to a transit stop and encourage them to drive instead. Thus, while the transit mode choice model results continue to give counterintuitive results—in which 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 to drive. The authors hypothesized that this was due to the fact that driving and transit, to some extent, offer some level of protection from neighborhood crimes, but walkers and cyclists feel more exposed in these same neighborhoods.

KEY CONCLUSIONS DRAWN FROM PHASE 2

The MNL modeling activities in Phase 2 showed improvements in the consistency and interpretability of their findings, particularly the influence of neighborhood crimes on mode choice. But the preliminary transit access mode choice model, in which the transit mode choice option was effectively eliminated from consideration, was the only model that gave interpretable results consistent with the hypothesis that high-crime neighborhoods influence people to choose driving. As a result, the authors hesitated to offer insights into the policy implications of these findings, but rather they put their attention on improving the measurement methods employed in Phase 2.

RATIONALE FOR PHASE 3

The reasons for undertaking this Phase 3 research were based on the findings and questions posed by the work in Phases 1 and 2. These findings suggested that while the crime metric had questionable validity as a variable to help predict mode choice (with counterintuitive findings for the influence of neighborhood crimes on transit mode choice), the improvements made in Phase 2 to the metric (measuring crimes within a set distance of each trip origin as opposed to within the trip origin's TAZ) and changing from a binary logistic to an MNL model structure produced significant although modest improvements in consistency and interpretability of these results.

Because these improvements to the metric and modeling techniques did not eliminate the counterintuitive findings found in both Phases 1 and 2, the research team also began to question the validity of the travel survey data (the 2000 Bay Area Travel Survey—hereinafter referred to as BATS 2000) used in both phases. Because BATS 2000 was designed to create a representative sample for a regional travel demand model, it is possible that it was inappropriate for use at the neighborhood-level analysis, as was done in the first two phases of this project. This Phase 3 research was designed to build on these earlier phases while identifying and testing alternative explanations for the root cause(s) of the confusing findings from those previous phases—most notably, that high-crime neighborhoods encourage people to choose transit over all other modes, including driving.

Key activities and associated findings from the Phase 3 study are reported in the following five improvements:

- Improvement 1: Testing the influence of the new travel data set
- Improvement 2: Separate drop-off and drive-alone modes analysis
- Improvement 3: Corridor-level variables
- Improvement 4: Average parcel size variable
- Improvement 5: Nested logit modeling

These Phase 3 activities and associated findings are summarized below.

Improvement 1: Testing the Influence of the New Travel Data Set

The low sample size for non-auto travel modes in the BATS 2000 data set may have caused these inconsistent and counterintuitive results. The models developed and tested in Phase 3 used a new travel data set that provides larger sample sizes for all modes of travel—the 2008 Bay Area Rapid Transit Station Profile Survey (hereinafter referred to as the BART 2008).

Improvement 2: Separate Drop-Off and Drive-Alone Modes Analysis

Mode choice categories were not properly specified in Phases 1 and 2. Due in part to the small sample sizes available from the BATS 2000 data set, the modes specified in the previous phases combined categories of travel that are sufficiently distinct to warrant their own separate categories. The models developed and tested in this phase separated the “drive alone” and “drop-off” categories into separate modes.

Improvement 3: Corridor-Level Variables

Trip origin- (home) and destination-centered variables did not capture the full effects of urban form and crimes on mode choice. The previous phases used urban form and crime variables that measured the density, diversity (mixed uses), design (intersection densities), and crimes by counting these characteristics within one-quarter- or one-half- mile buffers of the trip origins and destinations of the travelers from the BATS 2000 data set. However, it is possible that urban form and crime characteristics along the entire corridor of travel—and not just in the areas around the trip origins and destinations—play a significant role in mode choice decision-making. This Phase tested and compared the effects of using the neighborhood-based variables against a set of new, corridor-level variables.

Improvement 4: Average Parcel Size Variable

Phase 3 introduced a new measure of urban design to help capture these fine-grained effects because the authors hypothesized that urban form and crimes both play important roles in determining mode choice. Furthermore, they also hypothesized that the Phase 2 urban form variables may have not been geographically “fine-grained” enough to capture their micro-level effects on pedestrian and bicycle mode choice behaviors. This Phase tested and compared the effects of using a corridor-level measure of the average parcel size (APS) of retail uses along the travel corridors of each traveler in the 2008 BART Station Profile Survey. In theory, larger APS values along a corridor of travel indicate a less pedestrian-friendly environment that encourages driving.

Improvement 5: Nested Logit Modeling

Some mode choices are similar enough that MNL models are not sufficiently sensitive to differentiate and distinguish between them. Nested multinomial logit models have been developed to accommodate these similarities and are better able to distinguish between similar modes of travel. It is possible that the multinomial logit models used in Phase 2 of this study were ill equipped to distinguish between the modes specified in the study models. As a result, they were unable to properly and consistently account for the influences of the crimes variables on mode choice. This phase employed a nested logit model to determine if this influenced the consistency and interpretability of the crimes variables.

SPECIFIC RESEARCH QUESTIONS

The specific research questions explored by this study are:

1. How does the new BART 2008 travel data perform when compared with BATS 2000?
2. How do the models perform when drop-off and drive-alone modes are separated?
3. How do the new corridor-level crime and urban form variables perform compared with the neighborhood-level variables they replaced?
4. How does the new APS (urban design) variable compare with the urban design variable (number of 4-legged intersections per acre) used in Phases 1 and 2?
5. How do the nested logit models perform compared with the MNL models used in Phase 2?

For all of these research questions, the performance of each improvement was evaluated in terms of:

1. Model goodness-of-fit
2. The statistical significance, consistency, and interpretability of all model variables, particularly the crime variables

These results were interpreted to shed light on the following, over-arching research question:

What were the causes of the confusing (yet consistent) finding in Phases 1 and 2 that even when controlling for household auto ownership, household income, and neighborhood income levels, people choose transit over driving when they live in high-crime neighborhoods?

STUDY RESULTS

The results are summarized below for each of the five improvements described above.

Improvement 1 Results: Testing the Influence of the New Travel Data Set

Comparisons of the best-performing MNL model results from Phase 2 using BATS 2000 data and those developed for Improvement 1 (Phase 3) using BART 2008 data suggest that the counterintuitive findings from Phases 1 and 2 may have been due entirely to the inappropriate use of the BATS 2000 data set for neighborhood-level analysis. The crime variables used in Phase 2—the number of violent crimes within a half-mile or quarter-mile, depending on the model—of the trip origin (home) yielded significant and positive signs for transit mode choice in the Phase 2 models. However, the same variable, using 2008

crimes to match the BART 2008 data, yielded significant and negative signs in Phase 3 using the BART 2008 data.

Improvement 2 Results: Separate Drop-Off and Drive-Alone Modes Analysis

A small sample size in the BATS 2000 data set necessitated keeping drop-off and drive-alone modes together in Phases 1 and 2. The increased sample size available for BART 2008 data allowed the research team to separate drop-off and drive-alone modes, which is consistent with standard mode choice modeling practice.

Separating drive-alone from drop-off mode choice categories produced mixed results, with the work model no longer producing a statistically significant, negative influence of neighborhood crimes on transit mode choice, as it did in the Improvement 1 model. Meanwhile, it produced a significant, negative sign for transit mode choice in the non-work model when compared with the Improvement 1 non-work model, which was insignificant. While these mixed results do not lend themselves to conclusive interpretation, the fact that the Improvement 2 changes are consistent with accepted mode choice modeling practice led the team to conclude that the improvement produces a more theoretically valid set of results.

Improvement 3 Results: Corridor-Level Variables

The third improvement used a new set of variables designed to capture the urban form and socio-demographic conditions of the entire travel corridor and the neighborhood of the trip origins (for socio-demographic characteristics) for each survey respondent, as opposed to merely the Transportation Analysis Zone (TAZ) of trip origins that was used in previous models.

In general, findings for these corridor- and neighborhood-level variables were stronger in terms of statistical significance. And they were more consistent with the researchers' theoretical expectations in terms of signs than the analogous neighborhood variables used in the Improvement 2 and previous models. However, the findings for the corridor-level crime variable were mixed, suggesting that the corridor-level crime variable was a better predictor of mode choice compared with the neighborhood-level measure used in Improvement 2 work trip model. However, it was not as strong a predictor of non-work trip mode choice in the Improvement 3 models.

Improvement 4 Results: Average Parcel Size Variable

To determine if the inconsistent findings for neighborhood crimes in previous research projects (Phases 1 and 2) were due to inadequate measures of urban form, Improvement 4 models used a new measure of urban design: Average Parcel Size (APS). This new variable worked very well in the work model, with highly statistically significant findings for all modes, but it did not produce any statistically significant results in the non-work model.

In determining how the APS variable affected the corridor-level crime variable's performance, the addition of the APS variable did not change the signs or significance of the violent crimes (P1V) within one-quarter mile of travel route variable in either the work

or non-work models.

Improvement 5 Results: Nested Logit Modeling

Overall, there were no measurable benefits to running the mode choice models with nested logit techniques. The N2 models, which grouped modes into auto and non-auto modes, produced findings for the crime variable roughly equivalent to those found in the Improvement 4 models. However, the N1 models, designed to test the Neighborhood Exposure Hypothesis—identified in Phase 2 by grouping modes into “open” and “closed” groups—produced fewer statistically significant results than comparable Improvement 4 models. Taken together, these results suggest that the inconsistent findings for crime variables in models run in Phases 1 and 2 were not due to either the lack of nested logit techniques used in those phases or to the Neighborhood Exposure Hypothesis.

IMPLICATIONS FOR PRACTICE

The third phase of this research has confirmed the team’s hypothesis that high levels of neighborhood- and corridor-level crimes discourage transit use, walking, and bicycling while encouraging driving, at least in the case of transit station access trip mode choice. When planners and policy-makers wish to reduce auto emissions, suburban sprawl, obesity rates, and other societal ills that come with auto dependency, they must look at a range of interventions. Arguments in favor of reducing auto dependency through land use and urban design interventions have attracted serious attention in recent years, but 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.

These findings are particularly important for encouraging non-auto access modes for transit riders. Transit agencies should consider working in close collaboration with police departments in the jurisdictions surrounding their transit stations and stops in order to reduce crimes, increase non-auto access to their transit systems, and potentially increase transit ridership overall.

Finally, transit agencies, local governments, and emergency service providers should consider working collaboratively to integrate crime prevention through environmental design (CPTED) methods into local planning and building codes, and in particular, into transit-oriented development (TOD) plans and policies. This will help maximize the beneficial effects of TOD over the long term because it will help create safe, transit- and pedestrian-oriented communities around transit stations.

I. LITERATURE REVIEW

INTRODUCTION

This literature review is an update to those provided in the reports for Phases 1 and 2. To provide a comprehensive, up-to-date picture of the previous work this project builds on, the authors have included edited and supplemented text from the Phase 1 and 2 report literature review sections. It is composed 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, discusses potential methodological concerns with respect to endogeneity of crime and urban form and the potential for omitted variables bias, and finally discusses concerns around accuracy of reported crime rates and statistics. 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 sound. Also, a discussion about the accuracy of reported crime rates and statistics concludes the literature review, highlighting the impacts of media, legal cynicism, and the Hierarchy Rule.

EVIDENCE FOR IMPACTS OF CRIME ON MODE CHOICE

Research on the impacts of crime on travel behavior distinguishes tangible impacts from intangible impacts. Dolan and Peasgood describe these two categories, noting that tangible impacts would include direct costs for medical losses and additional security, while an intangible cost would be related to psychological impacts of crime-related trauma.² Within this framework, they argue that changes in different types of behavior (e.g., 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. That is, 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 it also reduces levels of physical activity and home sale prices.

Mode Choice

Three recent studies use disaggregate choice models and find an impact of crime on urban travel behavior. Kim, Ulfarsson, and Hennessy describe how crime affects mode choice using data from St. Louis, Missouri light rail riders' trips between home and station.³ The authors built a MNL regression model to compare the likelihood of riders to drive and park compared with 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 with the other three modes.

Likewise, Ferrell, Mathur, and Mendoza, in Phase 1 of this study, uncovered 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 with the likelihood of

other modes. They used crime data from seven San Francisco Bay Area cities aggregated to the level of the Transportation 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 they 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 (e.g., 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.

Ferrell, Mathur, Meek, and Piven, in Phase 2 of this study, found that high-crime neighborhoods were “positively associated with transit mode choice,” while they were negatively associated with walking.⁵ The authors hypothesized that this counterintuitive transit result may be due to inaccurate urban form measures, mode choice influences to transit, and/or self-selection bias. The authors tested this result further by separating the San Francisco data from the rest of the Bay Area data to compare if high crime rates affected a person's propensity to use transit, bike, or walk. They discovered that high crime rates in San Francisco were negatively associated with pedestrian mode choice, and high crime did not affect bicycle or transit mode choice for work trips. For all the non-San Francisco trips, walking and transit use were positively associated with high-crime neighborhoods and non-work related trips were negatively associated with high crime. However, high crime increased the likelihood that non-work, non-San Francisco trips would be done via transit, providing further confirmation of the counterintuitive earlier results.

To better understand these results, the authors outlined the Neighborhood Exposure Hypothesis, which theorizes that enclosed modes, such as automobiles and transit, promote a sense of safety due to the control and protection they afford the rider. They theorized that transit access trips should be affected similarly by these perceptions. Their results indicated that if violent crimes occur near the home, a person is less likely to walk or bike and will instead drive to the transit station. This study supports the hypothesis that crime can affect mode choice, leading individuals to walk or bike to transit even if they live in high-crime neighborhoods, but they are less likely to walk or bike if violent crimes occur near their homes.

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 both the presence and perception of crimes are significant deterrents against public transit usage in the Los Angeles area.⁶ 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.⁷ They argue that in the presence of crime, ridership and revenues fall, and they provide numerous case studies to illustrate the point. Yavuz and Welch studied gender differences concerning fear of crime and a person's willingness to take transit. They concluded from a Chicago Transit Authority customer satisfaction survey that women are less likely than men to take transit (specifically trains or buses) due to

concerns for personal safety, with issues such as social incivilities—litter and graffiti—poor lighting along pathways, isolated transit stops, and unstaffed stations as the main factors. Men are less likely to take transit if they lack control over the environment or are surrounded by strangers in a public space.⁸

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.⁹ They surveyed both residents and bus riders in Greensboro, North Carolina and found that the city's residents rarely used transit (i.e., most transit riders were from out of town). While both groups were found to be concerned for their personal safety, and residents were two to three times as concerned as bus riders, neither group was specifically concerned for the safety of the transit system itself. Rather, they 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.

Taylor, et al. provided further evidence of the effect of crime on transit ridership. They studied the factors that contributed to the nationwide gains in transit ridership seen during the economic boom times of the 1990s and found that, among other factors, a reduction in crime around public transit stations contributed to increased ridership.¹⁰

Hess studied the aging population (60 and older) and their decrease in physical activity and propensity to take public transit. The author argued that better access to public transit would increase independence among older adults as well as prevent obesity and other negative health issues due to increased physical activity from walking.¹¹ Hess assessed both perceived and measured walking distance and its effect on the likelihood that older adults will take public transit. He determined that a perceived five-minute walk or a measured quarter-mile walk was an acceptable walking distance for older adults to reach transit. Interestingly, Hess concluded that suburban neighborhoods have less average crime and fewer transit riders, while cities had higher crime rates but more transit riders. The author surmised that the higher levels of transit usage in cities, even when they have higher crime rates than the suburbs, was due to the fact that individuals may not have other transportation options, such as automobiles, and transit riders are poorer and less likely to have a driver's license than non-transit riders.

In summary, the above reviewed studies suggest that crime plays a key role in driving down transit use, and hence, it 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 found strong evidence that high crime rates and fears for personal safety significantly reduce levels of physical activity, especially among ethnic minorities and youth.¹² But not all studies find a relationship between crime levels and physical activity. This section summarizes this

disagreement in the literature. It also reviews studies on both sides of the argument that street lighting influences physical activity levels through its effect on crime.

The concept of *self-efficacy*, which is defined as the sense of confidence that one has in performing an activity, explains why researchers expect to find a relationship between crime levels and physical activity. Hofstetter, Hovell, and Sallis argue that self-efficacy is a major determinant of a young person's decision to be physically active. 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.¹³

The evidence for crime's negative effect on physical activity is substantial. For example, McDonald studied the effect of crime on the number of walk trips taken by minority populations in Oakland, California.¹⁴ The study finds that a reduction in violent crimes significantly increases the number of minutes walked. However, property crimes or quality of life crimes (e.g., weapons offenses, prostitution, drug arrests, and disorderly conduct) do not produce a measurable effect on walk trips.

Booth, et al. provide further support for the argument that crime discourages physical activity.¹⁵ In a survey of older (age 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, in which survey respondents' inability to find safe sidewalks negatively impacted their physical activity levels.

The question of whether crime influences physical activity has been addressed by numerous other studies, including King, et al;¹⁶ Gordon-Larsen, McMurray, and Popkin;¹⁷ Humpel, Owen, and Leslie;¹⁸ and Eyler, et al.¹⁹ However, 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, the authors review Wilcox, et al.²⁰ 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 to 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.

Werner, Brown, and Gallimore assessed whether living in a walkable community, as defined by the macro-level 3Ds (density, diversity, and design), influences whether residents walk to local light-rail transit stations. They conducted a micro-level analysis using the Irvine Minnesota Inventory (IMI), which is both reliable and comprehensive, providing more detailed, block-specific (versus zip-code- or census-tract-level) qualities along a person's walking corridor in order to determine what is pedestrian-friendly and promotes walking

to a transit stop.²¹ Using a pre- and post-test survey, the authors found that walking to a transit stop was positively correlated with the block-level walkability qualities, including crime safety, density, and diversity.

Physical activity levels for children may also be affected by the perceptions of crime. Miranda, et al. explored this relationship and concluded that children are 40% more likely to be overweight and 61% more likely to be obese if the parents feel their neighborhood is unsafe.²² Specific variables that negatively affected weight in children were violent crime, nuisances, total crime, and property disorder but not territoriality, vacancy, housing damage, or tenure.

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

Several studies reveal a link between crime and physical activity by examining 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 have a beneficial effect on crime levels.²³ First, improved lighting encourages surveillance of potential offenders on the street, both through improved visibility and increased number of people on the street in general. Second, improved lighting sends a signal to potential criminals and the community in general that the neighborhood is improving and that there will be increased community pride, cohesiveness, and informal social controls.

Farrington and Welsh performed a meta-analysis of sixteen studies examining the effects of street lighting on crime and found that about one-half of the studies find a significant effect of improved street lighting on crime, while the other half do not. While Farrington and Welsh found no clear reasons for these differing results, they point out that those studies that found a significant effect were more likely to have measured the crime levels during both the daytime and nighttime periods.²⁴ 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.

Several studies find evidence that street lighting influences travel behavior through its impact on crime or on perception of crime. For example, Wallace, et al. studied the effects of transit safety measures—including improved lighting in transit facilities and vehicles—on passenger levels of perceived safety.²⁵ Their study finds that increased police presence and improved lighting are two of the most effective in terms of reducing the safety concerns of transit users.

In addition, Painter conducted surveys of residents in two neighborhoods in London before and after street lighting improvements were made.²⁶ 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.

Börjesson determined how perceived insecurity affects transit usage among men and women. The survey respondents were asked to choose a walking corridor to a bus stop

based on four corridor scenarios depicted in drawings—open and in daylight; closed and in daylight; open but dark; close and dark. The results indicated that women had more perceived insecurities and preferred the daylight and open corridors. The author concluded that investments in streetlights and installation and maintenance of shorter vegetation would lead to greater perceptions of safety, which are linked to greater transit use.²⁷

Borjesson's findings are reinforced by Haans and de Kort. Focusing on Appleton's 1975 prospect-refuge theory, which indicated that through evolution, humans require prospect (ability to see what is around them), escape (means to avoid a threat), and concealment (shelter from a threat) to feel secure.²⁸ This study's 29 female participants preferred to have ample light surrounding them when walking at night in order to increase their sense of security.

It is noteworthy that not all studies examining the impact of street lighting on crime come to the same conclusion. 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,²⁹ find no detectable changes in travel behavior among neighborhood residents. The residents seemed to engage in the same patterns of avoiding certain streets and places even after street lighting improved. These results suggest that improved street lighting alone 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 shown 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.³⁰ While the overall effect of crime on home prices was insignificant, the study found 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.³¹

Ceccato and Wilhelmsson studied the relationship between property values and crime in Stockholm, Sweden, and found that fear of crime is an important concern for prospective home buyers as proximity to transit stations can be perceived as attracting criminals. However, rail stations have been found to both increase and decrease nearby property values, leading to mixed effects.³² The authors find that social incivilities such as graffiti, litter, and property damage are found to negatively affect housing prices and to increase fear of crime because this disorder indicates that the neighborhood is deteriorating.

Mathur studied the relationship between housing prices for new and existing high-quality housing and low-quality housing and jurisdictional-level attributes such as crime rates in King County, Washington from 1991 to 2000.³³ The study showed that existing housing's value had a negative association with high violent crime rates, while some new housing's values were positively associated with high violent crime rates. A decrease in crime rates from high to medium could increase housing values, on average, by 15%.

These studies of home values, physical activity, and mode choice add support to the argument 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 point to people's associations of transit with dense, often crime-ridden, urban areas.³⁴ With the growth of the suburbs came the commonly held perception of these new neighborhoods as sanctuaries from the inner city crime.³⁵ 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.³⁶

The sections below look first at whether the perceived association between transit and crime is accurate. To do so, the authors examine how the presence of transit stations affects the pattern of crime around them. Then, they 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, they identify strategies from the literature, primarily related to environmental design, that 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 the causal link between transit and crime, but it finds no consistent effect—positive or negative—of transit on crime.

Liggett, et al. studied the effects of introducing light rail service along the Los Angeles Green Line on crime levels in the surrounding neighborhoods.³⁷ 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 research team found that the transit line did not significantly impact crime trends or location in the station areas, and it did not transport crimes from high-crime areas to low-crime areas.

However, Block and Davis found concentrations of crime around transit stations. The study 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.³⁸ 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.

To further confuse the issue, two studies found that the introduction of transit reduced crime. The first study, by Billings, Leland, and Swindell, examining the new light rail transit system in Charlotte, North Carolina argued that the announcement and opening of a light rail transit station may have increased safety in that area due to increased “public investments” such as street lighting enhancements, as well as encouraged social interaction and “eyes on the street.”³⁹ Their study examined crime changes before and after the light rail construction announcement and found a monthly average of 20% decrease in property crimes after the announcement, virtually no effect on violent crimes, a 25% decrease in larceny crimes, a 26.3% decrease in burglary, and a 32.4% decrease in robbery. The study found that once the station was fully operational, property crimes did not regress to preannouncement levels.

A second study by Brown and Werner in Salt Lake City, Utah showed that residents experienced a decrease in the perception of crime, decreased levels of obesity, increased neighborhood satisfaction, fewer car trips, and “stronger place attachment” after the introduction of light rail transit.⁴⁰ Residents also felt that the new light rail stop improved pedestrian and child safety as well as increased neighborhood interaction.

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.⁴¹ Most of these ten bus stops were located in downtown commercial areas, at the intersections of multi-lane streets, and were often not visible from nearby shops and lack adequate lighting, public phones, or a nearby police presence. Many were located near vacant lots or abandoned buildings, with easy escape routes for criminals in alleys and mid-block connections, and with generally dilapidated conditions.

Cozens, et al. used virtual reality walkthrough scenes to test people’s fear of crime in the British rail system environs.⁴² They found that rail station designs that provided high levels of visibility for passengers were perceived as offering high levels of perceived safety, and they 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 crimes and focus specifically on neighborhoods surrounding transit stations.⁴³ 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 levels and the presence of liquor stores in the station neighborhood. Further, the busiest stations (i.e., 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 high percentages of population 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 measureable role in determining crime levels at transit stations.

How the Built Environment can Discourage Crime

Strategies that focus on changing the built environment to reduce crime have received increased attention in recent years. 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 physical disorder found, was most spatially correlated with concentrations of crime.⁴⁴

Beyond graffiti reduction, 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.⁴⁵ More specifically, any theory of crime should explain and describe the interactions between the propensity for criminal behavior (i.e., criminality) and the opportunities for crime presented in the environment. Traditional criminology has assumed that explaining the behavioral dispositions for criminal behavior is the same as explaining crime. Based on this opportunity-based theoretical perspective, Clarke lists four 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

Mayhew, et al.⁴⁶ and Jeffery⁴⁷ were among the first researchers to articulate the relationships between crime and environment. They 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—an approach 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.⁴⁸ 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, 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 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 reducing crime.⁴⁹ 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 that 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; and 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 US, including socioeconomic characteristics, management effectiveness, quality of city police and security services, and form of ownership.⁵⁰ 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% of the fear, 67% of the community's instability, and 39% 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.⁵¹ 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% reduction in cut-through traffic and 40% reduction in traffic accidents. Reported crime in the neighborhood reduced by 26% and violent crimes by 50%, while city-wide, crime went up 1%. Fears of crime displacement from the study area to surrounding neighborhoods were also shown to be unfounded because crime in the communities immediately surrounding Five Oaks dropped by 1.2% during the same period. A university survey of residents in Five Oaks found that 53% of residents thought there was less crime and 45% 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.⁵² They studied the effects of zoning, physical design changes, and community policing initiatives in the “crime ridden” North Trail area of Sarasota, Florida. With local resident and business owner cooperation, city planners created a new zoning ordinance that required all new developments to submit site plans with design elements based on CPTED principles. Recommendations (which were often willingly complied with) included outside lighting; landscaping that allowed visibility; mixed uses; porches, balconies, and residential space above retail to allow “eyes on the street;” and shared parking. Analysis of local land use links to crime revealed that prostitution was enabled in the area by the abundance of small hotels. Review of these sites revealed that many were unable to renovate and expand due to restrictive street setback requirements, along with 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 examined 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.

Allied with the defensible space concept, “neighborhood territoriality,” as discussed by Renton, et al., Miranda, et al., Cozens, and Foster, Giles-Corti, and Knuiman, suggests that removing signs of neglect in and around homes (e.g., litter, unkempt lawns, graffiti) can reduce crime by indicating to the criminal that these homes and neighborhood (and one could argue a transit station) are protected by the community.^{53,54,55,56} They also discuss natural surveillance and maintenance as territoriality enhancement strategies. Foster, Giles-Corti, and Knuiman elaborate further that when fear of crime is high, residents are less likely to interact with their neighbors, engage in physical activity, or use transit. They also conclude that having a transit station near the home was directly related to less fear of crime, and that fear of crime was associated with living in higher-density housing and lower fear of crime with single-family detached housing. Lastly, they conclude that mixed-use areas can promote fear of crime because more outsiders gather in the area “making it more difficult for residents to distinguish strangers from locals.”⁵⁷

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) and Ferrell, Mathur, Meek, and Piven (Phase 2 study) in three ways: by employing nested logit model, by using a travel survey with a more fine-grained sample

suitable for neighborhood-level analysis, and by including new crime and urban form variables to reduce the probability of omitted variable bias. There is broad support for both methodological improvements in the literature.

Basis for Using Nested Multinomial Logit Methods

Multinomial logit (MNL) modeling methods have 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 model travel demand by focusing on the factors influencing individuals' travel decisions.

McFadden first defined the framework for studying travel demand.⁵⁸ 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, developed in 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.⁵⁹ They argue 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 that "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*."⁶⁰ 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, the authors 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 2002 study by Cervero, who calls mode choice theory an "application of consumer choice theory" in which agents make decisions among competing alternatives to maximize either personal utility or net benefit.⁶¹ 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 variables such 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 of land uses

(a measure of the evenness of population and employment totals within a given area), and the ratio of sidewalk miles to road miles in the area.

As mode choice modeling has progressed, the effects of urban form on travel behavior have received increased attention. Schwanen and Mokhtarian used an MNL model to analyze the effects of urban form on mode choice.⁶² They included four modes in their model: personal vehicles, bus, rail, and slow, which is their term for bicycling, walking, and jogging. Schwanen and Mokhtarian applied a similar specification to Cervero in that a combination of attributes about the trip, the traveler, and the neighborhoods on both ends of the trip were included.⁶³

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.⁶⁴ His goal was to identify the factors that encourage walking to and from BART stations so station area land use planning and urban design can more precisely target improvements that will produce 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, et al. (2007) 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 using other access modes.⁶⁵

All four of the above reviewed studies are recent examples of MNL applications to mode choice, demonstrating the model specifications that are common in literature. However, MNL has one major limiting assumption, called the Independence of Irrelevant Alternatives (IIA). IIA assumes that the utility derived from each alternative is independent of the utility derived from the other alternatives. Consequently, a person's choice of a travel mode (e.g., walking) is independent of the availability of other travel modes. From a modeling perspective, IIA assumes that the error terms associated with each alternative are uncorrelated with each other. This assumption is problematic for this study because a person's decision-rule for mode choice might club, or nest, mode choices. For example, in the presence of crime, a person might decide whether s/he would like to choose an open mode (walk/bike) or a closed mode (drive/drop-off/bus). Similarly, a person might decide between an automobile (drive/drop-off) or a non-automobile (bus/walk/bike) mode. From the modeling perspective, the error terms in the mode choices within a nest might be correlated, thus violating MNL's IIA assumption. Nested logit allows the correlation of error terms within a nest.⁶⁶ Therefore, this study uses nested logit models to check the robustness of MNL model results.

Measuring the Built Environment

Ewing and Cervero (2010) performed a meta-analysis of studies examining the links between characteristics of the built environment and travel behavior. They found that walk trips to transit and other destinations are strongly associated with the built environment's diversity and design, specifically "intersection density, jobs-housing balance, and distances to stores."⁶⁷ They also concluded that close proximity to transit stops could encourage walking to the station and ridership.

D. Van Dyck, et al. studied walkability and neighborhood satisfaction with GIS and a mailed questionnaire and found that neighborhood walkability was "negatively associated with neighborhood satisfaction."⁶⁸ However, their results showed that even though higher density, more walkable neighborhoods were associated with many negative characteristics, they were also associated with higher levels of physical activity. Overall, adults living in highly walkable neighborhoods were not satisfied with their neighborhoods; specifically, neighborhood density was significantly associated with dissatisfaction with the neighborhood, while land use mix and street connectivity were not strongly correlated. From this, it may be concluded that less crime leads to more neighborhood satisfaction, while high density erodes neighborhood satisfaction, effectively negating some of the gains made by making the neighborhood green, safe, and walkable.

Finally, Appleyard (2010) compared the methods for measuring the built environment and its effects on station access trip mode choice in the San Francisco Bay Area.⁶⁹ The author's review of the literature focuses on studies by Ewing, et al. (2006) and Ewing and Handy (2009), which discuss perceptions of the built environment. Cervero and Kockelman's 3Ds (density, diversity, and design) quantified dimensions of the "built environment and travel behavior" and concluded that a complementary relationship exists between the 3Ds and travel; this means that as the 3Ds' interactions increase and harmonize, NMT travel could increase while automobile and transit use could decrease, due to a more walkable and human-scale built environment.⁷⁰

The presence of an NMT-friendly environment does not consistently predict travel behavior, however. Appleyard's research revealed that, while the urban environment does affect travel behavior, the effect is likely modest, perhaps due to the predominance of the auto-oriented city, which promotes automobile dependence and policies (e.g., "free" parking and suburban developments).⁷¹

Perceptions of distance, as opposed to actual distance, can determine whether or not a person chooses to walk to a transit station or the local coffee shop. Appleyard cites Handy's discussion of real and perceived distance to a destination as having "the strongest, most direct influence on whether one decides to walk."⁷² Appleyard theorizes that diversity, specifically land use mix, rather than density promotes NMT because increased land use mix provides an increased variety of destinations for a person, whereas density may only increase the amount of a particular land use. For example, there may be high-density residential but low diversity, which does not provide an interesting promenade for the traveler. Appleyard's work sought to bridge two knowledge gaps: (1) understanding how "travel behavior is influenced by the perceptual qualities of the built environment" and (2) understanding "what factors influence the decision to bicycle" and walk.

Appleyard's work specifically attempted to bridge this gap between objective and subjective measures of urban by developing objective measures of the subjective "perceptual qualities" of the urban environment. To do this, Appleyard developed new methods of measuring the built environment through the Individual Access Corridor (IAC), which uses Geographic Information System (GIS) to develop unique buffers around the home origin, trip pathway, and station destination, including information about land uses, transit access, and traveler perceptions.⁷³ IAC helps better understand the effects of land use on mode choice at the parcel level. Appleyard used a combination of data from GIS street network, Google Transit, Bay Area Rapid Transit (BART) 2008 Station Profile Surveys, and his own geospatial calculations.

Appleyard's findings indicated that the usage of nonmotorized transit modes (NMT) is associated with the following characteristics of the IAC: small retail, mixed-use developments, employment centers, and retail and wholesale businesses (weak associations). Appleyard concluded that in order to increase NMT, transit station access corridors must include human-scale buildings with facades close to the street, front porches, visual richness, narrower well-connected streets that promote walking and bicycling, and small retail establishments. To further support the new IAC approach, Appleyard compared IAC to zonal D-variables, assessing if the IAC approach is as effective when assessing travel behavior. IAC was compared with intersection density, which relates to the D-Variables design, density, and diversity. Appleyard concluded that the IAC "parcel-based" land use measures are able to provide richer, nuanced information about what particular land use activities may be associated with rapid transit access travel behavior."

METHODOLOGICAL CONCERNS

The review of the literature brought to light two important methodological issues that are apparent 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

The authors explore three types of potential endogeneity. The first section examines 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. Finally, the authors explore the link between the income variable and the crime variables.

Urban Form/ Land Use and Crime

Urban form might be correlated with crime. Four studies examine the complex relationship between crime and urban form or land use. Matthews, et al., using spatial Poisson regression under a Bayesian analytical framework, write that several built environment variables affect the number of property crime incidents in Seattle, Washington.⁷⁴ 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, the presence of schools is correlated with arson, and the presence of parks is correlated with theft.

Stucky and Ottensmann estimated the impact of several land use variables on violent crimes in Indianapolis, Indiana. The land use variables included the proportion of area under residential, commercial, and industrial uses, the proportion under bodies of water, and the presence or absence of land uses such as parks, cemeteries, hospitals and schools.⁷⁵ The study found 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 and hospitals, and the percent of vacant land did not have an impact. These two studies provide empirical evidence that land use is correlated with crime.

Cozens and Hillier took a meta-analysis approach to analyze this question.⁷⁶ They compared the cul-de-sac with the grid street patterns of urban design and found that, while there are many advantages to the traditional grid 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 looked specifically at the complex relationship between retail uses and the distribution of crime.⁷⁷ He examined claims that high crime discourages retail development, and that retail development attracts crime. He disentangled 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 was a function of crime levels and a set of neighborhood characteristics. In another model, crime levels in a census tract were 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.

To address these questions, this phase's models employ a new urban form variable called Average Parcel Size (APS). The APS variable measures the average size of retail parcels along the travel route linking trip origins (homes) and destinations (BART stations). The APS variable improves on the urban form variables used in previous phases by: 1) providing a more fine-grained measure of urban design than the traditional intersection density metric; 2) measuring urban design at the corridor level, which holds potential for capturing the influence of the built environment on the entire length of a trip; and 3) focusing on retail land uses, which may have effects on crimes and travel behavior. This and previous phases of this project addressed the potential for endogeneity between urban form variables and crime levels by running bivariate correlation tests and removing any variables where endogeneity was suspected.

Broken Windows and Other Types of Crime

Several studies suggest that there might be a relationship between the broken windows variable used in previous phases of this study—and tested in preliminary model runs in Phase 3—and other crime variables. Wilson and Kelling were the first to propose the now famous “broken windows” theory of neighborhood deterioration and crime.⁷⁸ They

suggested that neighborhoods that provide a space where relatively less serious crimes are tolerated or go unpunished send a message to criminals that they can successfully commit more serious crimes. Therefore, signs of neighborhood disrepair—such as a broken window that remains un-repaired, or an abandoned car that is not towed away—cause residents to feel less safe and leads to a reduced level of community involvement and vigilance, creating a fertile environment for more serious criminal activity. 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 toward preventing crimes by altering our perceptions of the physical environment and its likelihood to support or deter criminal behavior.

Kelling and Sousa provided support for the Broken Windows theory in their study of the causes of the sharp decline in crime in New York City in the 1990s.⁷⁹ They found that these declines were not due to the improving economy, an aging population, and declining crack cocaine use, as has been suggested. Rather, they found that laws against minor crimes, known as “broken windows” policing, was a statistically significant cause of the decline in violent crime.

To address the potential for “broken windows” crimes to serve as an early indicator signal that there is a higher risk of neighborhood crime, all three phases of this study developed and tested variants of broken windows crime variables. Overall, findings from all three phases suggest that property crime variables worked better as indicators of the level of neighborhood safety (crime-related) than did the broken windows variables. The potential for endogeneity between variants of crime variables was addressed by testing for correlations between them, choosing the best-performing crime variables, and using these exclusively in the authors' MNL models (i.e., only one crime variable was used per model).

Income and Crime

Several papers provide evidence that there may be endogeneity between the income variable and crime variables used in this study. 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.⁸⁰ 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.⁸¹ 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. The potential for endogeneity between the income and crime variables was addressed through testing and selected removal, as was done for the urban form variables discussed above.

Omission of Perceived Crime Variable

Based on the research cited above, there is reason to believe that perceptions of crime may be equally important as crime, or more important than crime, in determining mode choice. Eyler, et al. is one of many studies that used perceptions of crime, rather than real crime, as a variable that influences travel behavior.⁸² In addition, Seefeldt, Malina, and Clark argue that perceptions of crime may be a more important determinant of travel behavior than reported crime levels.⁸³ 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. The lack of data on perceptions of crime and safety necessitates reliance on the reported crime-based variables used here and in previous phases.

II. RESEARCH METHODS

This chapter provides an overview of the rationale for the Phase 3 research, states the research objectives, provides an overview of the data sources, and describes the modeling techniques employed to analyze the data.

TRANSIT STATION ACCESS MODE CHOICE AND THE NEIGHBORHOOD EXPOSURE HYPOTHESIS

In Phase 2, the research team outlined what they termed the “Neighborhood Exposure Hypothesis” in an attempt to explain why transit and pedestrian mode choice behaviors respond differently to neighborhood crime levels. The researchers hypothesized that, compared with nonmotorized modes (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, the authors further hypothesized that a similar effect should be seen for transit access trips.

To test this hypothesis, a new set of Phase 2 models was developed 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 the Phase 2 transit mode choice model results continued to give counterintuitive results—in which 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 to transit stops. This finding was attributed to the fact that because 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 the research might find that the effects 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” in which 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 the 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.

The analysis of transit access trips from the BATS 2000 dataset in Phase 2 supported this hypothesis. The authors found that violent crimes were negatively associated with pedestrian and bicycling mode choices for transit-access work trips. The fact that the authors did not find a statistically significant result for non-work trips may be the result of the small sample size (just over 200 cases for non-work trips, versus 470 for work trips). Confirmation of these Phase 2 results using a more robust transit access trip travel data set was a primary motivation for this Phase 3 study.

RESEARCH OBJECTIVES

The reasons for undertaking this Phase 3 research were based on the findings and questions posed by the work in Phases 1 and 2. These findings suggested that, while the crime metric had questionable validity as a variable to help predict mode choice, the improvements made in Phase 2 to the metric (measuring crimes within a set distance of each trip origin as opposed to within the trip origin's TAZ) and changing from a binary logistic to an MNL model structure produced significant though modest improvements in consistency and interpretability of these results.

Because these improvements to the measurement and modeling techniques did not eliminate the counterintuitive findings found in both Phases 1 and 2, the research team also began to question the validity of the travel survey data (BATS 2000) used in both phases. Because BATS 2000 was designed to create a representative sample for regional analysis, it was possible that it was inappropriate for use at the neighborhood-level analysis, as done in the first two phases of this project. Phase 3 research was designed to build on these Phase 2 successes while simultaneously identifying and testing these questions and ideas, all with the intention of identifying the root cause of the confusing findings from previous phases that high-crime neighborhoods encourage people to choose transit over all other modes, including driving.

The specific research questions explored by this study are:

1. How does the new BART 2008 travel data perform compared with BATS 2000?
2. How do the models perform when drop-off and drive-alone modes are separated?
3. How do the new corridor-level crime and urban form variables perform compared with the neighborhood-level variables they replaced?
4. How does the new APS (urban design) variable compare with the urban design variable (number of 4-legged intersections per acre) used in Phases 1 and 2?
5. How do the nested logit models perform compared with the MNL models used in Phase 2?

For all of these research questions, the performance of each improvement was evaluated in terms of:

1. Model goodness-of-fit
2. The statistical significance, consistency, and interpretability of all model variables, particularly the crime variables

These results were interpreted to shed light on the following, over-arching research question:

What were the causes of the confusing (yet consistent) finding in Phases 1 and 2 that people choose transit over driving when they live in high-crime neighborhoods?

Key activities and associated findings from the Phase 3 study are reported in the following five improvements:

- Improvement 1: Testing the influence of the new travel data set
- Improvement 2: Separate drop-off and drive-alone modes analysis
- Improvement 3: Corridor-level variables
- Improvement 4: Average parcel size variable
- Improvement 5: Nested logit modeling

These Phase 3 activities are summarized below.

Improvement 1: Testing the Influence of the New Travel Data Set

The low sample size for non-auto travel modes in the BATS 2000 data set may have caused these inconsistent and counterintuitive results. The models developed and tested in the current Phase 3 used a new travel data set that provides larger sample sizes for all modes of travel—the BART 2008 Survey.

Improvement 2: Separate Drop-Off and Drive-Alone Modes Analysis

Mode choice categories were not properly specified in Phases 1 and 2. Due in part to the small sample sizes available from the BATS 2000 data set, the modes specified in the previous phases combined categories of travel that are sufficiently distinct to warrant their own separate categories. The models developed and tested in this Phase separated the “drive alone” and “drop-off” categories into separate modes.

Improvement 3: Corridor-Level Variables

Trip origin- (home) and destination-centered variables did not capture the full effects of urban form and crimes on mode choice. The previous phases used urban form and crime variables that measured the density, diversity (mixed uses), design (intersection densities), and crimes by counting these characteristics within one-quarter- or one-half-mile buffers of the trip origins and destinations of the travelers from the BATS 2000 data set. However, it is possible that urban form and crime characteristics along the entire corridor of travel—and not just the areas around the trip origins and destinations—may play a significant role in affecting mode choice. This phase tested and compared the effects of using the neighborhood-based against a set of new corridor-based variables.

Improvement 4: Average Parcel Size Variable

The authors hypothesized that urban form and crimes both play important roles in determining mode choice, and furthermore, they also hypothesized that the Phase 2 urban form variables may have not been geographically “fine-grained” enough to capture their micro-level effects on pedestrian and bicycle mode choice behaviors. Therefore, Phase 3 introduced a new measure of urban design to capture these fine-grained effects. This phase tested and compared the effects of using a corridor-level measure of the average parcel size (APS) of retail uses along the travel corridors of each traveler in the 2008 BART Station Profile Survey. In theory, larger APS values along a corridor of travel indicate a less pedestrian-friendly environment that encourages driving.

Improvement 5: Nested Logit Modeling

Some mode choices are similar enough that MNL models are not sufficiently sensitive to differentiate and distinguish between them. Nested multinomial logit models have been developed to accommodate these similarities and are better able to distinguish between similar modes of travel. It is possible that the multinomial logit models used in Phase 2 of this study were ill-equipped to distinguish between the modes specified in the models. As a result, they were unable to properly and consistently account for the influences of the crimes variables on mode choice. This phase employed nested logit models to determine if this influenced the consistency and interpretability of the crimes variables and to test the Neighborhood Exposure Hypothesis proposed in Phase 2.

DATA SOURCES

The objectives listed above served to guide the research efforts at identifying and collecting the appropriate data sources for this project. The three key data sets required were: 1) a travel data set that focused on transit station access trips; 2) disaggregated, neighborhood-level crime data for the same year and geographical coverage areas as the travel data set; and 3) urban form data.

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. The team's previous work with the BATS 2000 data set in Phases 1 and 2 and the consequent goal of testing the Neighborhood Exposure Hypothesis sent the team looking for a new travel data set that focused on transit station access trips. To meet these needs and requirements, they selected and used the Bay Area Rapid Transit (BART) 2008 Station Profile survey data.

Crime Data

Disaggregate crime data was sought, ideally geo-coded to specific street addresses, matching the neighborhoods of the people included in the BART 2008 data. The police departments of three cities in the San Francisco Bay Area—Berkeley, Oakland, and Alameda—were contacted via email or letter requesting crime data for 2008 to match the same year of the BART survey data. All three cities 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 crime data obtained from all three cities in this study formatted their data sets using the UCR. 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.⁸⁴ Part I crimes include:

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, the authors 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 to be:

3. 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.
4. Part II, Crimes Against Property: Crimes involving stolen property were put into the P2P category.
5. 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 they create an environment susceptible to crime. For the purposes of this study, it was hypothesized that these types of crimes may 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. In the City of Oakland, it must be noted that data were available regarding abandoned cars. For this city, this data was included in the Broken Window category. This category is abbreviated as BROKWIN.
6. 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 weapons-related offenses. These crimes 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.
7. Crimes that do not Affect Walkability: Many Part II-type crimes were determined not to 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 regarding whether residents would walk, bike, or take public transportation. The abbreviation used for this category is NOTAFEC.

Final List of Crime Categories

Thus seven crime categories were developed all together 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 16 in Appendix A.

Urban Form Data

Three measures of urban form were developed to determine the influence of urban form on automobile, transit, pedestrian, and bicycle mode choice. The measures are: the number of four-legged intersections per acre, the residential population per acre, and mixed-use (jobs-housing balance). In addition, the average parcel size variable (introduced in Improvement 4 as described above) was developed in Phase 3 and used as a proxy for urban design and replaced the number of four-legged intersections per acre variable.

For the residential population density variables, it was hypothesized that higher density values would promote the use of non-auto modes by providing more local opportunities (i.e., sidewalks, bike lanes, transit frequencies, and routing, etc.) to use transit, walk, and ride bicycles. Similarly, it was hypothesized that the more balanced housing and jobs are, the more likely people will walk, bicycle, or ride transit. For the four-legged intersection density measure, it was 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 (23.3-square-kilometer) area of San Francisco and Walnut Creek, California. Finally, it was hypothesized that the greater the APS value, the more walkable the corridor and the more likely a person will choose to walk, bicycle, or ride transit.

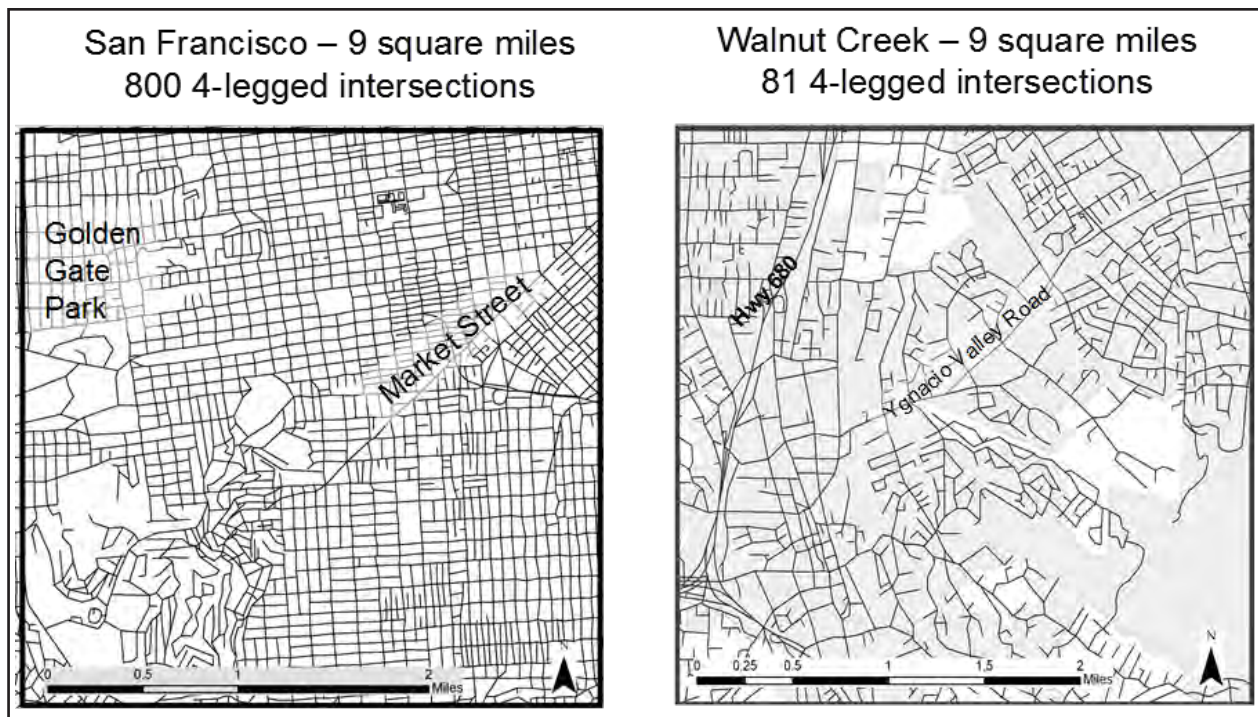


Figure 1. Gridiron vs. Suburban Street Network Patterns

The residential population density variable was calculated by dividing the total residential population of each study TAZ by the area of that TAZ, or in the case of the neighborhood-level density variable, the total number of residents within one-half mile of each travel survey home address. The TAZ-level residential data was obtained from the Metropolitan Transportation Commission (MTC). Using census tract to TAZ correspondence tables also provided by the MTC, the population per census tract estimates was converted to employment per TAZ estimates. The neighborhood-level residential data was obtained by from census block group-level data in the Smart Locations data set available from the Environmental Protection Agency (EPA).

Both the TAZ- and neighborhood-level mixed-use variables were calculated using an entropy-based measure based on the total number of population and employees (obtained pre-calculated from the Smart Locations data set) as shown in the following formula:

$$D_j = \frac{-\sum(A_{ij} \ln A_{ij})}{\ln N_j}$$

Where:

D_j = Land use diversity (mix) in TAZ j

A_{ij} = Percent of land use i in TAZ j

$\ln$ = natural log

N_j = Number of represented land uses in TAZ j

The number of four-legged intersections per acre variable was calculated by counting the number of four-legged intersections per TAZ or neighborhood and then dividing the total count by the area of the TAZ or neighborhood. The street intersection map and TAZ GIS map data files were both obtained from the Metropolitan Transportation Commission (MTC). The pre-calculated intersections per-acre values for each block group within each of the neighborhood buffers around each BART 2008 and BATS 2000 survey origin, destination, and travel route were obtained from the EPA's Smart Locations data set.

Finally, the average parcel size (APS) measure was calculated by adding up the total retail parcel acreage within 100 feet (30.5 meters) of each home-to-BART station travel route (the so-called, individual access corridor, or IAC) and dividing by the total number of retail parcels. Retail parcel data was obtained from city and county assessor's parcel data GIS maps.

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.⁸⁵

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

$$A_i = \sum_j (J_j * F_{ij})$$

Where:

A_i = accessibility of residential TAZ i

j = employment zone

J = # of jobs in employment TAZ j

F_{ij} = Time_{ij}^{-v}

Time = network travel times

-v = an empirically calculated friction factor using BATS 2000 data

While the accessibility measure was used in Phases 1 and 2, it was dropped from Phase 3 models (after use in Improvement 1), where it was found to perform contrary to the team's theoretical expectations (wherein greater accessibility to transit decreases the likelihood that a person will choose to ride transit).

DATASET PREPARATION

This study used two travel data sets: the BATS 2000 and BART 2008. BATS 2000 was used in Phases 1 and 2 of this study and used as a basis for comparison to the mode choice models developed in Phase 3 using BART 2008 travel data.

Bay Area Travel Survey (BATS) 2000

BATS 2000 data were prepared for analysis by first importing the BATS 2000 data files into a Microsoft Access database. Because 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.

4. Vehicle File: Describes each vehicle in the survey household. This data table was not utilized for this research effort.
5. 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.
6. 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 MTC. This process is explained in greater detail in "Trip Linking Procedures" working paper.⁸⁶

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 must 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, the BATS 2000 data tables were organized into a relational database structure in Access, linking different data file records by common identifiers for household, person, and activity.

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

BART Station Profile Data (2008)

The 2008 BART Station Profile Studies provides a snapshot of weekday customers at each individual BART station and for the overall system. The main objective of this survey was to provide insight into BART's market by gathering travel pattern and demographic data, and to track changes between the subsequent BART Station Profile Studies (1992,

1998, and 2008). These data were also gathered with the intent of being incorporated into the BART ridership forecasting model.

While BART's last Station Profile Study was conducted in 2008 (the data used here), this type of study dates back almost to BART's beginnings. BART began passenger service in September of 1972 and launched its first Station Profile Study in May 1973. The 2008 Station Profile Study marks the 13th such study conducted by BART.

As shown in Figure 2, the surveys themselves included information on access mode share, trip characteristics, travel patterns, demographics, and customer attitudes. In 2008, for example, BART interviewed 52,000 people through a stratified sampling protocol at each station about how, why, and where (origin and destination) they were accessing and departing from the system.



BART Survey & Contest

Your participation is very important for planning future service.

Grand Prize:
Trip to **HAWAII!**
Courtesy of Aloha Airlines and
Castle Resorts & Hotels
(Details on back.)



Please help BART serve you better by completing this survey about your BART ride. **Important:** Unless otherwise stated, **this survey covers the ONE-WAY trip you are now taking.** For example, if you receive this survey in the evening, tell us about your evening BART ride, not your morning BART ride. Please complete this survey even if you received one on a previous trip.

After you complete the survey, drop it in a collection box at any BART station (or fold, tape, and mail – postage paid).

START of This Trip

1a Which BART station did you just enter on this one-way trip?

(Entry station – where you received this survey)

1b About what time did you enter the faregate?

Hour : Minute ☐ AM ☐ PM

2 How did you get to this BART station for this trip?

☐ Walked all the way to BART

☐ Taxi

☐ Motorcycle/moped

☐ Bicycle (please specify)

☐ Parked bike at station ☐ Brought bike on train ☐ Brought folding bike on train

☐ Car (please specify)

☐ Drove alone ☐ Drove with others/carpooled ☐ Dropped off by car

Where did you park? What fee, if any, did you pay?

☐ BART lot ☐ None/Free ☐ Monthly fee
☐ Non-BART lot ☐ Daily fee ☐ Hourly fee
☐ Street parking

☐ Bus, Train, or Other Transit (please specify)

☐ AC Transit	☐ San Joaquin (Amtrak)
☐ AirBART (Oakland Airport)	☐ Santa Clara VTA
☐ AirTrain (SFO Airport)	☐ Tri Delta Transit
☐ Benicia Breeze	☐ Union City Transit
☐ Caltrain	☐ Vallejo Baylink bus
☐ Capital Corridor	☐ WestCAT
☐ County Connection	☐ Wheels (LAV/VA)
☐ Dumbarton Express	
☐ Emery Go Round	Other Transit
☐ Fairfield/Suisun Transit	☐ Ferry
☐ Golden Gate Transit bus	☐ Paratransit
☐ Muni bus (SF)	☐ Shuttle
☐ Muni Metro/streetcar (SF)	
☐ SamTrans	☐ Other:

How did you pay this bus or other transit fare?

☐ Cash Only ☐ Monthly Pass/Muni Fast Pass
☐ 10-Ride Ticket ☐ Transfer issued at BART
☐ TransLink Card ☐ BART Plus Ticket
☐ Free ☐ Other:

3a Where did you just come from? (Specify one)

☐ Home	☐ Sports Event
☐ Work	☐ Restaurant
☐ Work-related activity	☐ Theater or Concert
☐ School	☐ Hotel
☐ Medical/Dental	☐ Visit friends/family
☐ Shopping	☐ Personal errands
☐ Airplane (Trip)	☐ Other:

3b And where is this place located?

Please provide as much information as possible. It will be used to improve access to BART.

_____ (City) _____ (ZIP Code)
 _____ (Nearby intersection or street address)
 _____ (Place name – such as AT&T Park, Oakland Airport, etc.)

END of This Trip

4a At which station will you exit the BART system at the end of this one-way trip? (If transferring trains, write final exit station.)

(Exit station)

4b About what time do you expect to exit this station?

Hour : Minute ☐ AM ☐ PM

5 After you exit the BART system on this trip, how will you get to your destination?

☐ Walk all the way to destination

☐ Taxi

☐ Motorcycle/moped

☐ Bicycle (please specify)

☐ Parked bike at station ☐ Brought bike on train ☐ Brought folding bike on train

☐ Car (please specify)

☐ Drive alone ☐ Drive with others/carpool ☐ Get picked up by car

Where did you park? What fee, if any, did you pay?

☐ BART lot ☐ None/Free ☐ Monthly fee
☐ Non-BART lot ☐ Daily fee ☐ Hourly fee
☐ Street parking

☐ Bus, Train, or Other Transit (please specify)

☐ AC Transit	☐ San Joaquin (Amtrak)
☐ AirBART (Oakland Airport)	☐ Santa Clara VTA
☐ AirTrain (SFO Airport)	☐ Tri Delta Transit
☐ Benicia Breeze	☐ Union City Transit
☐ Caltrain	☐ Vallejo Baylink bus
☐ Capital Corridor	☐ WestCAT
☐ County Connection	☐ Wheels (LAV/VA)
☐ Dumbarton Express	
☐ Emery Go Round	Other Transit
☐ Fairfield/Suisun Transit	☐ Ferry
☐ Golden Gate Transit bus	☐ Paratransit
☐ Muni bus (SF)	☐ Shuttle
☐ Muni Metro/streetcar (SF)	
☐ SamTrans	☐ Other:

How will you pay this bus or other transit fare?

☐ Cash Only ☐ Monthly Pass/Muni Fast Pass
☐ 10-Ride Ticket ☐ Transfer issued at BART
☐ TransLink Card ☐ BART Plus Ticket
☐ Free ☐ Other:

6a Where are you going? (Specify one)

☐ Home	☐ Sports Event
☐ Work	☐ Restaurant
☐ Work-related activity	☐ Theater or Concert
☐ School	☐ Hotel
☐ Medical/Dental	☐ Visit friends/family
☐ Shopping	☐ Personal errands
☐ Airplane (Trip)	☐ Other:

6b And where is this place located?

Please provide as much information as possible. It will be used to improve access to BART.

_____ (City) _____ (ZIP Code)
 _____ (Nearby intersection or street address)
 _____ (Place name – such as AT&T Park, Oakland Airport, etc.)

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OVER

Figure 2. 2008 BART Station Profile Survey Questionnaire

BART used the following survey protocol: The sample design was structured to achieve 400 returns for each of four time periods at each station. For some station time periods, it was predetermined that this would not be achieved because fewer than 400 customers were expected to pass through the fare gates. Passengers were selected to participate through

an every n^{th} “random” method as they processed their tickets to enter BART. The actual number varied depending on the station and time period. At very busy stations and times, selection patterns were used (e.g., choosing one out of every 15 passengers processing a ticket at the fare gates. However, at slower stations/times, all passengers were offered a survey. One potential threat to validity includes oversampling riders accessing the system by a particular mode at stations with fewer riders.

In 2008, about 52,000 usable surveys were returned and processed, while in 1998, about 40,000 were gathered. Important pieces of information gathered from the 2008 survey for this report are: 1) the geocoded trip origins for 32,000 (2008) individuals; and 2) the modes used to access specific stations at specific times.

Crime Data Coding

The cities of Berkeley, Oakland, and Alameda, California provided both Part I and Part II data for 2008. An overview of the coding process for these cities is given below.

The crime data for Berkeley had 14,143 police activity records for 2008. Each record has sufficient descriptive information for easy categorizing into the seven crime groupings. The city of Oakland provided the most comprehensive dataset. The authors received 63,129 records of Part I and Part II crimes and incidents for 2008. 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. The remaining records were categorized and geo-coded. A number of records were found to fall outside the Oakland city limits. These records were removed from the study. Finally, 3,926 Part 1 and 2 crime records were provided by the city of Alameda for 2008. Data from San Francisco were received with no case numbers.

III. MODELING APPROACH

The reasons for undertaking this Phase 3 research were based on the findings and questions posed by the work in Phases 1 and 2. These findings suggested that, while the crime metric had questionable validity as a variable to help predict mode choice, the improvements made in Phase 2 to the metric (measuring crimes within a set distance of each trip origin as opposed to within the trip origin's TAZ) and changing from a binary logistic to an MNL model structure produced significant though modest improvements in consistency and interpretability of these results. Because these improvements to the metric and modeling techniques did not eliminate the counterintuitive findings found in both Phases 1 and 2, the research team also began to question the validity of the travel survey data (BATS 2000) used in both phases. Because BATS 2000 was designed to create a representative sample for regional analysis, it was possible that it was inappropriate for use at the neighborhood level of analysis, as was done in the first two phases of this project. Phase 3 research was designed to build on these Phase 2 successes while simultaneously identifying and testing these questions and ideas. All this was done with the intention of identifying the root cause of the confusing findings from previous phases that high crime neighborhoods encourage people to choose transit over all other modes (including driving).

The crime variables tested in Phases 1 and 2 were found to yield inconsistent, and at times, counterintuitive results. It was hypothesized that one or more of the following issues may have been the cause:

1. BATS 2000 travel data set insufficient sample size: The low sample size for non-auto travel modes in the BATS 2000 data set may have caused these inconsistent and counterintuitive results.
2. Mode choice categories were not properly specified: Due in part to the small sample sizes available from the BATS 2000 data set, the modes specified in the previous phases combined categories of travel that may be sufficiently distinct to warrant their own separate categories.
3. Trip origin- (home) and destination-centered variables did not capture the full effects of urban form and crimes on mode choice: The previous phases used urban form and crime variables that measured the density, diversity (mixed uses), design (intersection densities), and crimes by counting these characteristics within one-quarter- or one-half-mile buffers of the trip origins and destinations of the travelers from the BATS 2000 data set. However, it is possible that urban form and crime characteristics along the entire corridor of travel—and not just the areas around the trip origins and destinations—may play a significant role in affecting mode choice.
4. Insufficient urban form variables: It was hypothesized that urban form and crimes both play important roles in determining mode choice. Furthermore, it was also hypothesized that the Phase 2 urban form variables may not have been geographically “fine-grained” enough to capture their micro-level effects on pedestrian and bicycle mode choice behaviors.

5. “Nested” logit model needed: Some mode choices are similar enough that multinomial logit models are not sufficiently sensitive to differentiate and distinguish between them. Nested multinomial logit models have been developed to accommodate these similarities and are better able to distinguish between similar modes of travel. It is possible that the multinomial logit models used in Phase 2 of this study were ill-equipped to distinguish between the modes specified in the models. As a result, they were unable to properly and consistently account for the influences of the crimes variables on mode choice.

Key activities in this Phase 3 study are reported in the following five improvements:

- Improvement 1: Testing the influence of the new travel data set
- Improvement 2: Separate drop-off and drive-alone modes analysis
- Improvement 3: Corridor-level variables
- Improvement 4: Average parcel size variable
- Improvement 5: Nested logit modeling

These Phase 3 activities are summarized below.

IMPROVEMENT 1: TESTING THE INFLUENCE OF THE NEW TRAVEL DATA SET

The low sample size for non-auto travel modes in the BATS 2000 data set may have caused these inconsistent and counterintuitive results. The models developed and tested in Phase 3 used a new travel data set that provides larger sample sizes for all modes of travel—the 2008 BART Survey.

IMPROVEMENT 2: SEPARATE DROP-OFF AND DRIVE-ALONE MODES ANALYSIS

Mode choice categories were not properly specified in Phases 1 and 2. Due in part to the small sample sizes available from the BATS 2000 data set, the modes specified in the previous phases combined categories of travel that are sufficiently distinct to warrant their own separate categories. The models developed and tested in this Phase separated the “drive alone” and “drop-off” categories into separate modes.

IMPROVEMENT 3: CORRIDOR-LEVEL VARIABLES

Trip origin- (home) and destination-centered variables did not capture the full effects of urban form and crimes on mode choice. The previous Phases used urban form and crime variables that measured the density, diversity (mixed uses), design (intersection densities), and crimes by counting these characteristics within one-quarter- or one-half-mile buffers of the trip origins and destinations of the travelers from the BATS 2000 data set. However,

it is possible that urban form and crime characteristics along the entire corridor of travel—and not just the areas around the trip origins and destinations—may play a significant role in affecting mode choice. This phase tested and compared the effects of using the neighborhood-based against a set of new corridor-based variables.

IMPROVEMENT 4: AVERAGE PARCEL SIZE VARIABLE

It was hypothesized that urban form and crimes both play important roles in determining mode choice. Furthermore, it was also hypothesized that the Phase 2 urban form variables may not have been geographically “fine-grained” enough to capture their micro-level effects on pedestrian and bicycle mode choice behaviors. Therefore, Phase 3 introduced a new measure of urban design to capture these fine-grained effects. This Phase tested and compared the effects of using a corridor-level measure of the average parcel size (APS) of retail uses along the travel corridors of each traveler in the 2008 BART Station Profile Survey. In theory, larger APS values along a corridor of travel indicate a less pedestrian-friendly environment that encourages driving.

IMPROVEMENT 5: NESTED LOGIT MODELING

Some mode choices are similar enough that MNL models are not sufficiently sensitive to differentiate and distinguish between them. Nested multinomial logit models have been developed to accommodate these similarities and are better able to distinguish between similar modes of travel. It is possible that the multinomial logit models used in the models. As a result, they were unable to properly and consistently account for the influences of the crimes variables on mode choice. This phase employed a nested logit model to determine if this influenced the consistency and interpretability of the crimes variables.

THE NESTED MULTINOMIAL LOGIT (MNL) MODEL

The standard MNL model allows separate estimation of the probability (Pr) of an individual (i) choosing a specific mode choice out of several “j” choices as described in the following formula:⁸⁷

$$U_{it} = V_{it} + \varepsilon_{it}$$

Where:

U_{it} = the true utility of the alternative i to the decision maker t ,

V_{it} = the deterministic or observable portion of the utility, and

ε_{it} = the error or the portion of the utility unknown to the analyst.

The choice set in this study includes driving to a BART station by an automobile, being dropped off at the station in a car, taking the bus to a station, or walking or biking to a station. The MNL model assumes that each individual selects the mode that maximizes her utility (U). U is the sum of the estimated utility modelled using deterministic models (V) and an error (ε), or unexplained component of the utility.

However, MNL has one major limiting assumption, called the Independence of Irrelevant Alternatives (IIA). IIA assumes that the utility derived from each alternative is independent of the utility derived from the other alternatives. Consequently, a person's choice of a travel mode is independent of the availability of other travel modes.

From a modeling perspective, IIA assumes that the error terms associated with each alternative are uncorrelated with each other. This assumption is problematic for the study because a person's decision-rule for mode choice might club, or nest, mode choices. For example, in the presence of crime, a person might decide whether s/he would like to choose an open mode (walk/bike) or a closed mode (drive/drop-off/bus). Similarly, a person might decide between an automobile (drive/drop-off) and a non-automobile (bus/walk/bike) mode. In this case, from a modeling perspective, the error terms in the mode choices within a nest might be correlated, thus violating MNL's IIA assumption.

Nested logit techniques allow for the correlation of error terms within a nest.⁸⁸ Therefore, the robustness of the MNL models is checked by estimating two nested logit models. The first nest, N1, groups the travel modes into two categories—open (walk and bike) and closed (bus, drop-off, and drive) modes. The second nest, N2, nests mode choices into two categories—auto (drive and drop-off) and non-auto (bus, walk, and bike) modes.

IV. MODELING RESULTS

Each of the potential shortcomings and associated improvements listed above were introduced successively to the models to test their influences on overall model goodness of fit, the strength and significance of the urban form and crimes variables, their consistency between model runs, and their consistency with theoretical expectations.

IMPROVEMENT 1: TESTING THE INFLUENCE OF THE NEW TRAVEL DATA SET

The research team developed work and non-work travel purpose mode choice models using the BART Station Profile 2008 Survey and compared their performance to those developed in Phase 2 using the BATS 2000 travel survey data. To isolate the effects of the data sample size and survey methods as best as possible, the BART data models were specified using variables and model structures that matched as close as possible to those used to develop the models in Phase 2 using BATS 2000 data.

Work Trips

Table 2 provides the detailed Phase 2 MNL regression results for the work model using the BATS 2000 data set.

Table 2. BATS 2000 Survey Multinomial Logistic Regression Results for Work Trip Mode Choice

Variable	Transit		Walk		Bicycle	
Person Variables						
Race (1=White, 0=Non-White)	-0.0780		1.0370	***	0.7370	**
Age Categories						
1=under 19	N/D		N/D		N/D	
2=19-39	-1.0050	***	-0.1940		-0.9740	
3=40-59	-0.4960	*	0.2320		-0.4510	
4=above 59	Referent		Referent		Referent	
Gender (2=Male, 1=Female)	0.1480		-0.0660		1.0260	***
Household Variables						
Household Income (0=\$50k & under, 1=over \$50k)	-0.2230	*	0.2290		0.1390	
Tenure (2=Own Home, 1=Don't Own Home)	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	

Variable	Transit	Walk	Bicycle
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.

Table 3 provides the detailed Phase 3 MNL regression results for the work model using the 2008 BART Station Profile Survey data set.

Table 3. 2008 BART Station Profile Survey Multinomial Logistic Regression Results for Work Trip Mode Choice

Variable	Transit	Walk	Bicycle
Person Variables			
Race (1=White, 0=Non-White)	0.1590	0.5840 ***	1.8660 ***
Gender (1=Female, 2=Male)	0.4500 **	0.6450 ***	1.3480 ***
Age Categories			
1=18-34 Years	-0.7130 **	0.4210 *	0.7950 **
2=35-54 Years	-0.4960 *	0.3420	0.8180 **
3=Over 54 Years	Referent	Referent	Referent
Household Variables			
Household Income (0=\$50k & under, 1=over \$50k)	-1.0860 ***	-0.5030 **	-1.0000 ***
Vehicle Available (0=No, 1=Yes)	-2.0920 ***	-1.8360 ***	-1.6660 ***
Trip Characteristics			
Total Trip Distance (Miles)	-0.1980 **	-3.9880 ***	-0.6140 ***
Neighborhood Variables			
Home TAZ Transit Accessibility Score	-2.46E-06 ***	-2.61E-06 ***	-2.71E-06 ***
Home TAZ Population Density	-0.0130	-0.0240 ***	0.0240 **
Home TAZ Mixed Use (Jobs-Housing Balance)	-0.4140	0.2840	-0.6780

Variable	Transit		Walk		Bicycle	
Home TAZ # 4-Legged Intersections/Acre	4.7500	***	5.1780	***	-11.9800	***
Home TAZ Median Income	-2.00E-05	***	2.22E-05	***	4.54E-05	***
Home TAZ Percent White	1.9530	**	-0.1190		-6.5210	**
Destination TAZ Population Density	1.30E-02		4.50E-02	***	6.30E-02	***
Destination TAZ Mixed Use (Jobs-Housing Balance)	-5.1070	***	-2.9580	***	1.3280	
Destination TAZ Median Income	-5.05E-05	***	-1.28E-05	*	-1.61E-05	*
Violent Crimes (P1V) w/in 1/4-Mile of Home	-0.0050	*	-0.0100	***	-0.0020	
Constant	8.7990	***	11.9040	***	7.9090	***
Model Fit						
N					2312	
-2 Log likelihood					2408.00	
Nagelkerke R Square					0.768	

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% of the variation in the BATS 2000 data set, while Nagelkerke results for the BART data set were substantially higher, explaining nearly 77% of the variation.

Person Variable Results

While race was not a statistically significant variable determining work trip transit mode choice, Caucasian (White) respondents were more likely to choose to walk or bicycle than drive or ride in a car in both the BATS 2000 and BART models.

In both models, the older a person was, the less likely they were to choose to ride transit. However, although age did not play a role in determining the propensity to walk or ride a bike in the BATS 2000 model, older survey respondents in the BART model were significantly less likely to walk or ride their bikes for work trips.

Finally, gender played an important role in determining bicycle mode choice in both models—with men more likely to bicycle to work than women. However, while the BATS 2000 model did not find any statistically significant effect of gender on bicycle or walking mode choice, the BART model found strong effects for these modes, with males more likely to choose to walk or bicycle compared with driving.

Household Variable Results

While it was surprising to find in Phase 2 that the BATS 2000 model did not find a consistent, statistically significant effect of household income on work trip mode choice, the BART

model yielded significant results of income for all three non-auto modes (transit, walking, and bicycling). Generally, the higher the household income of BART survey respondents, the more likely they were to choose to walk, ride transit, or bicycle for work trips.

While the BATS 2000 data set included a home ownership (tenure) variable, the work trip model developed using these data in Phase 2 found homeowners were more likely to drive than ride a bicycle for work trips. This variable was not provided in the BART data set, and as a result, was not included in models using these data.

Similarly, the number of bicycles per household was a statistically significant determinant for riding transit or bicycling—with more bicycles in the household, the more likely household members were to bicycle or ride transit to work. But the BART data set did not provide this variable, and there was no reasonable substitute available.

The BATS data set provided data that allowed the research team in Phases 1 and 2 to construct the number of “Household Vehicles per Licensed Driver” variable, but the BART data did not provide these same data components. However, the BART data set provided the number of household vehicles, which the researchers used as a proxy for the BATS 2000 model’s Household Vehicles per Licensed Driver variable. Consistent with theoretical assumptions, both models showed that the more vehicles available in a household, the less likely a household member will choose to ride transit, walk, or bicycle for work trips.

Trip Characteristics Variable Results

It was hypothesized that trip length would be negatively associated with the propensity to take transit, walk, or ride a bicycle. This hypothesis was confirmed by both models 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 BART data set did not provide a time of travel variable, so while the BATS 2000 model found that 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), the BART model did not have a start-time variable.

Neighborhood Variable Results

Overall, statistically significant results for the Phase 2 BATS 2000 work trip model’s urban form variables were somewhat spotty. The Home TAZ Transit Accessibility Score was not significantly related with the propensity to ride transit (contrary to expectations) and to walk. However, it was a highly statistically significant determinant of bicycling mode choice, with higher accessibility scores leading to a greater propensity to cycle to work. In the BART work model, the significance of this variable was greatly improved (with p-values less than 0.001 for all three non-auto modes) but with negative signs. This suggests that the higher the transit accessibility of the trip origin’s neighborhood, the less likely people who lived there were to use transit, walk, or bicycle. These counterintuitive findings from the BART model, added to the statistically weak findings from the BATS 2000 model, suggested to the research team that this variable may suffer from multi-collinearity with other variables

in the model. That would include, perhaps, the crime variable, potentially explaining its somewhat unreliable performance in the models developed in previous phases. As a result, the research team focused on this variable in subsequent model runs in an effort to evaluate if it should be dropped.

Results for the Home TAZ Population Density variable from the BATS 2000 model were statistically insignificant across all three non-automotive modes, while they were significant for both the walk and bicycle modes in the BART model. However, the negative sign associated with walk mode choice—a finding contrary to the team’s theoretical expectations—suggests that either the theory suggesting higher densities increase walking is in error, or the specification of both models are suspect. This is possibly due to multi-collinearity between this variable and the previously mentioned Home TAZ Transit Accessibility Score variable.

The Mixed Use variable in the BATS 2000 work model yielded a significant, negative sign for transit mode choice, in which the more balanced jobs and housing are within a neighborhood, the less likely a person will be to choose transit. Conversely, the BART work model yielded no statistically significant findings for this variable. The absence of a problem (a statistically significant finding contrary to theory) suggests a slight improvement, while the lack of measurable effect of mixed uses on non-auto mode choice further indicates that the model may be mis-specified.

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, and the more pedestrian friendly it will feel to its residents. The statistically significant, positive sign for this variable in both models 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. Additionally, the highly statistically significant findings for the transit and bicycling modes in the BART model adds further evidence to the hypothesis that the BART data set is more appropriate for modeling the effects of urban form on mode choice at this geographic scale.

The socio-demographic characteristics of the home neighborhood also play an important role for work trip transit mode choice in both models. That is, the higher the neighborhood’s median income and the higher the share of Caucasians, the greater the likelihood that a person will choose to take transit. However, the BATS 2000 model is sensitive only to these two variables for transit mode choice compared with driving, while the BART model also yielded statistically significant effects for neighborhood median income on walking and bicycling (both positive effects) and for the percentage of Caucasians on transit use (a negative association).

Both models included a number of variables to measure the urban form characteristics of the destination neighborhoods of each trip. However, because the ultimate destination of each trip was not recorded in the BART survey, the station where riders entered the BART system was used as the destination location. This was, in effect, the destination of all BART access trips. The BATS 2000 work trip model found that population densities

at the destination TAZ were positively correlated with the propensity to choose transit and negatively correlated with bicycling. Meanwhile, the BART work trip model found that higher destination densities were associated with people walking and bicycling. The authors speculate that these somewhat different findings for the two work trip models may be due to the different effects of population densities at the ultimate trip destination (i.e., the workplace) and the effects of densities at BART stations.

Reflecting the curious result for the Home TAZ Mixed Use variable in both work models (BATS 2000 and BART 2008), 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. Although it was hypothesized in the Phase II report that this unexpected finding may have been due to a sampling problem in the BATS 2000 data set, similar findings from the BART work model confirm these earlier results.

The economic characteristics of the destination neighborhood play an important role for work trip mode choice in both models. For work trips, the higher the neighborhood's median income, the lower the likelihood a person will choose to take transit or walk in the BATS 2000 model. In the BART work model, people are less likely to take transit, walk, or bicycle to higher-income destination TAZs. It is suspected that these findings may be due, in part, to the large amount of lower-income housing in employment centers, where work trips generally end. Furthermore, in the case of the BART models, it is likely that there are more park-and-ride lots and spaces in lower-income station neighborhoods, where land costs are lower. This provides an incentive for people to choose to drive rather than walk, ride transit, or bicycle to the BART station.

Neighborhood Crime Rate Variable Results

Neighborhood crime variables were selected for the Phase 2, BATS 2000 work model based on their performance in preliminary modeling exercises and on theoretical considerations. For the work model, the continuous/count variable for the number of violent crimes within one-eighth mile of each trip origin worked best. For the Phase 3, BART work model, a count of violent crimes within one-quarter mile of each trip origin yielded the most consistent and interpretable results.

The BATS 2000 work model found that the number of crimes within one-eighth mile of a survey respondent's home was positively related to transit mode choice, which was a counterintuitive result, and more crimes were correlated with a lower propensity to walk, which was consistent with the hypothesis. However, the BART work model found that more crimes were correlated with less transit riding and walking. The BART model findings, consistent with expectations for how crimes should affect mode choice, suggest that the inconsistent Phase 2 BATS 2000 model findings were either due to sampling problems with that data set—a problem that is rectified by using the BART data set. Or it is because transit access mode choice is affected by neighborhood crime levels differently than it is for other trip types, which supports the Neighborhood Exposure Hypothesis.

Non-Work Trips

Table 4 provides MNL regression results for the Phase II BATS 2000 non-work model using the best-performing crime variable.

Table 4. BATS 2000 Survey 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	-0.3820	-0.9740 **	0.3240
3=40-59	0.4000	-0.0170	1.2680
4=above 59	Referent	Referent	Referent
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 # 4-Legged Intersections/Acre	-3.5200 *	0.3490	1.7420
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:

* = $p < 0.10$

** = $p < 0.05$

N/A = Not Applicable.

N/D = No Data.

Table 5 provides the detailed Phase 3 MNL regression results for the non-work model using the BART Station Profile data set.

Table 5. 2008 BART Station Profile Multinomial Logistic Regression Results for Non-Work Trip Mode Choice

Variable	Transit		Walk		Bicycle	
Person Variables						
Race (1=White, 0=Non-White)	-1.0970	***	-0.0090		1.7010	***
Gender (1=Female, 2=Male)	-0.1600		0.5020	*	0.9480	***
Age Categories						
1=18-34 Years	0.3320		0.8770	**	1.8220	***
2=35-54 Years	0.4780		0.6720	*	1.6780	***
3=Over 54 Years	Referent		Referent		Referent	
Household Variables						
Household Income (0=\$50k & under, 1=over \$50k)	-0.7940	**	-0.8360	***	-0.5240	**
Vehicle Available (0=No, 1=Yes)	-2.2480	***	-2.1010	***	-2.3830	***
Trip Characteristics						
Total Trip Distance (Miles)	-0.0970		-3.8030	***	-0.6010	***
Neighborhood Variables						
Home TAZ Transit Accessibility Score	-4.44E-06	**	-4.61E-06	***	-5.61E-06	***
Home TAZ Population Density	0.0190		0.0100		0.0210	
Home TAZ Mixed Use (Jobs-Housing Balance)	0.3880		-0.0830		1.7690	**
Home TAZ # 4-Legged Intersections/Acre	2.4930		5.0010	**	-15.6610	***
Home TAZ Median Income	-2.48E-05	**	5.21E-05	***	6.62E-05	***
Home TAZ Percent White	1.9310		-2.1260	*	-9.4770	
Destination TAZ Population Density	5.10E-02	*	-1.00E-02		4.60E-02	
Destination TAZ Mixed Use (Jobs-Housing Balance)	-5.2160	**	-7.0410	***	-2.2170	
Destination TAZ Median Income	-3.77E-05	**	-2.88E-05	**	-3.67E-05	**
Violent Crimes (P1V) w/in 1/4-Mile of Home	0.0004		-0.0160	***	-0.0060	
Constant	11.3730	**	18.9870	***	16.6900	***
Model Fit						
N					825	
-2 Log likelihood					894.93	
Nagelkerke R Square					0.760	

Notes:

* = $p < 0.10$

*** = $p < 0.01$

*** = $p < 0.01$

N/A = Not Applicable.

N/D = No Data.

Nagelkerke R-Square results for the non-work model runs indicate the model explains roughly 49% of the variation in the BATS 2000 data set, while results for the BART data set were substantially higher, explaining roughly 76% of the variation.

Person Variable Results

Similar to the BATS 2000 work trip model, race was not a significant variable influencing non-work mode choice in the BATS 2000 non-work trip model. This contrast also applies when comparing the BATS 2000 non-work model race findings with those from the BART non-work model, with the BART model reporting that white respondents were more likely to choose to bicycle than drive or ride in a car, and less likely to ride transit than drive or ride in a car.

In both non-work models, the older a person was, the less likely they were to walk. However, just as seen with the work models, age did not play a role in determining the propensity to ride transit or a bike in the BATS 2000 model. Conversely, older survey respondents in the BART model were significantly less likely to use these modes for non-work trips.

Gender played an important role in determining transit mode choice in the BATS 2000 non-work model—with women more likely to ride transit for non-work trips than men. But this model did not find any statistically significant effect of gender on bicycle or walking mode choice. However, the BART non-work model found strong effects for these modes, with males more likely to choose to walk or bicycle compared with driving.

Household Variable Results

Again, similar to the surprising lack of statistically significant influences of household income on mode choice in the Phase II BATS 2000 work model, the non-work BATS 2000 model found no significant effects for household income. However, the BART non-work model produced significant results for all three modes (transit, walking and bicycling) compared with driving. Matching the findings from the work model, the higher the household income of BART survey respondents, the more likely they were to choose to walk, ride transit, or bicycle for non-work trips.

The BATS 2000 data set included a home ownership (tenure) variable. The non-work trip model developed in Phase 2 found homeowners were more likely to drive than ride a bicycle for non-work trips. This variable was not provided in the BART data set, and as a result, was not included in models using these data.

The number of bicycles per household was a statistically significant determinant for walking and bicycling. That is, with more bicycles in the household, the more likely household members were to walk or ride a bike for non-work trips. However, the BART data set did not provide this variable, and there was no reasonable substitute available.

Consistent with theoretical assumptions, the more vehicles available in a household, the less likely a household member will choose to ride transit, walk or bicycle for non-work trips. This variable was statistically significant for all modes in both non-work models (BATS 2000 and BART 2008).

Trip Characteristics Results

Both non-work models (BATS 2000 and BART 2008) found that the longer the trip distance, the less likely a person will choose to walk. Furthermore, the BART model also found that longer trip distances suppressed bicycling mode choice.

The BART data set did not provide a time of travel variable. The BATS 2000 model found that 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. However, the BART model did not have a start time variable.

Neighborhood Variable Results

Just as seen for the work trip models, statistically significant results for the Phase 2 BATS 2000 non-work trip model's urban form variables were rare and, at times, inconsistent. The Home TAZ Transit Accessibility Score was not significantly related with the propensity to ride transit (contrary to expectations) and to walk. However, it was a highly statistically significant determinant of bicycling mode choice, with higher accessibility scores leading to a greater propensity to cycle for non-work purposes. As seen in the BART work trip model, the significance of this variable was greatly improved in the non-work model, with p-values less than 0.05 for all three non-auto modes. But the negative signs run counter to theoretical expectation, suggesting the higher the transit accessibility of the trip origin's neighborhood, the less likely people who lived there were to use transit, walk, or bicycle in the BART non-work model. These counterintuitive findings from the non-work BART model, added to the statistically weak findings from the BATS 2000 non-work model, add further evidence to the hypothesis suggested in the work model sections above that this variable may be collinear with the other urban form variables.

Results for the Home TAZ Population Density variable from the BATS 2000 model were statistically insignificant for all modes except walking, where more density encourages people to choose this mode over driving. However, the BART non-work model found no statistically significant results for any of the modes. This is the only case—on a variable-by-variable basis—in which the BART model underperformed the BATS 2000 model.

The BATS 2000 non-work model yielded significant, negative sign for the Home TAZ Mixed-Use variable for transit mode choice, in which the more balanced jobs and housing are within a neighborhood, the less likely a person will be to choose transit. However, the BART non-work model found a positive, significant sign for bicycling mode choice, in which more balanced jobs and housing leads to higher likelihood that a person will choose to ride a bike.

The more four-legged intersections in a neighborhood, the more grid-like the street network, and the more pedestrian friendly it will feel to its residents. The statistically significant, positive sign for this variable in the BATS 2000 non-work model for bicycling mode choice suggests that the more grid-like the street pattern, the more likely a person will choose to bicycle. The lack of a statistically significant finding for pedestrian mode choice for this variable in the BATS 2000 non-work model is somewhat puzzling because

the theoretical assumption was that this variable would be an important determinant for walking. Furthermore, this model's significant and positive sign for bicycling mode choice is also contrary to expectations because more intersections can present more opportunities for vehicle collisions. Therefore, they should inhibit bicycling mode choice. However, the findings of the BART non-work model are more consistent with expectations, with more intersections in the trip origin neighborhood leading to a higher likelihood of walking and a lower likelihood of bicycling.

The socio-demographic characteristics of the home neighborhood did not play a statistically significant role for non-work trip transit mode choice in the BATS 2000 model, while they influenced pedestrian and bicycling mode choice in the BART model. For the BART model, the higher the neighborhood's median income, the less likely people were to walk. The higher the share of Caucasians, the greater the likelihood that a person will choose to walk. The BART model also yielded statistically significant effects for neighborhood median income on transit (a positive effect) and bicycling (a negative association).

Both models included a number of variables to measure the urban form characteristics of the destination neighborhoods of each trip. However, because the ultimate destination of each trip was not recorded in the BART survey, the station where they entered the BART system was used as the destination location. This was the destination of all BART access trips. While the BATS 2000 work trip model found that population densities at the destination TAZ were positively correlated with the propensity to choose transit and negatively correlated with bicycling, the BART work trip model found that higher destination densities were associated with people walking and bicycling. It is speculated that these somewhat different findings for the two work trip models may be due to the different effects of population densities at the ultimate trip destination (i.e., the workplace) and the effects of densities at BART stations.

Reflecting the curious result for the Home TAZ Mixed Use variable in both work models (BATS 2000 and BART 2008), 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. It was hypothesized in the Phase 2 report that this unexpected finding may have been due to either a sampling problem in the BATS 2000 data set or the Neighborhood Exposure Hypothesis. Similar findings from the BART work and non-work models add support to these earlier conclusions.

The economic characteristics of the destination neighborhood play an important role for work trip mode choice in both models. For non-work trips, the higher the neighborhood's median income, the lower the likelihood a person will choose to take transit or walk in the BATS 2000 model. In the BART work model, people are less likely to take transit, walk, or bicycle to higher-income destination TAZs.

Neighborhood Crime Rate Variable Results

For the Phase 2 non-work model, the continuous/count variable of the number of violent crimes within one-eighth mile of each trip origin worked best. For the Phase 3, BART non-

work model, a count of violent crimes within one-quarter mile of each trip origin yielded the most consistent and interpretable results.

The BATS 2000 non-work model found that the number of crimes within one-quarter mile of a survey respondent's home was positively related to transit mode choice—a counterintuitive result. In addition, more crimes were correlated with the theoretical expectations.

IMPROVEMENT 2: SEPARATE DROP-OFF AND DRIVE-ALONE MODES ANALYSIS

The second improvement involved separating the drop-off driving trips from drive-alone trips using the BART 2008 data set. Otherwise, the models were specified exactly the same as those produced in Improvement 1.

Work Trips

Table 6 provides the Improvement 2 MNL regression results for the work model using the BART Station Profile data set with drop-off and drive-alone modes separated.

Table 6. BART Station Profile 2008 Multinomial Logistic Regression Results for Work Trip Mode Choice-Separated Drive-Alone and Drop-Off Modes

Variable	Transit	Walk	Bicycle	Drop-Off
Person Variables				
Race (1=White, 0=Non-White)	0.1780	0.6300 ***	1.9110 ***	0.2040
Gender (1=Female, 2=Male)	0.3510	0.5050 ***	1.2040 ***	-0.2200
Age Categories				
1=18-34 Years	-0.4830	0.6640 **	1.0880 ***	0.5490
2=35-54 Years	-0.5420 *	0.2790	0.7570 **	-0.3500 *
3=Over 54 Years	Referent	Referent	Referent	Referent
Household Variables				
Household Income (0=\$50k & under, 1=over \$50k)	-1.0380 ***	-0.4160 *	-0.9350 ***	0.1540 ***
Vehicle Available (0=No, 1=Yes)	-2.8650 ***	-2.7590 ***	-2.6120 ***	-1.9610 ***
Trip Characteristics				
Total Trip Distance (Miles)	-0.2830 ***	-4.0990 ***	-0.7640 ***	-0.5270 ***
Neighborhood Variables				
Home TAZ Transit Accessibility Score	-1.64E-06 *	-1.49E-06 *	-1.50E-06 *	1.42E-05 *
Home TAZ Population Density	-0.0150	-0.0260 ***	0.0230 **	0.0280
Home TAZ Mixed Use (Jobs-Housing Balance)	-0.2660	0.4700	-0.4310	1.9850
Home TAZ # 4-Legged Intersections/Acre	3.6010 **	3.7240 **	-12.7790 ***	-3.7010 **
Home TAZ Median Income	-1.05E-05 *	3.38E-05 ***	5.86E-05 ***	8.06E-05 *
Home TAZ Percent White	0.0720	-2.0600 ***	-8.5420 ***	-7.2180
Destination TAZ Population Density	1.40E-02	4.50E-02 ***	6.50E-02 ***	3.00E-03

Variable	Transit		Walk		Bicycle		Drop-Off	
Destination TAZ Mixed Use (Jobs-Housing Balance)	-5.7030	***	-3.7380	***	0.3260		-2.0480	***
Destination TAZ Median Income	-5.98E-05	***	-2.23E-05	***	-2.67E-05	***	-3.47E-05	***
Violent Crimes (P1V) w/in 1/4-Mile of Home	-0.0050		-0.0100	***	-0.0020		0.0000	
Constant	7.7230	***	9.9520	***	5.6410	*	-42.8980	***
Model Fit								
N							2312	
-2 Log likelihood							985.79	
Nagelkerke R Square							0.781	

Notes:

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

N/A = Not Applicable.

N/D = No Data.

Goodness of Fit

By separating drive-alone and drop-off trips, the model performance improved slightly. Nagelkerke R-Square results for the work logistic model run indicate the Improvement 2 model explains roughly 78% of the variation in the BART 2008 data set, compared with the Improvement 1 work model that explained 77% of the variation.

Person Variable Results

Comparing Improvement 1 with Improvement 2 work model person variable results, the transit, walk and bicycle modes were generally consistent, with a few differences. While the Improvement 1 work model transit gender and age categories (18-34 years and 35-54 years) were statistically significant, only the 35-54 age category variable was significant in the Improvement 2 work model. Otherwise, all statistically significant variables found in the Improvement 1 model remained significant and retained consistent signs in the Improvement 2 model.

Person variable results for the Improvement 2 drop-off mode produced only one statistically significant result—the 35-54 age category variable. This finding suggests that people over 54 years of age are more likely to drive alone to BART than to have someone drop them off.

Household Variable Results

Household variable results for the Improvement 2 work model were consistent with those from Improvement 1's work model. Both variables (Household Income and Vehicle Available) retained their signs and significance for the transit, walk, and bicycle modes.

Household variable results for the Improvement 2 drop-off mode were significant for both variables. The Household Income variable finding suggests that people from households with incomes greater than \$50,000 per year are more likely to choose to be dropped off

at a BART station than they are to drive alone. The Vehicle Available variable finding indicates that people who come from households with a vehicle available are more likely to drive alone than be dropped off.

Trip Characteristics Variable Results

Trip characteristic variable (Total Trip Distance) results for the Improvement 2 work model were consistent with those from Improvement 1's work model. The Trip Distance variable retained its negative signs and significance for the transit, walk and bicycle modes.

The Total Trip Distance variable result for the Improvement 2 drop-off mode was statistically significant and a negative sign, indicating people who live far away from the nearest BART station are more likely to drive alone.

Neighborhood Variable Results

Neighborhood variable results for the Improvement 2 work model were generally consistent with those from Improvement 1's work model, with a few differences. While the Home TAZ Percent White variable was statistically significant for the transit mode in the Improvement 1 model, it was insignificant in the Improvement 2 model. However, for the walk mode, this variable was insignificant in the Improvement 1 model and significant in the Improvement 2 model.

Neighborhood variable results for the Improvement 2 drop-off mode were significant for the Home TAZ Transit Accessibility Score, the Home TAZ # 4-Legged Intersections/Acre, the Home TAZ Median Income, the Destination TAZ Mixed-Use, and the Destination TAZ Median Income variables. These findings suggest that households with high transit accessibility, a low density of neighborhood four-legged intersections, and a high neighborhood median income are more likely to choose to be dropped off at a BART station instead of driving alone. The findings for the neighborhood characteristics at the destination (the BART station) TAZ variables indicate people are more likely to drive alone compared with being dropped off when their destination neighborhood has high incomes and many mixed uses.

Neighborhood Crime Rate Variable Results

Comparing the crime variable results from the Improvement 1 and Improvement 2 work models, the only change was found for the transit mode category in which the number of violent crimes within one-quarter mile of the survey respondent's home was statistically significant with a negative sign for the Improvement 1 model and insignificant for Improvement 2. The crime variable was statistically insignificant for the drop-off mode.

Non-Work Trips

Table 7 provides the Improvement 2 MNL regression results for the non-work model using the BART Station Profile data set with drop-off and drive-alone modes separated.

Table 7. BART Station Profile 2008 Multinomial Logistic Regression Results for Non-Work Trip Mode Choice-Separated Drive-Alone and Drop-Off Modes

Variable	Transit		Walk		Bicycle		Drop-Off	
Person Variables								
Race (1=White, 0=Non-White)	-1.2350	***	-0.2120		1.4960	***	-0.3350	***
Gender (1=Female, 2=Male)	0.1150		0.7450	**	1.1990	***	0.6950	
Age Categories								
1=18-34 Years	0.5750		1.1250	***	2.1110	***	0.7920	
2=35-54 Years	0.5760		0.7730	*	1.8410	***	0.6220	
3=Over 54 Years	Referent		Referent		Referent		Referent	
Household Variables								
Household Income (0=\$50k & under, 1=over \$50k)	-0.7240	*	-0.7640	**	-0.4480		0.2410	*
Vehicle Available (0=No, 1=Yes)	-3.4720	***	-3.4090	***	-3.7650	***	-2.6580	***
Trip Characteristics								
Total Trip Distance (Miles)	-0.2050		-3.8810	***	-0.6840	***	-0.1580	
Neighborhood Variables								
Home TAZ Transit Accessibility Score	-4.04E-06	**	-3.81E-06	**	-4.64E-06	**	1.57E-05	**
Home TAZ Population Density	0.0070		-0.0020		0.0100		0.0020	
Home TAZ Mixed Use (Jobs-Housing Balance)	0.9150		0.3040		2.3140	**	1.9540	
Home TAZ # 4-Legged Intersections/Acre	0.8470		3.5060		-16.5170	***	-4.4470	
Home TAZ Median Income	-1.52E-05		6.19E-05	***	8.02E-05	***	7.58E-05	
Home TAZ Percent White	-0.5410		-4.3480	***	-12.1640	***	-8.2240	
Destination TAZ Population Density	7.90E-02	**	1.90E-02		7.50E-02	**	8.00E-02	**
Destination TAZ Mixed Use (Jobs-Housing Balance)	-7.1960	***	-9.0870	***	-4.4680		-5.8570	***
Destination TAZ Median Income	-4.97E-05	***	-3.92E-05	***	-4.97E-05	***	-2.74E-05	***
Violent Crimes (P1V) w/in 1/4-Mile of Home	-0.0050		-0.0210	***	-0.0120	*	-0.0100	
Constant	12.1530	**	18.3670	***	15.4970	**	-47.1500	**
Model Fit								
N							825	
-2 Log likelihood							985.79	
Nagelkerke R Square							0.781	

Notes:

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

N/A = Not Applicable.

N/D = No Data.

Goodness of Fit

As seen with the work models, separating drive-alone and drop-off trips improved non-work model performance slightly. Nagelkerke R-Square results for the non-work logistic model run suggests the Improvement 2 model explains roughly 78% of the variation in the

BART 2008 data set, compared with the Improvement 1 work model that explained 76% of the variation.

Person Variable Results

Comparing Improvement 1 with Improvement 2 non-work model person variable results, the transit, walk and bicycle modes were consistent. Person variable results for the Improvement 2 drop-off mode produced one statistically significant result—the race variable—indicating people who self-identify as white are more likely to drive alone to BART than to be dropped off.

Household Variable Results

Household variable results for the Improvement 2 work model were largely consistent with those from Improvement 1's work model. The only change was for the household income variable, which was significant for the Improvement 1 model and insignificant for Improvement 2.

Similar to the work trip Improvement 2 findings, non-work model household variable results for the Improvement 2 drop-off mode were significant for both variables. The household income variable finding suggests that people from households with incomes greater than \$50,000 per year are more likely to choose to be dropped off at a BART station than they are to drive alone. The vehicle available variable finding indicates that people who come from households with a vehicle available to them are more likely to drive alone than to be dropped off.

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results for the Improvement 2 non-work model were consistent with those from Improvement 1's work model. The total trip distance variable result for the Improvement 2 drop-off mode was not statistically significant.

Neighborhood Variable Results

Similar to the work model results discussed above, neighborhood variable results for the Improvement 2 non-work model were generally consistent with those from Improvement 1's non-work model, with a few exceptions. While the Home TAZ # 4-Legged Intersections/Acre variable was significant with a positive sign for the walk mode category in the Improvement 1 model, it was insignificant in the Improvement 2 non-work model. Looking at the Home TAZ Percent White variable, while it was statistically insignificant for the bicycle mode in the Improvement 1 model, it was significant with a negative sign in the Improvement 2 model.

A difference could also be found between the Improvement 1 and Improvement 2 non-work models in the results for the Destination TAZ Population Density variable. While this variable was insignificant for the Improvement 1 model in the bicycle mode choice category, it was statistically significant with a positive sign in bicycle category of the Improvement #2 non-work model.

Neighborhood variable results for the Improvement 2 non-work model drop-off mode were significant for the Home TAZ Transit Accessibility Score, the Destination TAZ Population Density, the Destination TAZ Mixed-Use, and the Destination TAZ Median Income variables. These findings indicate that households with high transit accessibility, high densities, low mixed uses, and low median incomes around their nearby BART station are more likely to choose to be dropped off at a BART station instead of driving alone.

Neighborhood Crime Rate Variable Results

Comparing the crime variable results from the Improvement 1 and Improvement 2 non-work models, both models found that the more violent crimes within one-quarter mile of the homes of BART survey respondents, the more likely they were to choose to drive alone instead of walking. However, the Improvement 2 model also found that this variable was significant and negative for the bicycle mode choice category, suggesting people who live in high-crime neighborhoods fear for their safety and avoid walking. The crime variable was statistically insignificant for the drop-off mode.

IMPROVEMENT 3: CORRIDOR-LEVEL VARIABLES

The third improvement represents a dramatic shift in the approach taken to modeling transit station access compared with the previous two improvements. The previous models used variables that described the urban form and socio-demographic conditions of the neighborhoods (as represented by TAZs) around the trip origins (homes) of BART 2008 survey respondents and the neighborhoods surrounding their nearest BART stations. Improvement 3 models were designed to capture the urban form conditions of the entire travel corridor each survey respondent used.

These models also tested improvements to the socio-demographic variables used in previous models by measuring the median income and racial characteristics within one-quarter mile of each home's location instead of using income and racial characteristics of the each home's TAZ. This is a less precise geographic unit because a home may be located near the edge of a TAZ that has significant variability in the measured characteristic, or the TAZ may be an irregular shape or size. In addition, the socio-demographic characteristics of the home/trip origin's neighborhood were used instead of the characteristics of the travel corridor based on the theoretical assumption that neighborhood socio-demographics affect travel choice more than the characteristics of more distant neighborhoods that a person is traveling through.

Finally, the Home TAZ Transit Accessibility variable was found to be unreliable in previous model runs, likely as a result of collinearity with other urban form/transportation variables in the model. Therefore, this variable has been removed in this and subsequent model runs.

Work Trips

Table 8 provides the Improvement 3 MNL regression results for the work model using the BART Station Profile data set with corridor-level variables.

Table 8. BART Station Profile 2008 Multinomial Logistic Regression Results for Work Trip Mode Choice-Corridor-Level Variables

Variable	Transit		Walk		Bicycle		Drop-Off	
Person Variables								
Race (1=White, 0=Non-White)	0.0470		0.7060	***	1.6330		0.0340	
Gender (1=Female, 2=Male)	0.4150	**	0.5850	***	0.4150	**	-0.2310	
Age Categories								
1=18-34 Years	0.8350	***	-0.2830		-0.8430	***	-0.1400	
2=35-54 Years	0.6610	***	-0.0710		-0.7760	***	0.5720	**
3=Over 54 Years	Referent		Referent		Referent		Referent	
Household Variables								
Household Income (0=\$50k & under, 1=over \$50k)	-1.0380	***	-0.3450	*	-0.7240	***	0.1450	
Vehicle Available (0=No, 1=Yes)	-3.2250	***	-2.9110	***	-2.8530	***	-1.9800	***
Trip Characteristics								
Total Trip Distance (Miles)	-0.1290	*	-4.2200	***	-0.6870	***	-0.2640	***
Neighborhood & Corridor Variables								
Corridor Population Density	0.1130	***	0.0950	***	0.0920	***	0.0840	***
Corridor Mixed Use (Jobs-Housing Balance)	5.2410	***	2.3540	***	3.7920	***	2.2230	***
Corridor # 4-Legged Intersections/Acre	0.0020		0.0060	***	0.0100	***	-0.0040	***
Median Income w/in 1/4-Mile of Home	-3.94E-05	***	8.57E-06	*	3.88E-05	***	4.13E-05	***
Percent White w/in 1/4-Mile of Home	2.9660	***	2.4570	***	-6.7930	***	-10.1820	***
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	-0.0065		-0.0060	***	-0.0060	*	-0.0030	*
Constant	-6.3750	***	-0.8420		-4.7490	***	-1.0550	***
Model Fit								
N							2896	
-2 Log likelihood							3965.00	
Nagelkerke R Square							0.772	

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 run suggests that the Improvement 3 model explains roughly 77% of the variation in the BART 2008 data set, compared with the Improvement 2 work model that explained 78% of the variation. This represents a slight reduction in overall model performance.

Person Variable Results

Comparing Improvement 3 to Improvement 2 work model race variable results, the transit, walk, bicycle, and drop-off modes were generally consistent. The only difference was an

insignificant finding for the bicycle mode choice in the Improvement 3 model in which the Improvement 2 model found that race was a significant factor determining willingness to choose to ride a bike to the BART station.

While the gender variable results of the two work models were also generally consistent, the Improvement 3 model found that gender was a significant determinant of transit mode choice, while the same variable was statistically insignificant in the Improvement 2 model.

The age variable results were substantially different in the Improvement 3 model from what was found previously. While the Improvement 2 work model found that persons 35-54 years old were less likely than those over 54 years to choose transit, the Improvement 3 model found the opposite, with 35-54 year-olds more likely to choose transit than those over 54 years. In addition, the Improvement 3 model found that 18-34 year-olds were also more likely to take transit than those older than 54.

Other differences between the two models for the age variable included: an insignificant finding for the age 18-34 category for the walk mode choice in the Improvement 3 compared with the significant and positive finding in the Improvement 2 model; significant and negative signs for the bicycle mode choice for both the 18-34 and 35-54 age categories in the Improvement 3 model compared with significant and positive findings for both in the Improvement 2 model; and a significant and positive finding for drop-off mode choice in the Improvement 3 model compared with a significant and negative finding in Improvement 2.

These divergent age variable findings may reflect the fact that the Improvement 3 model controls for urban form and crime factors along the travel route that may be critically important to commuters, depending on age, in choosing modes. Understanding these differences will require additional study beyond the scope of this report.

Household Variable Results

With one exception, household variable results for the Improvement 3 work model were consistent with those from Improvement 2's work model. The only change was for the household income variable for the drop-off mode, which was significant for the Improvement 2 model and insignificant for Improvement 3. Vehicle available findings were consistent between the two work models, both in terms of signs and significance.

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results were consistent—both in terms of signs and significance—between the Improvement 3 and Improvement 2 models.

Neighborhood and Corridor Variable Results

In general, the findings for the neighborhood and corridor-level in the Improvement 3 model were stronger in terms of statistical significance and more consistent with the researchers' theoretical expectations in terms of signs than the analogous neighborhood variables used in the Improvement 2 and previous models.

For example, the Home TAZ Population Density variable used in Improvement 2 was negatively related to walking mode choice and positively related to bicycling mode choice. In theory, density should be positively associated with both, and it should be positively and significantly related to transit mode choice as well. In the Improvement 3 model, however, the closest match to this variable—corridor population density—was statistically significant with positive signs for four modes, indicating that higher densities encourage people to choose alternative modes to driving alone to BART stations.

Similarly, the Home TAZ Mixed Use variable used in Improvement 2 was not statistically significant for any of the four mode categories compared with driving alone. However, the corridor mixed use variable used in the Improvement 3 model was statistically significant for all four modes, with positive signs. These strong and consistent results suggest that the more mixed uses in a travel corridor, the more likely a person will choose to walk, bike, ride transit, or take a ride to a BART station.

Comparing the Home TAZ #4-Legged Intersections/Acre variable used in the Improvement 2 model to the Corridor # 4-Legged Intersections/Acre variable used in Improvement 3, the Home TAZ variable was statistically significant for all four modes, with positive signs for transit and walking and negative signs for bicycling and drop-off. Meanwhile, the Improvement 3 model's corridor-level variable produced significant and positive signs for walking and bicycling, plus a significant, negative sign for drop-off. The Improvement 3 model did not produce a statistically significant result for transit.

Findings for comparable median income variables—Home TAZ median income for Improvement 2 and median income within one-quarter mile of home for Improvement 3—were consistent. Both models found that commuters were less likely to choose transit if their home neighborhood has high median-income levels, while they were more likely to walk, ride a bike, or take a ride if income levels were high.

Comparing home neighborhood race variable results from both models shows less consistency. While the Home TAZ Percent White variable was not statistically significant for the transit mode choice category in the Improvement 2 model, the comparable percent white within one-quarter mile of home variable in Improvement 3 was significant and positive. Findings for this variable in the walk mode choice category were contradictory, with significant and negative in the Improvement 2 model and significant and positive in Improvement 3. The only consistent finding between the two models for this variable was found in the bicycling category, both of which produced significant, negative signs. Finally, results for this variable were insignificant in the Improvement 2 model, and significant and negative in the Improvement 3 model.

Corridor Crime Rate Variable Results

Comparing the crime variable results from the Improvement 2 and 3 work models, both models found that the more violent crimes—either within one-quarter mile of the homes or of the travel routes of BART survey respondents—the more likely they were to drive alone instead of walking. However, while the Improvement 2 model did not produce any other statistically significant results for its crime variable, the Improvement 3 model also found

that this variable was significant and negative for the bicycle and drop-off mode choice categories. This suggests that people who must travel through high-crime neighborhoods on the way to their nearby BART station fear for their safety and avoid walking, bicycling, and finding a ride.

Non-Work Trips

Table 9 provides the Improvement 3 MNL regression results for the non-work model using the BART Station Profile data set with corridor-level variables.

Table 9. BART Station Profile 2008 Multinomial Logistic Regression Results for Non-Work Trip Mode Choice-Corridor-Level Variables

Variable	Transit	Walk	Bicycle	Drop-Off
Person Variables				
Race (1=White, 0=Non-White)	-0.7420 **	-0.2850	1.4780	-0.5150
Gender (1=Female, 2=Male)	0.3180	0.9530 ***	0.3180	0.4070
Age Categories				
1=18-34 Years	-0.2690	-0.7590 **	-1.8770 ***	-0.8140 *
2=35-54 Years	-0.0790	-0.2110	-1.2410 **	-0.2990
3=Over 54 Years	Referent	Referent	Referent	Referent
Household Variables				
Household Income (0=\$50k & under, 1=over \$50k)	-0.4390	-0.1360	-0.2790	0.0150
Vehicle Available (0=No, 1=Yes)	-3.5070 ***	-3.3520 ***	-3.5410 ***	-2.1960 ***
Trip Characteristics				
Total Trip Distance (Miles)	-0.1920 *	-3.3230 ***	-0.6250 ***	-0.1370
Neighborhood & Corridor Variables				
Corridor Population Density	0.0680 ***	0.0460 **	0.0410 *	-0.0009 *
Corridor Mixed Use (Jobs-Housing Balance)	3.3600 **	3.2020 **	3.5740 **	0.2820 **
Corridor # 4-Legged Intersections/Acre	0.0080 **	0.0060 **	0.0110 ***	0.0010 ***
Median Income w/in 1/4-Mile of Home	-2.38E-05 **	1.20E-05	4.11E-05 ***	3.95E-05
Percent White w/in 1/4-Mile of Home	1.9050	4.4550 ***	-6.2840 ***	-8.7210
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	0.0020	-0.0060 *	-0.0008	-0.0120
Constant	-5.9110 ***	-2.6320 **	-4.8790 ***	-0.0820 ***
Model Fit				
N				1065
-2 Log likelihood				1459.00
Nagelkerke R Square				0.750

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 non-work logistic model run suggests the Improvement 3 model explains roughly 75% of the variation in the BART 2008 data set, compared with the Improvement 2 work model that explained 78% of the variation. This represents a reduction in overall model performance of roughly 3%.

Person Variable Results

Comparing Improvement 3 with Improvement 2 non-work model race variable results, the only consistent finding was for the transit mode category, in which both models yielded a negative, significant sign. While the Improvement 2 model found a significant positive sign for bicycle mode choice and a significant negative sign for the drop-off category, the Improvement 3 model did not produce significant results in these categories.

Gender variable results for the two models showed a similar decline in statistically significant results for the Improvement 3 model, with the Improvement 2 model producing significant positive signs for the walk and bicycle mode choice categories, while the Improvement 3 model produced a significant, positive sign only for the walk mode choice category.

Similar to the work model described above, the age variable results were substantially different in the Improvement 3 model from what was found previously. While the Improvement 2 model found significant, positive results for the 18-34 and 35-54 categories, the Improvement 3 model produced a significant, negative sign for the 18-34 category only. Similarly, while the Improvement 2 model produced significant, positive results for the 18-34 and 35-54 categories, the Improvement 3 model produced statistically significant and negative signs for both categories. Finally, while the Improvement 2 model did not produce any significant findings for the drop-off category, the Improvement 3 model produced a significant, negative result for the 18-34 group.

As suggested above in the work model discussion, these divergent age variable findings may reflect the fact that the Improvement 3 model controls for urban form and crime factors along the travel route that may be critically important to commuters, depending on age.

Household Variable Results

Household Income variable results for the Improvement 3 model were insignificant across all mode choice categories, while the Improvement 2 non-work model was statistically significant and negative for the transit and walk categories, and significant and positive for the drop-off category. Vehicle available findings were consistent between the two non-work models, both in terms of signs and significance.

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results were generally consistent—both in terms of signs and significance—between the Improvement 3 and Improvement 2 models. However, while the Improvement 2 model did not produce a significant finding for

the transit category, the Improvement 3 model produced a significant, negative finding for this category.

Neighborhood and Corridor Variable Results

Just as seen in the results of the Improvement 3 work model, the findings for the neighborhood and corridor-level in the Improvement 3 non-work model were stronger in terms of statistical significance and more consistent with the researchers' theoretical expectations in terms of signs than the analogous neighborhood variables used in the Improvement 2 and previous non-work models.

For example, while the Improvement 2 Home TAZ Population Density variable did not yield any statistically significant findings, the analogous variable used in the Improvement 3 model (corridor population density) was statistically significant, with positive signs for all four modes. These findings are consistent with the theoretical expectation that higher densities encourage people to choose alternative modes to driving alone to BART stations.

Mixed use along the corridor of travel was also a more statistically powerful predictor of non-work mode choice in the Improvement 3 model than the Home TAZ Mixed Use variable used in Improvement 2. While Home TAZ Mixed Use was statistically significant with a positive sign only for the bicycle mode choice category, the corridor mixed use variable used in the Improvement 3 model was statistically significant for all four modes with positive signs.

Urban design in the corridor also plays an important role determining non-work mode choice, while urban design in the home neighborhood did not. In the Improvement 2 model, the Home TAZ # 4-Legged Intersections/Acre variable was only statistically significant for the bicycle mode choice category, with a negative sign suggesting the more pedestrian-oriented the urban design, the less likely a person would choose to bicycle. However, the Corridor # 4-Legged Intersections/Acre variable used in the Improvement 3 non-work model generated significant, positive signs for all four modes, indicating that pedestrian-oriented urban design encourages people to choose alternatives to driving alone.

Findings for comparable median income variables—Home TAZ Median income for Improvement 2 and Median Income within One-quarter Mile of Home for Improvement 3—were generally consistent but with a few differences. Both models found that non-work travelers were more likely to choose to ride a bike if their home neighborhood has high median-income levels. However, while the Improvement 2 model found a significant, positive sign for pedestrian mode choice, the Improvement 3 model did not. Furthermore, the Improvement 3 model found a significant, negative sign for transit mode choice, while the Improvement 2 model did not.

Comparison of the home neighborhood race variable results from Improvement 2 and Improvement 3 non-work models also reveals some inconsistencies. While the Home TAZ Percent White variable used in the Improvement 2 model produced a significant, negative sign (suggesting people living in white neighborhoods are less likely to take transit), the Improvement 3 model produced a significant, positive sign. However, the findings for the

bicycle mode choice category are consistent between these two models, suggesting that people who live in white neighborhoods are less likely to choose to ride a bike.

Corridor Crime Rate Variable Results

Comparing the crime variable results from the Improvement 2 and Improvement 3 non-work models yields generally consistent findings, although the crime variable was not as strong a predictor of mode choice in the Improvement 3 model as it was in the Improvement 2 model. Both models found that the more violent crimes—either within one-quarter mile of the homes or of the travel routes of BART survey respondents—the more likely people were to drive alone instead of walking. However, while the Improvement 3 model did not produce any other statistically significant results for its crime variable, the Improvement 2 model found that this variable was significant and negative for the bicycle mode choice categories.

IMPROVEMENT 4: AVERAGE PARCEL SIZE VARIABLE

The Average Parcel Size (APS) variable introduced in Improvement 4 was designed to address the possibility that the urban form variables used in previous models were insufficiently fine-grained (detailed) enough to capture the micro-scale urban design features that distinguishes a walkable from a non-walkable travel corridor or neighborhood. The research team developed work and non-work travel purpose mode choice models using the same model specifications used in Improvement 3 models but adding the APS variable.

Work Trips

Table 10 reports the results for the Improvement 4 (with the APS variable) work transit access trip mode choice logistic regression model.

Table 10. BART Station Profile 2008 Multinomial Logistic Regression Results for Work Trip Mode Choice-Average Parcel Size Variable

Variable	Transit		Walk		Bicycle		Drop-Off	
Person Variables								
Race (1=White, 0=Non-White)	0.0250		0.6760	***	1.6110	***	0.0210	
Gender (1=Female, 2=Male)	0.3870	**	0.5540	***	0.3870	**	-0.2560	
Age Categories								
1=18-34 Years	0.7960	***	-0.3260		-0.8870	***	-0.1730	
2=35-54 Years	0.6350	***	-0.1130		-0.0060	***	0.5530	**
3=Over 54 Years	Referent		Referent		Referent		Referent	
Household Variables								
Household Income (0=\$50k & under, 1=over \$50k)	-1.0470	***	-0.3460	*	-0.7290	***	0.1540	
Vehicle Available (0=No, 1=Yes)	-3.1610	***	-2.8310	***	-2.8070	***	-1.9430	***
Trip Characteristics								
Total Trip Distance (Miles)	-0.1870	**	-4.3050	***	-0.7390	***	-0.3060	***
Neighborhood & Corridor Variables								
Corridor Population Density	0.1120	***	0.0910	***	0.0890	***	0.0820	***

Variable	Transit		Walk		Bicycle		Drop-Off	
Corridor Mixed Use (Jobs-Housing Balance)	4.6700	***	1.7030	**	3.2420	***	1.7580	***
Corridor # 4-Legged Intersections/Acre	0.0030		0.0080	***	0.0120	***	-0.0020	***
Median Income w/in 1/4-Mile of Home	-3.85E-05	***	9.65E-06	**	3.99E-05	***	4.24E-05	***
Percent White w/in 1/4-Mile of Home	2.7830	***	2.1980	***	-7.0600	***	-10.4200	***
Corridor Average Parcel Size (APS)	-1.0580	***	-0.4030	***	-0.4150	***	-0.5000	***
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	0.0000		-0.0060	***	-0.0060	*	-0.0030	*
Constant	-5.5850	***	-0.2730		-4.2650	***	-0.6590	***
Model Fit								
N							2896	
-2 Log likelihood							3946.00	
Nagelkerke R Square							0.774	

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 both the Improvement 3 and Improvement 4 work logistic model runs suggest both models explain roughly 77% of the variation in the BART 2008 data set. From these results, it is fair to conclude that the addition of the APS variable did not appreciably change the explanatory power of the model.

Person Variable Results

Comparing Improvement 4 to Improvement 3 work model person-level variable results, the transit, walk, bicycle, and drop-off modes were almost identical. The only difference found was the significant, positive sign finding for the influence of race on bicycle mode choice in the Improvement 4 model, whereas this variable was insignificant in the Improvement 3 model for the bicycle mode choice category.

Household Variable Results

As seen in the person-level variable results, the household-level variable findings, in terms of signs and significance, were virtually identical for the Improvement 3 and Improvement 4 work models.

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results were consistent—both in terms of signs and significance—between the Improvement 3 and Improvement 4 models.

Neighborhood and Corridor Variable Results

Overall, the findings for Improvement 3 and Improvement 4 work model neighborhood- and corridor-level variables were virtually identical. Findings for the APS variable added to the Improvement 4 model were highly statistically significant with negative signs. These findings are consistent with the theoretical expectations that larger parcel sizes, typically associated with single-use, suburban urban design qualities, play an important role in influencing people to choose to drive alone as opposed to riding transit, walking, bicycling, or carpooling to their nearest BART station.

Corridor Crime Rate Variable Results

As seen with previously reported variables for the Improvement 4 model, the addition of the APS variable did not change the signs or significance of the violent crimes (P1V) within one-quarter mile of travel route variable.

Non-Work Trips

Table 11 reports the results for the Improvement 4 (with the APS variable) non-work transit access trip mode choice logistic regression model.

Table 11. BART Station Profile 2008 Multinomial Logistic Regression Results for Non-Work Trip Mode Choice-Average Parcel Size Variable

Variable	Transit	Walk	Bicycle	Drop-Off
Person Variables				
Race (1=White, 0=Non-White)	-0.7300 **	-0.2660	1.4750 ***	-0.5110
Gender (1=Female, 2=Male)	0.3070	0.9490 ***	0.3070	0.4110
Age Categories				
1=18-34 Years	-0.2530	-0.7640 **	-1.8760 ***	-0.8020 *
2=35-54 Years	-0.0840	-0.2280	-0.0100 ***	-0.2930
3=Over 54 Years	Referent	Referent	Referent	Referent
Household Variables				
Household Income (0=\$50k & under, 1=over \$50k)	-0.4620	-0.1360	-0.2780	0.0100
Vehicle Available (0=No, 1=Yes)	-3.5170 ***	-3.3460 ***	-3.5410 ***	-2.1960 ***
Trip Characteristics				
Total Trip Distance (Miles)	-0.2420 **	-3.3250 ***	-0.6010 ***	-0.1210
Neighborhood & Corridor Variables				
Corridor Population Density	0.0640 ***	0.0450 **	0.0430 **	0.0010 **
Corridor Mixed Use (Jobs-Housing Balance)	2.6050 *	2.9910 **	3.7410 **	0.5760 **
Corridor # 4-Legged Intersections/Acre	0.0080 **	0.0070 **	0.0110 ***	0.0000 ***
Median Income w/in 1/4-Mile of Home	-2.28E-05 **	1.25E-05	4.11E-05 ***	3.96E-05
Percent White w/in 1/4-Mile of Home	1.7160	4.3270 ***	-6.2630 ***	-8.7150
Corridor Average Parcel Size (APS)	-0.5850	-0.0950	0.0270	0.1640

Variable	Transit	Walk	Bicycle	Drop-Off
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	0.0020	-0.0050 *	-0.0006	-0.0120
Constant	-4.9820 ***	-2.4600 *	-5.1410 ***	-0.3080 ***
Model Fit				
N				1065
-2 Log likelihood				1454.00
Nagelkerke R Square				0.752

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 both the Improvement 3 and Improvement 4 non-work logistic model runs suggests the Improvement 3 model explains roughly 77% of the variation in the BART 2008 data set, while the Improvement 4 model explains roughly 78%. From these results, it is fair to conclude that the addition of the APS variable only slightly increased the explanatory power of the model.

Person Variable Results

Just as the research found comparing the Improvement 4 with Improvement 3 work model person-level variable results, the non-work model's transit, walk, bicycle, and drop-off modes were almost identical. Also similar to the work model, the only non-work model person-level variable difference was the significant, positive sign finding for the influence of race on bicycle mode choice in the Improvement 4 model, whereas this variable was insignificant in the Improvement 3 model for the bicycle mode choice category.

Household Variable Results

As seen in the person-level variable results, the household-level variable findings, in terms of signs and significance, were virtually identical for the Improvement 3 and Improvement 4 work models.

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results were consistent—both in terms of signs and significance—between the Improvement #3 and #4 non-work models.

Neighborhood and Corridor Variable Results

Overall, the findings for Improvement 3 and 4 non-work model neighborhood- and corridor-level variables were virtually identical. However, while the Improvement 4 work model findings for the APS variable were highly statistically significant with negative signs, the APS variable was not statistically significant for any of the non-work mode choice categories.

Corridor Crime Rate Variable Results

As seen with previously reported variables for the Improvement 4 work and non-work models, the addition of the APS variable did not change the signs or significance of the violent crimes (P1V) within one-quarter mile of travel route variable in the non-work model.

IMPROVEMENT 5: NESTED LOGIT MODELING

The robustness of the MNL models and the explanatory power of the Neighborhood Exposure Hypothesis were checked by estimating two nested logit models. The first nest, N1, groups the travel modes into two categories—open modes (walk and bike) and closed modes (bus, drop-off, and drive), reflecting those modes with more exposure to neighborhood crimes and those with more protection. The second nest, N2, groups mode choices into two categories as well—auto (drive and drop-off), or non-auto (bus, walk, bike), grouping non-auto and auto modes together. Two models—work trip and non-work trips models—are run for each nest for a total of four models—work N1 model (Table 12), work N2 model (Table 13), non-work N1 model (Table 14) and non-work N2 model (Table 15).

Work Trips

Table 12 reports the results for the Improvement 5 (nest N1—open/close) work transit access trip mode choice nested logistic regression model, and Table 13 reports the results for the work nest N2 (auto/non-auto).

Table 12. BART Station Profile 2008 Nested Logit Model Results for Work Trip Nest N1 (Closed/Open Mode Groups)

Variable	Transit		Walk		Bicycle		Drop-Off	
Person Variables								
Race (1=White, 0=Non-White)	0.0014		0.3897	***	1.1381	***	0.0407	
Gender (1=Female, 2=Male)	0.3861	*	0.3406	***	0.8228	***	-0.2800	
Age (0=18-34, 1=35+)	0.4461	***	-0.1200		-0.2206	**	-0.2158	*
Household Variables								
Household Income (0=\$50k & under, 1=over \$50k)	-1.2030	***	-0.1680		-0.4227	***	0.0074	
Vehicle Available (0=No, 1=Yes)	-3.3170	***	-1.4210	***	-1.3820	***	-2.0120	***
Trip Characteristics								
Total Trip Distance (Miles)	-0.2233	***	-3.2430	***	-0.1950	**	-0.3341	***
Neighborhood & Corridor Variables								
Corridor Population Density	0.1162	***	0.0485	***	0.0412	***	0.0794	***
Corridor Mixed Use (Jobs-Housing Balance)	5.1063	***	0.5000		1.7164	***	1.9977	**
Corridor # 4-Legged Intersections/Acre	0.0027		0.0052	***	0.0085	***	-0.0020	
Median Income w/in 1/4-Mile of Home	-4.07E-05	***	2.67E-06		2.70E-05	***	4.61E-05	***
Percent White w/in 1/4-Mile of Home	3.5981	***	2.6718	***	-4.9430	***	-10.9500	***
Corridor Average Parcel Size (APS)	-1.0120	***	-0.2599	***	-0.2984	**	-0.4738	**

Variable	Transit	Walk	Bicycle	Drop-Off
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	-0.0003	-0.0044 ***	-0.0030	-0.0040
Constant	-3.8530 ***	1.0270 *	-3.1810 ***	2.1363 ***
Model Fit				
N				2896
Log likelihood				-1971.61
McFadden Pseudo R-squared				0.561

Notes:

* = p < 0.10

** = p < 0.05

*** = p < 0.01

N/A = Not Applicable.

N/D = No Data.

Table 13. BART Station Profile 2008 Nested Logit Model Results for Work Trip Nest N2 (Auto/Non-Auto Mode Groups)

Variable	Transit	Walk	Bicycle	Drop-Off
Person Variables				
Race (1=White, 0=Non-White)	-0.0240	0.6190 ***	1.5394 ***	0.0591
Gender (1=Female, 2=Male)	0.3359 *	0.5233 ***	1.1091 ***	-0.2890
Age (0=18-34, 1=35+)	0.3921 ***	-0.1490	-0.2699 **	-0.1950
Household Variables				
Household Income (0=\$50k & under, 1=over \$50k)	-1.0300 ***	-0.3226 *	-0.6467 ***	0.0128
Vehicle Available (0=No, 1=Yes)	-2.7820 ***	-2.4600 ***	-2.4150 ***	-2.0850 ***
Trip Characteristics				
Total Trip Distance (Miles)	-0.1210	-4.1100 ***	-0.6077 ***	-0.3216 ***
Neighborhood & Corridor Variables				
Corridor Population Density	0.0977 ***	0.0788 ***	0.0757 ***	0.0821 ***
Corridor Mixed Use (Jobs-Housing Balance)	4.2666 ***	1.3939 *	2.8888 ***	1.9174 **
Corridor # 4-Legged Intersections/Acre	0.0026	0.0072 ***	0.0111 ***	-0.0020
Median Income w/in 1/4-Mile of Home	-4.00E-05 ***	6.00E-06	3.50E-05 ***	4.50E-05 ***
Percent White w/in 1/4-Mile of Home	3.3266 ***	2.7425 ***	-6.3050 ***	-10.9100 ***
Corridor Average Parcel Size (APS)	-1.0370 ***	-0.3584 ***	-0.3685 **	-0.4826 **
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	0.0002	-0.0059 ***	-0.0052 *	-0.0030
Constant	-3.4480 ***	1.3349 *	-3.6100 ***	2.0603 **
Model Fit				
N				2896
Log likelihood				-1983.99
McFadden Pseudo R-squared				0.586

Notes:

* = p < 0.10

** = p < 0.05

*** = p < 0.01

N/A = Not Applicable.

N/D = No Data.

Person Variable Results

Comparing Improvement 5 to Improvement 4 work model person-level variable results, the transit, walk, bicycle, and drop-off modes were nearly identical—so much so, that discussion of these small differences would yield no meaningful benefits here.

Household Variable Results

As seen in the person-level variable results, the household-level variable findings, in terms of signs and significance, were virtually identical for the Improvement 5 and Improvement 4 work models, except that income is statistically insignificant for the walk mode in Improvement 5.

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results were consistent, both in terms of signs and significance, between the Improvement 4 and Improvement 5 N1. However, for the Nest N2 model (Table 13), the variable is statistically insignificant for the transit mode, while it is significant for Improvement 4 (Table 10).

Neighborhood and Corridor Variable Results

Overall, the findings for Improvement 4 and Improvement 5 work model neighborhood- and corridor-level variables were virtually identical except that several of the variables that were statistically significant for the walk mode in Improvement 4 were insignificant in Improvement 5 models. They are: corridor mixed use (insignificant for the walk mode in Nest N1) and median income within one-quarter mile of home (insignificant for both Nests N1 and N2, while it was significant in the Improvement 4 work model).

Corridor Crime Variable Results

While the Improvement 4 work model found that crime reduces the propensity to walk, bicycle, and being dropped-off, the Improvement 5 Nest N1 found crime reduces only the propensity to walk, while the Nest N2 model did somewhat better, though still not as good as the Improvement 4 model, finding that crime reduces the propensity to walk and ride a bike.

Non-Work Trips

Table 14 reports the results for the Improvement 5 (Nest N1—open/close) non-work transit access trip mode choice nested logistic regression model, and Table 15 reports the results for the non-work Nest N2 (auto/non-auto).

Table 14. BART Station Profile 2008 Nested Logit Model Results for Non-Work Trip Nest N1 (Closed/Open Mode Groups)

Variable	Transit	Walk	Bicycle	Drop-Off
Person Variables				
Race (1=White, 0=Non-White)	-0.7716 **	0.2686	1.8453 ***	-0.5750
Gender (1=Female, 2=Male)	-0.0910	0.5921 ***	0.6433 **	0.1943
Age (0=18-34, 1=35+)	-0.3400	-0.1750	-0.5399 ***	-0.3250
Household Variables				
Household Income (0=\$50k & under, 1=over \$50k)	-0.7252 **	0.1521	0.0265	-0.2070
Vehicle Available (0=No, 1=Yes)	-3.8360 ***	0.3167	0.0215	-1.9780 ***
Trip Characteristics				
Total Trip Distance (Miles)	-0.3157 ***	-2.6470 ***	-0.1780	-0.1460
Neighborhood & Corridor Variables				
Corridor Population Density	0.0763 ***	-0.0050	-0.0110	-0.0040
Corridor Mixed Use (Jobs-Housing Balance)	3.3656 **	0.8043	1.4865	0.8002
Corridor # 4-Legged Intersections/Acre	0.0060	-0.0001	0.0040	-0.0020
Median Income w/in 1/4-Mile of Home	-2.00E-05 **	1.20E-05 *	3.70E-05 ***	3.20E-05 ***
Percent White w/in 1/4-Mile of Home	5.5926 ***	3.9441 ***	-5.6660 ***	-7.9960 ***
Corridor Average Parcel Size (APS)	-0.2720	0.0589	0.1251	0.5501
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	-0.0066 *	-0.0036 *	0.0014	-0.0194 *
Constant	-0.7910	-1.6190	-3.9100 ***	3.4041 *
Model Fit				
N				1065
Log likelihood				-721.26
McFadden Pseudo R-squared				0.556

Notes:

* = p < 0.10

** = p < 0.05

*** = p < 0.01

N/A = Not Applicable.

N/D = No Data.

Table 15. BART Station Profile 2008 Nested Logit Model Results for Non-Work Trip Mode Choice Nest N2 (Auto/Non-Auto Mode Groups)

Variable	Transit	Walk	Bicycle	Drop-Off
Person Variables				
Race (1=White, 0=Non-White)	-0.7886 ***	-0.2980	1.3188 ***	-0.3830
Gender (1=Female, 2=Male)	0.2712	0.8391 ***	0.9604 ***	0.4467
Age (0=18-34, 1=35+)	-0.1120	-0.3863 **	-0.7970 ***	-0.4213 **
Household Variables				
Household Income (0=\$50k & under, 1=over \$50k)	-0.3800	-0.1400	-0.1450	-0.1020
Vehicle Available (0=No, 1=Yes)	-3.0590 ***	-3.0100 ***	-3.1510 ***	-1.9480 ***
Trip Characteristics				
Total Trip Distance (Miles)	-0.1160	-3.0390 ***	-0.4010 **	-0.1010

Variable	Transit	Walk	Bicycle	Drop-Off
Neighborhood & Corridor Variables				
Corridor Population Density	0.0511 ***	0.0346 *	0.0298	0.0030
Corridor Mixed Use (Jobs-Housing Balance)	1.6997	1.9031	2.7043 *	0.0642
Corridor # 4-Legged Intersections/Acre	0.0063 *	0.0050 *	0.0093 ***	-0.0001
Median Income w/in 1/4-Mile of Home	-1.00E-05	1.80E-05	4.60E-05 ***	3.90E-05 ***
Percent White w/in 1/4-Mile of Home	0.0496	2.6408	-7.7000 ***	-7.8350 ***
Corridor Average Parcel Size (APS)	-0.6841 **	-0.1790	-0.0500	0.0265
Violent Crimes (P1V) w/in 1/4-Mile of Travel Route	0.0018	-0.0053 **	-0.0006	-0.0040
Constant	0.5872	1.6109	-1.0950	2.3438
Model Fit				
N				1065
Log likelihood				-726.05
McFadden Pseudo R-squared				0.599

Notes:

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

N/A = Not Applicable.

N/D = No Data.

Person Variable Results

Comparing Improvement 5 to Improvement 4 work model person-level variable results, the transit, walk, bicycle, and drop-off modes were almost identical, except that gender is statistically significant for the bicycle mode in Improvement 5 Nest N1, while it is statistically insignificant in Improvement 4 and Improvement 5 Nest N2.

Household Variable Results

As seen in the person-level variable results, the household-level variable findings, in terms of signs and significance, were virtually identical for the Improvement 5 and Improvement 4 models, except that household income variable is statistically significant in Improvement 5 Nest N1 (Table 14).

Trip Characteristics Variable Results

The trip characteristic variable (total trip distance) results were largely consistent, both in terms of signs and significance, between the Improvement 4 and Improvement 5 models, except for two differences—the variable is statistically insignificant for the bicycle mode in Nest 1 (Table 14), and it is statistically insignificant for transit mode in Nest 2 (Table 15).

Neighborhood and Corridor Variable Results

Overall, the findings for Improvement 4 and Improvement 5 model neighborhood- and corridor-level variables vary considerably. For example, while several corridor-level variables

are statistically significant in Improvement 4, they are insignificant in Improvement 5 nest N1. These variables include corridor population density, corridor mixed-use, and corridor # 4-legged intersections/acre. Further, a few variables that were statistically insignificant in Improvement 4 are significant in Improvement 5 N1. They include: median income and percent white (Table 14).

Corridor Crime Variable Results

Improvement 4 and Improvement 5 N2 non-work models find that crime reduces the propensity to walk compared with driving at $p=0.10$ level. (In Improvement 5, the variable is statistically significant at $p=0.01$ level, while for Improvement 4, the variable is significant only at $p=0.10$ level.) However, the Nest N1 model finds that, apart from walking, crime also reduces the propensity to take transit and being dropped-off compared with driving.

V. SUMMARY AND CONCLUSIONS

This study (Phase 3) found additional substantiation for the proposition that neighborhood crime rates influence the propensity to choose nonmotorized modes of transportation for home-based trips. The two previous phases found statistically significant findings consistent with the researchers' expectations—that more neighborhood crimes are associated with a higher likelihood of driving. But there were also contradictory findings that were inconsistent with the research team's expectations, with high-crime neighborhoods associated with increased likelihood of non-auto mode choice. The methods developed and tested in Phase 3 were designed to help identify the reasons for these counterintuitive and contradictory findings from the previous two phases. Phase 3 developed a series of five improvements to the previous two phases. These improvements were:

- Improvement 1: Replacing the BATS 2000 travel data set used in Phases 1 and 2 with the 2008 BART Station Profile Survey.
- Improvement 2: Separating drive-alone from drop-off mode choices into their own mode choice categories, consistent with current modeling practices.
- Improvement 3: Replacing urban form and socio-demographic metrics measured at the TAZ level of aggregation with travel corridor- or neighborhood-level metrics.
- Improvement 4: Adding a new, fine-grained measure of urban design variable: average parcel size of the survey respondents' travel corridors.
- Improvement 5: Running nested logit models, consistent with current mode choice modeling practices.

The Phase 3 research project investigated the following possible explanations for the inconsistent and counterintuitive Phase 1 and Phase 2 results:

IMPROVEMENT 1: NEW TRAVEL DATA

Comparisons of the Phase 2 model using BATS 2000 travel survey data with the Phase 3 model results using the BART 2008 travel data found that overall, the BART data yielded a more interpretable, consistent, and theoretically sound set of findings. For instance, the Phase 2 models found that while neighborhood crimes were positively correlated with choosing transit instead of driving, they were negatively correlated with the likelihood of walking instead of driving. However, the Phase 3 models using the BART data found that high-crime neighborhoods encourage driving and discourage transit and walking—a finding consistent with the research team's theoretical expectations.

Improvement 2: Separating Drive-Alone and Drop-Off Mode Choice Categories

Separating drive-alone from drop-off mode choice categories produced mixed results. While violent crimes correlated with a lower propensity to choose transit for work trips in

the Improvement 1 model (consistent with the team's expectations), it was not statistically significant in the Improvement 2 work model. In contrast, the Improvement 1 non-work model did not produce a statistically significant result for transit mode choice, while crimes were statistically significant, with a negative sign, for transit mode choice in the Improvement 2 non-work model. These mixed results do not lend themselves to conclusive interpretation, but the fact that the Improvement 2 changes are consistent with accepted mode choice modeling practice led the team to conclude that the improvement produces a more theoretically valid set of results.

Improvement 3: Corridor- and Neighborhood-Level Variables

The third improvement used a new set of variables designed to capture the urban form and socio-demographic conditions of the entire travel corridor (for urban form) and the neighborhood of the trip origins (for socio-demographic characteristics) for each survey respondent, as opposed to merely the TAZ of trip origins as was used in previous models.

In general, findings for these corridor- and neighborhood-level variables were stronger in terms of statistical significance and more consistent with the researchers' theoretical expectations in terms of signs than the analogous neighborhood variables used in the Improvement 2 and previous models. However, the findings for the corridor-level crime variable were mixed.

Replacing the TAZ-level variables used in previous improvement models with corresponding corridor- and neighborhood-level variables generally produced consistent findings. The corridor-level crime variable was a better predictor of mode choice compared with the neighborhood-level measure used in Improvement 2 work trip model, with the corridor-level crime variable a statistically significant predictor of bicycle and drop-off mode choice. But it was not as strong a predictor of non-work trip mode choice in the Improvement 3 models, with the neighborhood-level crime variable a statistically significant predictor of bicycle mode choice, while the corridor-level crime variable was insignificant for bikes.

Improvement 4: Average Parcel Size Variable

To see if the inconsistent findings for neighborhood crimes in previous research projects (Phases 1 and 2) were due to inadequate measures of urban form, Improvement 4 models used a new measure of urban design: APS. This new variable worked very well in the work model, with highly statistically significant findings for all modes, but it did not produce any statistically significant results in the non-work model.

Examining how the APS variable affected the corridor-level crime variable's performance, the addition of the APS variable did not change the signs or significance of the violent crimes (P1V) within one-quarter mile of travel route variable in either the work or non-work models.

Improvement 5: Nested Logit Modeling

Overall, there were no measurable benefits to running the mode choice models with nested logit techniques. The N2 models, which grouped modes into auto and non-auto

modes, produced findings for the crime variable roughly equivalent to those found in the Improvement 4 models. However, the N1 models, designed to test the Neighborhood Exposure Hypothesis identified in Phase 2 by grouping modes into “open” and “closed” groups, produced fewer statistically significant results than comparable Improvement 4 models. Taken together, these results suggest that the inconsistent findings for crime variables in models run in Phases 1 and 2 were not due to either the lack of nested logit techniques used in those phases or the Neighborhood Exposure Hypothesis.

INTERPRETING PHASE 3 RESULTS AND SUGGESTED FUTURE RESEARCH

The Phase 2 report identified four possible reasons for the confusing results found in Phases 1 and 2—specifically, that high levels of neighborhood crimes were associated with a higher likelihood of people choosing transit and a lower likelihood they will choose to walk or ride a bicycle. These four possible explanations and the research team’s interpretation of the modeling results from each of the five improvements designed to test them are provided below.

First, it could be that the BATS 2000 travel data set was not suitable for travel behavior analysis at this small geographical scale—the neighborhood-level, as opposed to the city and regional levels for which it was designed. The sample size at the neighborhood level may simply be too small. Improvement 1 compared the final models used in Phase 2, using BATS 2000 data, with a best-matching model specification using BART 2008 data. These comparisons found that the models using BART 2008 data effectively eliminated the confusing results from Phase 2. The research team concluded from these findings that either the BATS 2000 data was inadequate for this modeling task or, due to the narrowed scope of trips measured with the BART 2008 data, transit access trips are fundamentally different from other trips in terms of the effects of neighborhood crimes on mode choice.

Second, it could be that the so-called Neighborhood Exposure Hypothesis—in which people seek the relative safety of an enclosed transit vehicle where they feel less exposed to neighborhood crimes—explains why people would choose to ride transit where they feel safer in the presence of other transit riders and a vehicle operator. Model results from Improvement 1—in which crimes were found to have either an insignificant or significant and negative influence on transit mode choice—and Improvement 5—in which the N1 models that grouped modes into unexposed (closed) and exposed (open) modes were found to have lower goodness-of-fit statistics and fewer statistically significant crime variables than those run in Improvement 4 or the N1 (auto versus non-auto mode groupings). These results suggest that the Neighborhood Exposure Hypothesis does not explain the confusing results found in the models run in Phases 1 and 2.

Third, urban form and crimes may be interwoven as causal determinants of mode choice, and therefore, improved urban form and crime variables might help distinguish the effects of one from another. In doing so, they may produce a more interpretable set of model results. Results from Improvement 3—in which corridor-level urban form and crime variables replaced TAZ-level variables used in previous models—and Improvement 4—in which the APS variable was introduced to better-represent urban design—both found modest gains in statistical significance for select urban form variables. But they did not significantly affect the signs or significance of the crime variables.

Finally, the modeling methods used in Phase 2 may have been inadequate for accurately representing the effect of neighborhood crimes on mode choice. The methods may have been inadequate in two respects. First, the categorization and specification of modes used in Phase 2 models may have been inadequate. Improvement 3 addressed this issue by separating drive-alone from drop-off modes. This improvement did not substantially affect the signs or significance of the crime variables. Second, multinomial logit models used in Phase 2 may have been inadequate for accurately representing mode choice decisions. Phase 3 (Improvement 5) employed nested logit modeling techniques, standard practice in travel demand modeling. This was done partly in the hope that this may generate more interpretable results than those found in Phases 1 and 2. Overall, the nested logit models did not provide substantial improvements to overall model goodness-of-fit or the signs or significance of individual crime variable results. These findings suggest it is unlikely that the modeling methods used in previous phases were the cause of the confusing crime variable results.

Although all improvement models yielded stronger, more consistent, and interpretable results than the models developed in Phases 1 and 2, Improvement 1 (exchanging BATS 2000 for BART 2008 data) produced the biggest gains. The Improvement 1 models were also consistent with the findings of the Phase 2 preliminary models of transit access trip mode choice, which found that people in high-crime neighborhoods were more likely to drive than walk or ride a bike to transit. This suggests that the Neighborhood Exposure Hypothesis, which anticipated explaining the rather confusing findings in those models that higher-crime neighborhoods encourage people to choose transit, may not be the primary—or even a contributing—factor explaining the confusing results found in Phases 1 and 2.

However, at this juncture it is impossible to say for sure whether the more interpretable, consistent and theoretically sound findings produced in Improvement 1's model results are due to some inherent quality of that data set, such as a higher sample density, or if these gains are attributable to narrowing the scope to transit access trips—using the BART 2008 data—as was done with the BATS data in the aforementioned preliminary Phase 2 results. Answering this question is one possible topic for follow-on research. Employing a data set that has representative sampling at the neighborhood scale, as in the BART 2008 data set, and surveys all modes of travel, as in the BATS 2000 data set, would help answer this question.

Implications for Practice

The third phase of this research has successfully confirmed the team's hypothesis that high levels of neighborhood- and corridor-level crimes discourage transit use, walking, and bicycling while encouraging driving. While automobiles confer many benefits to people across economic strata, planners also need to examine the societal ills (e.g., auto emissions, suburban sprawl, obesity rates, etc.) that come with auto dependency. In doing so, planners and policy-makers can consider a range of interventions—from land use changes, to gas taxes to neighborhood policing—that can encourage non-auto mode choice. 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. While crime

prevention and suppression techniques are important in-and-of-themselves for providing social stability, improved crime intervention strategies that can reduce the safety concerns of residents living in high-crime neighborhoods. This can 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.

These findings are particularly important for encouraging non-auto access modes for transit riders. Transit agencies should consider working in close collaboration with police departments in the jurisdictions surrounding their transit stations and stops in order to reduce crimes, increase non-auto access to their transit systems, and potentially, increase transit ridership overall.

Finally, transit agencies, local governments, and emergency service providers should consider working collaboratively to integrate crime prevention through environmental design (CPTED) methods into local planning and building codes, and in particular, into transit-oriented development (TOD) plans and policies. This will help maximize the beneficial effects of TOD over the long term because it will help create safe, transit- and pedestrian-oriented communities around transit stations.

Beyond Phase 3 improvements: New Research Directions

Based on the findings and analysis of Phase 3 of this research, we have a number of recommendations for further research.

First, it is highly desirable to have further confirmation that fine-grained, neighborhood-level travel survey data, such as provided by the BART 2008 data set, produces results consistent with the theory that high-crime neighborhoods encourage automobile use. With this confirmation, recommendations and guidelines could be made for planning professionals on the proper development, use, and interpretation of neighborhood- and corridor-level crime variables for use in travel demand modeling practice. Analysis of the potential influences of fine-grained socio-demographic neighborhood characteristics—such as the possible correlations between clusters of low income, low auto ownership households, crime, and transit use—would also be possible with these data.

Second, the effects of police resource deployments and the methods used for crime prevention at the neighborhood scale could be introduced to the models developed in Phase 3 to determine the return on investment of police services on both crimes and travel mode choice. This may require the construction of time-series models that will capture the effects of changes in police resource deployments on crimes and travel behavior.

APPENDIX A: CRIME CATEGORIES

Table 16. 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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85. Because these data cover only the nine-county San Francisco Bay Area, employment locations outside the Bay Area but adjacent to it are necessarily missing from this analysis. Consequently, calculated accessibility values for some households located near the outer edges of the Bay Area may be lower than in reality. However, there are very few locations near the edges of the Bay Area where significant employment opportunities lie within a reasonable traveling distance and, consequently, it was determined that, on the whole, the calculated accessibility values for the region are reasonably accurate for the purposes of this study.
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