

Representing the Underrepresented in Travel Demand Modeling Tools

Tierra Bills

tsbills@ucla.edu

University of California, Los Angeles <https://orcid.org/0000-0002-2899-8031>

Research Article

Keywords: Travel Demand Modeling, data representativeness, transportation equity

Posted Date: October 14th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11356811/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Representing the Underrepresented in Travel Demand Modeling Tools

Tierra Bills, ORCID NUMBER: 0000-0002-2899-8031

Abstract

Transportation equity remains an important concern in both research and practice yet available approaches for regional equity analysis fail to meet important technical needs. Most transportation equity analysis methods, whether applied in academic studies or public practice applications, rely on spatial, demographic analyses and proximity-based evaluations of transportation-related outcomes, which can mischaracterize complex travel behavior and associated equity impacts. The use of travel demand models is a growing practice among transportation equity analysts, as it offers a powerful platform for projecting the likely behavior responses of travelers and households to transportation scenarios and enables fine-grained distributional assessments of transportation-related outcomes.

This study addresses an ongoing challenge with the application of travel demand models for transportation equity analysis. These models are estimated using household travel surveys, which often underrepresent vulnerable populations that are the focus of transportation equity analyses. As travel demand models are a system of interconnected, data-driven econometric models, the development of such models using data that poorly reflect vulnerable travelers may lead to systematic distortions in modeled outcomes. Beyond the potential ramifications for broader travel demand modeling practices and transportation planning assessments, these distortions are likely to move counter to the goals of transportation equity analyses and mischaracterize the distribution of transportation-related outcomes.

This study aims to test the hypothesis that travel demand models, estimated on standard household travel surveys, can misrepresent the mode choices and related travel preferences of travelers that are poorly represented in the survey data. Towards this aim, a small, targeted travel survey is used to capture the travel behaviors and needs of vulnerable travelers in Benton Harbor, Michigan, including low-income, carless, and lower-education travelers. Compared to a standard household travel survey for the same region, the targeted survey is used to reflect the travel behaviors of those most likely to be underrepresented in the standard survey. The targeted and standard surveys are combined using a core-satellite data fusion framework to enhance the demographic and behavioral representativeness and a series of mode choice models are estimated: one using only the targeted (satellite) survey data, one using only the standard (core) survey data, and one jointly estimated using both surveys. The results reveal significant differences in mode preferences, value of time, and nesting structures across the models, highlighting the distinct travel behaviors of vulnerable populations. Elasticity analyses further demonstrate that models based solely on conventional surveys may understate travelers' sensitivity to travel time and cost, to varying degrees across modes.

These findings underscore the importance of targeted data collection and data fusion for enriching larger scale travel surveys and improving subgroup representativeness in widely used travel demand models. Recognizing distinct behaviors and travel preferences of vulnerable groups can enhance the reliability of equity assessments, support more informed transportation planning, and potentially reduce the risk of misallocating regional transportation investments.

1. Introduction

Transportation equity has become a central concern in both research and practice, yet approaches for regional transportation equity analysis vary widely. While no single method fits all contexts, most approaches in both academic and practice-based literature remain dominated by spatially aggregated evaluations, in which traveler groups and transportation outcomes are summarized for geographic units such as census tracts or traffic analysis zones (TAZs) (Karner & Niemeier, 2013; NASEM, 2024). Even analyses that define population groups by socioeconomic characteristics, such as income or race, commonly identify those groups and measure their outcomes at the zonal level. These spatial methods, however, face significant challenges in assessing fairness across communities. Because they rely on aggregate geographic definitions of travelers and broad measures of transportation costs and benefits, spatial comparison techniques risk introducing biases, distorting community-level impacts, and ultimately undermining the usefulness of equity analyses.

To overcome these limitations, some regional transportation agencies rely on regional travel demand models to evaluate the equity implications of transportation plans. This modeling approach projects the expected transportation and land use changes resulting from a project or plan and then examines the distribution of outcomes across the population. A central advantage of travel demand models is that they capture the trade-offs travelers and households are likely to make in response to transportation scenarios, thereby providing a more behaviorally grounded assessment of distributional outcomes (Bills & Walker, 2017; Nahmias-Biran & Shiftan, 2020; Bills, 2024; Cabello et al., 2025).

However, like any data-driven modeling tool, the reliability of these models is limited by the quality of their underlying data. Household travel surveys, the primary input for travel demand models, consistently underrepresent vulnerable travelers (Wang et al., 2022; Lubitow et al., 2021). Errors stemming from noncoverage, nonresponse, and other sources of survey bias disproportionately affect low-income and other vulnerable groups, which may lead to systematic distortions in model outputs. As a result, models estimated from underrepresentative data may mischaracterize transportation needs and outcomes, reducing their effectiveness in advancing equity.

Recent research has highlighted strategies for improving subgroup representation in household travel surveys. One promising framework is the core–satellite paradigm, in which a representative core survey is complemented by targeted satellite surveys designed to capture the behaviors of underrepresented subpopulations (Goulias et al., 2013; Li et al., 2025). Core surveys provide broad, stable data collection, while satellite surveys offer more detailed or subgroup-specific insights. Yet, few applications of this approach have addressed connections to underrepresentation of vulnerable subgroups in the travel demand models used for equity analysis.

In this study, we demonstrate how a targeted satellite survey can be fused with a regional household travel survey to improve the representation of vulnerable travelers in travel demand models. Multi-sample (joint) estimation with scale parameters is an established technique in discrete choice modeling, most commonly used to combine revealed and stated preference data. Our contribution lies in applying this technique to the representativeness of vulnerable subgroups, an issue that is central to transportation equity analysis but rarely addressed in model estimation. Using a targeted Travel Needs Survey of residents of Benton Harbor, Michigan (2017–2019) and the Benton Harbor sample of the Michigan Department of Transportation's 2015 MI Travel Counts household travel survey, we estimate mode choice models from each

dataset and jointly from both datasets, and compare their values of time, behavioral heterogeneity and elasticities. We show that a conventional household travel survey can fail to identify key behaviors of low-income travelers, most notably their sensitivity to travel cost, even when low-income households are present in the sample, and that combining it with targeted data recovers these behaviors. In this way, this study differs from previous work on household travel survey bias, which has focused on survey coverage and weighting, by examining the consequences of underrepresentation for the behavioral parameters that drive model-based equity analyses.

The remainder of this chapter is organized as follows. Section 2 reviews the literature on transportation equity analysis, the use of travel demand models and household travel surveys for equity analysis, approaches for capturing population heterogeneity, and the use of multiple data sources in model estimation. Section 3 describes the study setting, the two surveys and the modeling methods. Section 4 presents descriptive statistics and model results, including a comparison of model elasticities, and Section 5 discusses the implications for representativeness, equity analysis and planning practice, along with the limitations of the study.

2. Background

This section reviews the literature that motivates our approach. Section 2.1 defines transportation equity analysis and explains why it has become central to transportation planning. Section 2.2 reviews quantitative methods for equity analysis, and Section 2.3 describes the major types of travel demand models and their growing use for equity analysis. Section 2.4 examines how household travel surveys, the primary data source for these models, can underrepresent vulnerable travelers. Section 2.5 reviews approaches for capturing population heterogeneity in discrete choice models, and Section 2.6 reviews the use of multiple data sources in model estimation, which forms the basis of our approach.

2.1. What is Transportation Equity Analysis?

Transportation equity analysis serves as a critical framework and process for informing transportation planning and policy decisions that promote equitable access to opportunities and improve quality of life across communities. Transportation equity analysis (also referred to as Environmental Justice Assessment (Duthie et al., 2007)) is a systematic process for assessing the fairness of impacts resulting from transportation investments and determining whether these impacts are distributed equitably across traveler groups and communities. The analysis generally seeks to determine who benefits, who bears burdens, and whether transportation outcomes are distributed in a manner consistent with defined equity goals and community needs. Definitions for determining fairness vary considerably. While we do not offer a comprehensive treatment of definitions of transportation equity in this chapter, readers are referred to Di Ciommo and Shiftan (2017), Pereira et al. (2017) or Lucas et al. (2019) for a full discussion. Notably, what is considered fair differs by perspective: the literature offers varying definitions of what constitutes a fair distribution of transportation benefits and burdens (van Wee & Mouter, 2021), while in practice, the task of transportation agencies is generally framed around identifying and mitigating disproportionate harms to vulnerable populations, rather than resolving individual notions of fairness (Executive Order 12898, 1994; Karner & Niemeier, 2013).

While the practice of equity analysis is not exclusive to the transportation domain, transportation planning and engineering fields have seen ongoing advancements in the technical methods for assessing the equity outcomes. This is (in part) driven by two primary factors:

First, equity analysis has been legally mandated for federally funded transportation plans and programs across the United States, since Executive Order 12898 of 1994 (Executive Order 12898, 1994). It directed federal agencies and recipients of federal funding—including Metropolitan Planning Organizations (MPOs)—to assess the impacts of policies, programs, and activities on Environmental Justice (EJ) populations, including low-income, historically underserved, and other vulnerable groups. These requirements were reinforced by Executive Order 13985, issued in 2021, which directed federal agencies to identify methods for evaluating equity and to assess whether underserved communities face systemic barriers to accessing public benefits and opportunities. The order further called for agencies to address historic patterns of underinvestment and unequal access to resources and services (Executive Order 13985, 2021). Even though these executive orders were rescinded in 2025 by Executive Orders 14148 and 14173 (Executive Order 14148, 2025; Executive Order 14173, 2025), equity remains an important transportation planning and policy focus for many transportation agencies in the US and across the world (e.g., NASEM, 2025; MTC & ABAG, 2026; MVRPC, 2026).

Second, assessing fairness in transportation outcomes is inherently complex because transportation experiences and responses are shaped by numerous heterogeneous and interconnected real-world processes. These include: (a) the interactions between transportation infrastructure and land use, which jointly influence accessibility, development patterns, and economic opportunities; (b) heterogeneous individual level travel behavior and population characteristics, including differences in preferences, constraints, resources, and decision-making processes across individuals, households, and groups; and (c) the operational and performance effects of transportation systems and policies, which influence and are influenced by traveler behavior. Together, these dynamics contribute to significant heterogeneity in transportation outcomes across communities and make the measurement and evaluation of transportation equity an ongoing challenge for practitioners (Chen & Li, 2021).

2.2. Quantitative Methods for Transportation Equity Analysis

Transportation equity analysis methods range based on various aspects, including the scope of the analysis, the types of projects and/or policies being evaluated, benefits and burdens (outcome) of focus, and the available data and measures for capturing outcomes. It is important to distinguish these methods, based on two core analysis scopes, I) analyses of existing transportation conditions, or II) analysis of future transportation impacts. The first scope reflects equity analysis approaches that focus on analyzing the distribution of transportation outcomes due to existing transportation infrastructure or policies (NASEM, 2004; NASEM, 2025). The core distinguishing factor here is that analyses under this scope emphasize present equity-related conditions that do not capture travel behavior dynamics associated with the transportation system/policy changes, nor fully capture changes in demand-sensitive network and operational impacts. For example, consider the case of constructing a new high occupancy toll lane. The equity outcomes of pricing changes cannot be fully assessed based on the distribution of tolls/prices across traveler groups alone. This is because the incidence of price effects (the prices paid, conditioned on travelers' behavioral responses) across groups will be governed by changes in travel behavior (e.g. some travelers will adapt to price increases by changing their travel mode, time-of-day, or route choices when faced with a price increase). Further, the degree of behavioral changes (or substitution effects) will be heterogeneous across groups, based on their circumstances, needs, and preferences. Lower income travelers, for instance, can be expected to be more elastic to price increases, relative to higher-income travelers (Mishra et al., 2014).

Therefore, analyses seeking to assess the equity impacts of future transportation projects would require either comprehensive case-study comparisons to capture expected behavioral responses across groups, or the use of a forecasting tool, such as a travel demand model.

Analysis of Existing Transportation Conditions: Equity analyses of existing transportation conditions have historically relied on place-based and spatial evaluation methods. These approaches typically aggregate traveler characteristics, residential locations, and travel destinations to geographic units such as census tracts, traffic analysis zones (TAZs), or spatial buffers surrounding transportation infrastructure and services (USDOT, 2000; NASEM, 2004; Klein, 2007). Using geographic information systems (GIS), analysts identify populations located within defined areas of influence and compare transportation benefits and burdens across communities. For example, many transportation equity (or environmental justice) analyses use buffers around transit routes, stations, highways, or transportation corridors to identify populations served by transit investments, benefiting from transportation improvements, or experiencing environmental impacts associated with transportation facilities (USDOT, 2000; NASEM, 2004).

Although these spatial approaches remain widely used in both research and practice, they have several well-documented limitations. Aggregating individual residential and travel locations to larger geographic units can introduce spatial aggregation bias and obscure important variations in transportation experiences among individuals (Duthie et al., 2007). Further, averaging outcomes across residents within the same geographic area assumes that all of these individuals experience transportation benefits and burdens similarly, potentially masking substantial differences among individuals living within the same community (Bills et al., 2012; Bills & Walker, 2017). As a result, place-based impact assessments (when applied alone) may overlook inequities experienced by specific traveler groups and may not fully capture the distribution of transportation outcomes across communities.

Analysis of Future Transportation Changes: Equity analysis of future transportation changes has also been performed using GIS-based demographic analysis methods, as well as travel demand models to simulate travel behavior changes. In the case of GIS-based analyses, communities are identified and mapped to examine their spatial relationship to transportation infrastructure, services, investments, and environmental burdens (Mills & Neuhauser, 2000; USDOT, 2000). Many metropolitan planning organizations and transit agencies have frequently employed GIS tools to designate "communities of concern" or "environmental justice groups" and assess whether transportation resources and outcomes would be distributed equitably across geographic areas (MTC, 2013; Williams & Golub, 2017; MTC & ABAG, 2026). Yet, in response to calls to account for the travel behavior impacts of transportation plans, many agencies have begun to implement transportation equity analysis using travel demand models, as we discuss further in Section 2.3.

It is important to note that while best practices seem to reinforce the significance of aligning equity analysis methods based on the scope of analysis (Lucas et al., 2019), the example applications found in the literature suggest that these methods need not be exclusive to these categories. For example, many prior studies have employed GIS-based approaches for estimating future equity impacts of transportation projects (USDOT, 2000), and forecasting tools like travel demand models can be applied to assess equity impacts of existing transportation infrastructure. Nevertheless, the use of GIS-based approaches, in absence of some form of estimation technique that captures heterogeneous behavioral responses to transportation changes, will likely

misrepresent the expected transportation impacts to some degree and the associated equity-related outcomes.

Technical Steps of Equity Analysis Processes: The technical steps for transportation equity analyses range considerably, and many examples of transportation equity analysis exist in the literature (for a more comprehensive review, see NASEM, 2025). However, whether the focus is on examining existing conditions or future changes, the technical process of transportation equity analysis can be summarized into some general steps, including:

1. Define target and comparison population subgroups
2. Identify and calculate measures of the transportation benefits and burdens for each subgroup. When examining future changes, transportation scenarios are developed to reflect the transportation project and/or policy changes of interest, and the associated level-of-service and environmental outcomes are forecast, conditioned on heterogeneous travel behavior responses.
3. Compare measured results across subgroups (and across scenarios, if applicable).

An additional and important step is to judge the fairness of the outcomes for subgroups to determine whether the distribution of benefits and burdens is equitable, yet this step is rarely taken (Lucas et al., 2019; Bills, 2024; Karner et al., 2023).

2.3. Use of Travel Demand Models for Transportation Equity Analysis

The use of travel demand models for transportation equity analysis has become an increasingly common practice among transportation and planning agencies across the United States. This trend reflects a growing recognition that traditional GIS-based demographic analyses, which often assume that communities' proximity to transportation infrastructure or services can adequately represent expected transportation impacts, are insufficient for capturing the complexity of travel behavior and equity outcomes. To address these limitations and reduce the potential for mischaracterizing equity-related impacts, many agencies have adopted travel demand models to support equity assessments. These applications range from traditional four-step trip-based models to activity-based travel demand models and integrated transportation–land use models. Such models are used to forecast transportation outcomes under alternative planning scenarios and to evaluate how the resulting benefits and burdens are distributed across different population groups.

These model frameworks differ in how they represent travelers and outcomes. Four-step (trip-based) models, the long-standing standard in regional planning, forecast travel in four sequential steps: trip generation (how many trips are made), trip distribution (where trips go), mode choice (how trips are made) and route assignment (which network paths are used), with travelers and outcomes represented as aggregate flows between traffic analysis zones (McNally, 2007; Beimborn, 2006). Activity-based models instead simulate the full-day activity and travel schedules of each person and household in a synthetic population, so that travel is derived from the need to participate in activities and outcomes can be tracked for each simulated person (Bowman & Ben-Akiva, 2001; Castiglione et al., 2015). Integrated transportation–land use models further link travel models with models of household and firm location and real estate development, capturing how transportation investments reshape where people live and work over time (Waddell, 2002). For equity analysis, these frameworks differ mainly in how finely they can distinguish population groups and in which transportation and location-based outcomes they can forecast.

Numerous applications of travel demand models for transportation equity (or environmental justice) analysis have been documented in the literature. These include applications of four-step travel demand models (MTC, 2001; Bills et al., 2022), activity-based travel demand models (Deakin & Harvey, 1996; Castiglione et al., 2006; Sall et al., 2010; Bills, 2024), and integrated transportation–land use and macroeconomic models (Johnston et al., 2001; Rodier et al., 2009; Rezaei et al., 2024). Recent regional transportation plans continue to document such analyses as part of their equity and environmental justice assessments (e.g., MTC & ABAG, 2026; MVRPC, 2026), and NASEM (2025) reviews the data, tools and metrics currently used for these assessments.

Although activity-based travel demand models are computationally more complex than traditional four-step models, they offer considerable advantages for transportation equity analysis by reducing the need to aggregate travelers and equity measures into large spatial units. These models leverage person-level travel data and population synthesis techniques to produce more detailed and demographically sensitive representations of travel behavior and the trade-offs individuals make when choosing how, when, and where to travel (Bills & Walker, 2017; Nahmias-Biran & Shiftan, 2020; Bills, 2024). When applied at the regional scale, activity-based models use population synthesis to simulate the demographic and travel characteristics of an entire population, enabling detailed representations of daily travel activity under alternative planning scenarios. This combination of person-level travel data, activity-based modeling, and disaggregate measures of transportation benefits and burdens provides a more robust framework for evaluating the equity of transportation investments and policies than traditional aggregate approaches (Bills & Walker, 2017; Bills, 2024; Cabello et al., 2025).

It is important to note, however, that activity-based models are still typically applied with origins and destinations defined at the level of traffic analysis zones (or, in some regions, smaller micro-zones), so the spatial resolution of their inputs and network level-of-service measures remains aggregate to some degree. Their advantage for equity analysis lies in how outcomes can be summarized: because each person in the synthetic population is simulated, benefits and burdens can be estimated by person and by population group, rather than averaged over the residents of each zone (Bills et al., 2012; Bills & Walker, 2017).

2.4. Household Travel Surveys and Travel Model Representativeness

Household travel surveys are a foundational source of data for understanding travel behavior and how it varies across the population. They provide the primary data used to estimate travel demand models, which are widely applied to evaluate the impacts of transportation infrastructure and policies on society and the environment (Beimborn, 2006; Miller et al., 2018; Lawson et al., 2023). Despite the growing availability of big data sources, household travel surveys remain the cornerstone of transportation planning and analysis because they directly link travelers' demographic characteristics with detailed travel activity records and important contextual information, such as trip purpose, which cannot be reliably captured using most passive transportation datasets (Goodspeed et al., 2021). Household travel surveys collect detailed information on trip-making behavior, including trip-chaining patterns, mode choice, departure time, and destination, together with household and individual demographic characteristics and vehicle ownership information. This level of detail enables transportation analysts to develop econometric and simulation models of travel behavior that can be applied across a wide range of planning contexts, from local transportation projects to regional and statewide planning scenarios.

Household travel survey methodologies have evolved considerably over time to address challenges such as sampling error, declining response rates, and nonresponse bias (Sharp & Murakami, 2004; Lawson et al., 2023). However, researchers have only recently begun to examine these issues in the context of transportation equity analysis (Lubitow et al., 2021; Esekhaigbe et al., 2026). Emerging evidence suggests that despite standard practices that aim to maintain demographic representation of subgroups, household travel surveys may systematically underrepresent vulnerable travelers (Esekhaigbe et al., 2026), who are often the primary focus of transportation equity analyses. Consequently, the ability of transportation planning processes to identify and evaluate equitable transportation outcomes may be constrained when the data used to inform those decisions do not adequately represent the populations most affected by transportation investments (Lubitow et al., 2021). Moreover, if the travel behaviors of vulnerable nonrespondent groups differ systematically from those of survey respondents (with similar demographic characteristics), conventional survey expansion techniques, including sample weighting and post-stratification, may introduce additional bias rather than correct for it (Himelein, 2014; Esekhaigbe et al., 2026).

In this chapter, we use the term representativeness to refer to the degree to which survey respondents reflect the population they are intended to describe, not only in their demographic composition but also in their travel behaviors and preferences. Demographic representativeness is often assessed against external references, such as the U.S. Census Bureau's American Community Survey. Behavioral representativeness is more difficult to assess, because there is rarely a ground truth for how members of a population travel. This means that a survey may match the population on the share of low-income households and still misrepresent low-income travel behavior, if the low-income households who respond (for example, those with access to a vehicle) differ systematically from those who do not respond. Targeted satellite surveys provide one pathway to detecting such differences: by comparing the behaviors of similar groups across two samples, analysts can assess whether a conventional survey captures the behavior of the groups it underrepresents.

2.5. Population Heterogeneity in Discrete Choice Models

Travel behaviors and preferences can vary across individuals in ways that can impact equity analyses and other planning assessments: two travelers facing the same fare increase may respond very differently depending on their incomes, vehicle access, schedules and preferences. Discrete choice models, the form of econometric model that makes up travel demand modeling systems, capture this heterogeneity in several ways. The simplest approach captures observed (systematic) heterogeneity, in which model parameters vary with traveler characteristics, either by interacting travel attributes with characteristics such as income or by estimating separate parameters for market segments defined a priori (Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006). Latent class models assign travelers probabilistically to a given number of unobserved classes, each with its own preference parameters, with class membership explained by traveler characteristics (Bhat, 1997; Greene & Hensher, 2003). Further, mixed logit models treat preference parameters as random variables that vary continuously across the population, capturing unobserved taste heterogeneity, and can also accommodate panel effects and differences in scale across data sources (McFadden & Train, 2000; Hensher et al., 2008; Train, 2009).

Yet, these methods share an important limitation: each can only describe the heterogeneity that is present in the estimation data. If the members of a group who participate in a household

travel survey differ systematically from those who do not, no segmentation, latent class or random parameter specification can recover the preferences of the travelers who are missing. In this chapter, the heterogeneity of interest is therefore the difference in preferences, such as cost sensitivity and mode preferences, between travelers who are represented in conventional household travel surveys and travelers with similar observed characteristics (for example, income or education) who are often missing from such surveys. This heterogeneity is unobserved from the perspective of a model estimated on the conventional survey alone, because it results from who is sampled rather than from the measured characteristics of respondents. The work proposes that data fusion complements the methods above by adding observations of the missing travelers, so that their preferences can be estimated directly and tested against those of conventional survey respondents. In our models, we use observed heterogeneity (income- and education-specific parameters and demographic terms) within each dataset, and dataset-specific parameters to capture differences between the samples.

2.6. Use of Multiple Sources in Discrete Choice Model Estimation

The development of discrete choice models using multiple sources of data presents a promising pathway toward improving representation of subgroups not well reflected in the estimation datasets derived from household travel surveys.

The estimation of choice models using multiple data sources relies on the recognition that the scale parameters of an extreme-value random utility model's error terms may differ across datasets (Ben-Akiva & Lerman, 1985). In any random utility framework, the scale parameter is conventionally normalized (scale set equal to 1). While this normalization does not affect the estimated utility levels within a single dataset, the scale parameters can vary substantially across models estimated from different datasets, reflecting the distinct levels of variation in each (Ben-Akiva & Lerman, 1985).

A common application of this framework is the joint estimation of models from revealed preference (RP) and stated preference (SP) data, although it can also be applied to multiple RP or multiple SP datasets. The two data types have complementary strengths and weaknesses (Ben-Akiva et al., 1994). RP data reflect actual behavior or decisions made under market conditions and constraints but cannot describe responses to alternatives or attributes that do not yet exist. Observed attributes of revealed preference outcomes often vary over narrow ranges and are highly correlated, because the analyst only has a record of the trip a traveler actually took. This means that the travel attributes like time and cost for the modes they didn't use have to be imputed, either from network skims (Ortúzar & Willumsen, 2011) or from the respondent's own estimates, which can both be imprecise and biased toward the chosen mode.

SP experiments overcome these limitations by controlling the alternatives offered and varying attribute levels independently, which can improve the identification of model parameters. In addition, multiple choice situations can be presented to each respondent, yielding a larger number of observations from a potentially small sample and increasing the information available about respondents' behavior. Yet, because the choices are hypothetical, responses can be sensitive to the framing and format of the experiment, and models estimated from SP data alone may not accurately predict actual behavior (Ben-Akiva et al., 1994). Models estimated jointly from RP and SP data benefit from the strengths of both: choice observations made under real-world market conditions, together with a larger number of choice observations and a wider range of controlled attribute levels. Importantly, such joint estimation yields choice models that

can represent future alternatives and attributes not yet available in the market, while anchoring the parameters estimated from SP observations to observed choice behavior.

When estimating a model jointly from RP and SP data, a relative scale factor is estimated (rather than fixed to equal 1) to reconcile differences in error variance between RP and SP observations. This allows common parameters to be estimated consistently across the combined dataset, with RP data characterizing real world decisions and SP data contributing richer trade-off information and preferences for new or hypothetical alternatives (Hensher & Bradley, 1993; Ben-Akiva et al., 1994; Train, 2009; Gaker & Walker, 2013). The approach is widely recognized as a powerful strategy for fusing multiple behavioral datasets in model estimation (Swait et al., 1994; Hensher et al., 1998).

Multi-sample model estimation has emerged as an important pathway for improving the representation of underrepresented groups in travel demand models. By combining multiple data sources into a joint estimation dataset, analysts can better reflect the range of travel behaviors and preferences across the population and fill gaps in information for vulnerable traveler groups (Deschaintres et al., 2024; Wang et al., 2022).

The core-satellite survey framework is closely aligned with this approach. In this framework, a population-level core survey is complemented by a targeted satellite survey designed to capture the behaviors of underrepresented subpopulations (Goulias et al., 2013; Wang et al., 2022). Satellites can take several forms, including extensions of the core survey, linked satellite samples, independent satellite surveys and passively collected data, each designed to fill a specific gap in coverage. For example, Verreault and Morency (2018) showed that combining multiple surveys through weighting can reduce proxy-respondent bias in household travel surveys, and Wang et al. (2022) propose a hybrid method that blends simulation-based adjustments with the direct insertion of subgroup data to correct for coverage gaps and proxy-reporting bias.

3. Methods

This study is concerned with understanding the implications of subgroup underrepresentation in travel survey data on travel demand analysis, with emphasis on the underrepresentation of vulnerable subgroups. The core approach is to use core-satellite, multi-sample model estimation for developing and evaluating the performance of discrete choice models of travel mode choice, when the estimation data includes additional data samples from vulnerable subgroups.

The methodology is developed on two hypotheses: (1) vulnerable travelers face constraints in accessing critical destinations, such as work or healthcare, that shape their travel behaviors and preferences, and these travelers are underrepresented in conventional household travel surveys (Lubitow et al., 2021; Esekhaigbe et al., 2026); and (2) because their behaviors and preferences differ from those of the travelers who do respond to such surveys, models estimated from conventional surveys alone will misrepresent their travel behavior.

Mode choice models are estimated and systematically compared to demonstrate the consequences for travel demand analysis when vulnerable subgroups and their travel preferences are not accurately reflected in survey data.

We leverage these methods to jointly estimate mode choice models using a targeted (satellite) travel survey and a regional (core) household travel survey. The targeted survey—Travel Needs Survey—was conducted between 2017 and 2019 in Benton Harbor, Michigan, and was designed to oversample vulnerable travelers. These data are combined with the Benton Harbor sample of the statewide 2015 MiCounts household travel survey. Comparisons between

the joint model and single-sample models allow us to evaluate the benefits of the approach and its potential advantages for strengthening travel model-based transportation equity analyses.

3.1. Study Setting in Benton Harbor, Michigan

Benton Harbor, Michigan, is a small, post-industrial city on the southwestern shoreline of Lake Michigan that has undergone significant socioeconomic change over the past several decades. Once a thriving manufacturing hub and still home to the global headquarters of Whirlpool Corporation, the city has experienced economic decline typical of many cities in the American Rust Belt (Beauregard, 2009). As manufacturing jobs relocated over the years, economic opportunity in the city has become constrained, leading to employment challenges and population loss.

Today, Benton Harbor is home to approximately 8,953 residents, and a predominant African American population (approximately 81.5%). Residents earn lower incomes than the state average (\$18,667 per capita) and face a poverty rate of 40.1%, roughly three times the Michigan-wide rate of 13.2%. Notably, 28.4% of Benton Harbor households do not have access to a vehicle, compared with 7% statewide, which suggests that public transportation plays a significant role in supporting access to essential destinations (U.S. Census Bureau, 2026).

Public transportation in Benton Harbor is provided by the Twin Cities Area Transportation Authority (TCATA), which operates two fixed bus routes and an on-demand Dial-a-Ride service with a 23-vehicle fleet. These services cover the City of Benton Harbor and several surrounding jurisdictions, including Benton Township, the City of St. Joseph, and St. Joseph Township. In 2021, TCATA provided 43,725 trips on its fixed routes and 61,983 trips through Dial-a-Ride, which is open to the general public (FTA, 2021). As a small agency, transportation planning for TCATA is further supported by the Southwest Michigan Planning Commission (SWMPC), a tri-county regional planning agency, for planning services.

Despite this coverage, public transit remains a challenge for many residents. The two fixed routes serve a large area, yet many residents live far from a route, creating a classic first-mile/last-mile problem that constrains transit accessibility. In the absence of more frequent service and limits on geographic connectivity, these gaps make it particularly difficult to reach employment, education, and healthcare beyond city limits.

Given these accessibility challenges and the socioeconomic constraints facing many of its residents, Benton Harbor was identified as a critical site for examining travel needs and the potential for innovative transportation service improvements that address the challenges of vulnerable community members. To this end, a small-scale travel demand model was developed for the Benton Harbor region as part of a larger NSF-funded project to develop a collaborative, data-driven planning tool for local decision makers (Goodspeed et al., 2021). To support the model's development, a travel activity survey, the Benton Harbor Travel Needs Survey, was designed and administered.

3.2. Michigan Department of Transportation's 2015 MI Travel Counts Survey

The 2015 Michigan Travel Counts (MiCounts) survey serves as a comparison sample of data, reflecting standard best practices for household travel survey data collection in the United States. It is a statewide household travel survey conducted by the Michigan Department of Transportation (MDOT) to support statewide and regional travel demand models. Using address-

based sampling (ABS) from the U.S. Postal Service's Computerized Delivery Sequence file, households were randomly selected from 16 sample areas across Michigan, including the Benton Harbor region, and stratified by household size and income. Recruited households completed a web- or phone-based enrollment survey, were assigned a designated travel date, and subsequently reported all travel for that day through a retrieval survey administered online or by phone. A subsample of households participated in a GPS component, where members aged 16–75 carried wearable devices for three days to capture detailed travel behavior. The survey collected household- and person-level information, including demographics, vehicle ownership, and weekday and long-distance travel patterns. To encourage participation, each household received an invitation letter describing the process and a \$20 incentive (MDOT, 2016).

3.3. Benton Harbor Travel Needs Survey

3.3.1. Survey and Experiment Design

The Benton Harbor Travel Needs Survey was conducted between 2017 and 2019 to better understand the travel behaviors, transportation needs, and mobility constraints of residents in Benton Harbor, Michigan. The survey was specifically designed to address the underrepresentation of transportation-disadvantaged populations in conventional household travel surveys by oversampling vulnerable traveler groups found to be underrepresented in the MiCounts survey: low-income households, older adults, unemployed and underemployed individuals, households without access to a private vehicle, and transit-dependent travelers. This approach was motivated by two objectives: first, to expand understanding of the travel behaviors and preferences of groups that were insufficiently represented in the 2015 MiCounts survey; and second, to advance the project's data fusion goals by generating additional records for populations that are often missing from conventional household travel surveys.

Collecting both revealed and stated preference observations from the same respondents allows the strengths of each data type to offset the weaknesses of the other (as noted in Section 2.6). Revealed preference data reflect actual behavior, but they cannot describe responses to alternatives or service features that do not yet exist, such as app-based ride-hailing in Benton Harbor at the time of the survey. Observed attributes also tend to vary over narrow ranges and to be highly correlated (travel time and cost both rise with trip distance), and they are often measured imprecisely, particularly for alternatives the traveler did not choose. These limitations were expected to be more pronounced for the travelers this survey targeted, many of whom are captive to a single mode, so their observed choices reveal less about how they trade off time, cost and service quality. Stated preference experiments address these gaps by controlling which alternatives are offered and by varying attribute levels independently, including attributes such as transit hours of operation that rarely vary in practice. Conversely, stated choices are hypothetical and can be sensitive to the framing and format of the experiment, so models estimated from them alone may not accurately predict actual behavior. Anchoring stated choices to revealed choices, with a scale parameter that accounts for differences in error variance between the two data types, retains the behavioral realism of the revealed preference data while drawing on the richer trade-off information of the stated preference experiment.

As illustrated in Figure 1, the survey instrument was organized into three primary components: (1) individual and household demographic characteristics, (2) revealed travel behavior, including daily travel patterns and transportation resource availability, and (3) stated preference questions designed to capture travelers' mode choice preferences under alternative transportation scenarios. To maximize participation and reduce barriers to survey completion, the

survey was offered in both paper and online formats, allowing participants to select their preferred response mode. Participants received a \$15 grocery store gift card upon completion of the survey as compensation for their time; this modest incentive was intended to encourage participation while remaining accessible and minimizing the potential for undue influence. Participants were also invited to take part in an optional two-week GPS travel diary study that passively recorded their daily travel activity; these GPS data were not used in the modeling presented in this chapter.

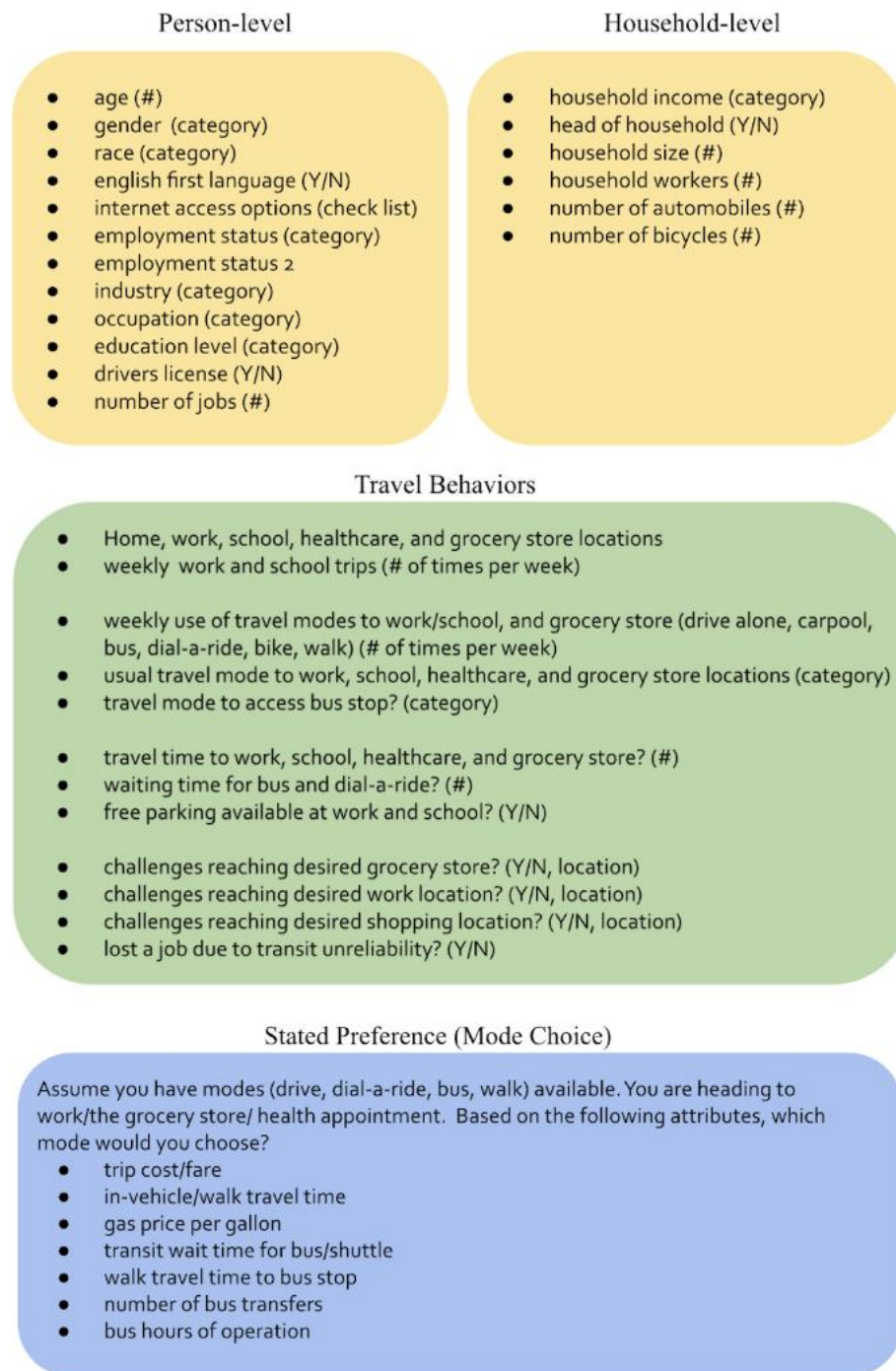


Figure 1. Description of Survey Questions

Stated Preference Experiment: In the stated preference portion of the survey, each respondent was asked to complete six hypothetical mode choice tasks covering three trip purposes that are central to accessibility for transportation-disadvantaged residents: traveling to work, to a grocery store, and to a doctor’s appointment. Each trip purpose was presented twice. Respondents were asked to assume that all listed modes were available to them and to choose the one they would use for the trip given its attributes. An example of a choice task is shown in Table 1, and the attribute levels are summarized in Table 2.

Table 1. Example stated preference mode choice task (work trip)

	Drive	Dial-A-Ride	Bus	Walk
Cost	\$6.84	\$3.00	\$1.50	/
Gas price (per gallon)	\$3.55	/	/	/
Wait time	None	30 mins	15 mins	None
Walking access	/	/	15 mins	/
Transfers	/	/	1	/
Travel time	14 mins	33 mins	31 mins	3hr45mins
Transit hours of operation	/	6am-6pm	4am-midnight	/

Construction of Attribute Values: To keep the hypothetical alternatives realistic, the travel times and costs of each mode were tied to the trip distance shown in the question, while the remaining service attributes were varied experimentally. The resulting attribute levels are summarized in Table 2.

Experimental Design: The service attributes were varied using a randomized design implemented in Qualtrics (Qualtrics, 2017). For each respondent and each of the six tasks, the level of every experimental attribute was drawn independently and at random from the levels shown in Table 2, so that each respondent saw a different combination of attribute levels in every task. Because levels were drawn independently, the experimental attributes are uncorrelated with one another by construction, which allows the effects of fares, waiting, access time, transfers, and service hours to be separated from one another. Travel times and the auto costs, in contrast, remain correlated with trip distance by design, which preserves the realism of the alternatives (Gaker & Walker, 2013).

Table 2. Stated preference attributes and levels

Attribute	Alternative(s)	Levels	Varied by
Trip distance	All	0.5, 5, 12, 19, 26, 33 miles	Random draw
Gas price per gallon	Drive	\$2.15, \$3.55	Random draw
Fare	Dial-a-Ride	\$2, \$3, \$4, \$5	Random draw
Fare	Bus	\$0.50, \$1.00, \$1.50, \$2.00, \$2.50	Random draw
Wait time	Dial-a-Ride; Bus	5, 15, 30, 40, 60 mins	Random draw (each mode separately)
Walking access time	Bus	5, 15, 30 mins	Random draw
Transfers	Bus	0, 1, 2	Random draw
Hours of operation	Dial-a-Ride; Bus	6am-6pm, 4am-midnight, 24 hours	Random draw (each mode separately)
Travel cost	Drive	\$0.25 to \$18.81	Distance and gas price
In-vehicle time	Drive,	1 to 38 mins	Distance
In-vehicle time	Dial-a-Ride	16 to 65 mins	Distance
In-vehicle time	Bus	1 to 77 mins	Distance and transfers
Travel time	Walk	9 min to 10 hr 19 mins	Distance

Household Characteristics and Revealed Travel Behavior: The remaining survey components collected person- and household-level characteristics and revealed travel behavior (Figure 1). Person-level questions covered age, gender, race, whether English is the respondent's first language, internet access, employment status, industry and occupation, education, driver's license holding, and number of jobs; household questions covered income, head of household, household size, number of workers, and the number of automobiles and bicycles. The revealed travel behavior section asked respondents to identify their home, work, school, healthcare and grocery store locations; their weekly trips and use of each travel mode for work, school and grocery trips; their usual mode and travel time to each of these destinations; how they access the bus stop; their usual waiting time for the bus and Dial-a-Ride; and the availability of free parking. Respondents also reported whether they had difficulty reaching their desired grocery store, work or shopping locations, and whether they had ever lost a job due to transit unreliability. The usual-mode responses for work, healthcare and grocery trips provide the revealed preference observations that complement the stated preference tasks, which were designed around the same three trip purposes.

3.3.2. Participant Recruitment

The recruitment strategy for this study was intentionally designed to reach vulnerable and transport-disadvantaged populations in Benton Harbor, with a particular focus on residents who are transit-dependent, unemployed or underemployed, and low-income. Multiple outreach channels were used to ensure inclusivity and to reduce barriers to participation.

Local partnerships were central to targeting vulnerable travelers living in Benton Harbor. The research team collaborated with Kinexus, a workforce training and career services hub, and with the Twin Cities Area Transportation Authority (TCATA), Benton Harbor's public transportation provider, to reach residents with low incomes, limited employment opportunities, or high transit dependence. Recruitment efforts included distributing flyers to Dial-a-Ride users and advertising to the Kinexus client list, which encompasses job seekers and recently employed residents. Additional outreach was deployed through Facebook ads, local radio announcements, newspaper postings, and press releases to increase community awareness. Recognizing that digital divide barriers could limit participation, the research team also organized in-person workshops at Kinexus. These sessions provided direct assistance to residents completing either paper or online surveys and offered technical support for installing the smartphone-based tracking application.

To further strengthen outreach, the team leveraged the partnership with TCATA to distribute surveys via its Dial-a-Ride and fixed-route systems. Surveys were also made available at community events, job training centers, healthcare clinics, and food pantries—venues that were strategically chosen to engage individuals who may otherwise be overlooked in traditional survey recruitment.

The study protocol and survey instruments were reviewed and approved by the University of Michigan Institutional Review Board, and all participants provided informed consent prior to participating.

3.3.3. Community Workshops

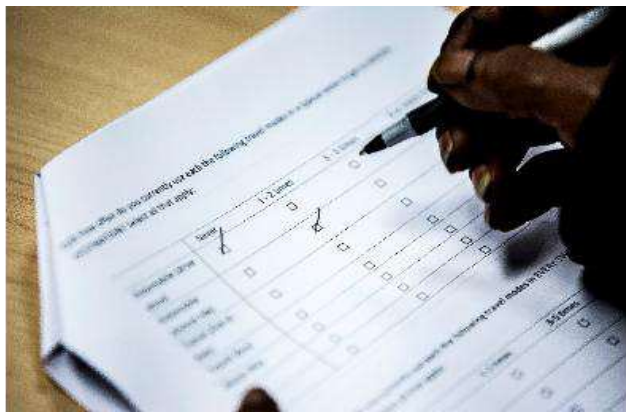


Figure 2. Image of Travel Needs participant responding to paper version of the survey.

A central aspect of the recruitment and administration strategies was a series of community workshops. A total of five community workshops were offered between August 2017 and November 2019. At these workshops, participants heard brief presentations from the study team on the motivation for the survey, the role it would play in broader transportation planning efforts in Benton Harbor, and options for participation. In-person participants were offered the option to complete the survey in paper form or online (using a provided desktop or laptop computer). The research team also assisted with survey administration when necessary. The workshops served both practical and relational purposes. They also provided opportunities for participants to receive technical support, ask questions about the study, and select the method of participation that best matched their needs and preferences. These sessions enhanced transparency and trust between the research team and community members, reinforcing the

legitimacy of the study within a context where vulnerable residents may otherwise feel disconnected from data collection efforts.

3.4. Mode Choice Modeling Methods

A series of multinomial logit (MNL) and nested logit (NL) mode choice models are estimated using the two data samples: (1) the travel needs survey (2017-2019) and (2) the 2015 MiCounts survey. We develop mode choice models from each dataset as well as a joint model estimated from both datasets, to compare results and interpretations of travel preferences and demonstrate the potential benefits of estimating travel demand modeling using fused or “enriched” datasets.

In this section, we describe the data used for model estimation and provide a brief overview of discrete choice model development, with emphasis on the nested logit model (the form of the final MiCounts and Joint models). We then discuss multi-sample model estimation, which is necessary for estimating the mode choice model from the fused dataset.

The Travel Needs data include 239 revealed preference (RP) trips reported by 114 respondents and 611 stated preference (SP) choices by 105 respondents (122 respondents in total), and the MiCounts data include 2,916 trips by 788 adult Benton Harbor respondents (detailed in Section 4.1). For the RP trips in both datasets, the level-of-service attributes of the chosen and non-chosen modes were estimated primarily from trip distances, so that the two datasets are measured consistently. The speeds, costs and fares used to construct these attributes, and their sources, are summarized in Table 3. For the SP choices, the attributes are those presented to respondents in the experiment (Tables 1 and 2).

Table 3. Level-of-service attributes for revealed preference trips

Attribute	Mode	Assumption	Source
In-vehicle time	Drive; Carpool	Distance ÷ 25 mph	(McGuckin & Fucci, 2018)
In-vehicle time	Bus	Distance ÷ 13 mph	(FTA, 2019; (APTA, 2019)
In-vehicle time	Dial-a-Ride	Distance ÷ 10 mph	(FTA, 2019)
Travel time	Walk	Distance ÷ 3 mph	(Fitzpatrick et al., 2006)
Travel cost	Drive	\$0.545 per mile	(IRS, 2017)
Travel cost	Carpool	Drive cost ÷ 2.5	Assumed average vehicle occupancy of 2.5 persons
Fare	Bus	\$1.00 per trip (\$0.50 reduced fare)	(TCATA, 2020, 2025)
Fare	Dial-a-Ride	\$2.00 per trip (\$1.00 reduced fare)	(Herald-Palladium, 2025; TCATA, 2025)
Reduced-fare eligibility	Bus; Dial-a-Ride	Adults 65 and older and persons with disabilities	TCATA reduced fare for adults 60 and older, children under 12 and persons with disabilities (TCATA, 2020); ages 60–64 cannot be identified in the survey age groups

Note: Attributes are computed from the trip distance for the chosen and non-chosen modes of the revealed preference trips in both the Travel Needs and MiCounts data. Stated preference attributes are those presented to respondents in the experiment (Tables 1 and 2).

3.4.1. Nested Logit

Nested logit (NL) models are a form of logit discrete choice model often used in travel demand modeling (Ortúzar, 1983; Train, 2009). Discrete choice models are based on random utility maximization theory (Ben-Akiva & Lerman, 1985). Like other discrete choice models, the NL model predicts the probability that a decision maker n (e.g., a traveler) will select each alternative i from a set of mutually exclusive alternatives, the choice set C_n . The utility of each alternative is composed of a systematic component, V_{ni} , which depends on observed attributes of the alternative (such as travel time and cost) and characteristics of the traveler, and a random component, ε_{ni} , that represents factors unobserved by the analyst:

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \beta' x_{ni} + \varepsilon_{ni} \quad (1)$$

where β is a vector of parameters to be estimated and x_{ni} is a vector of explanatory variables. Because part of the utility is unobserved, the alternative with the highest systematic utility is not chosen with certainty; rather, an alternative with higher systematic utility has a higher probability of being chosen. When the random components are independently and identically distributed extreme value, the choice probabilities take the multinomial logit (MNL) form:

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{j \in C_n} \exp(V_{nj})} \quad (2)$$

The MNL model implies that the unobserved factors are independent across alternatives. The NL model relaxes this assumption by grouping alternatives that share unobserved characteristics into nests, $m \in M$, so that alternatives in the same nest are closer substitutes for one another than for alternatives outside the nest (Koppelman & Wen, 1998; Train, 2009). While the NL structure is not appropriate in all circumstances (for example, where correlation is present between alternatives of different nests), it continues to serve as an important model structure for transportation modeling and decision-making (Hensher & Greene, 2002; Newman et al., 2018). Following the normalization used in Biogeme (Bierlaire, 2023), the probability that traveler n chooses alternative i in nest m is:

$$P_{ni} = \frac{\exp(\mu_m V_{ni})}{\sum_{j \in C_m} \exp(\mu_m V_{nj})} \cdot \frac{\exp(I_{nm})}{\sum_{k \in M} \exp(I_{nk})} \quad (3)$$

$$I_{nm} = \frac{1}{\mu_m} \ln \sum_{j \in C_m} \exp(\mu_m V_{nj}) \quad (4)$$

where C_m is the set of alternatives in nest m , I_{nm} is the inclusive value (logsum) of nest m , and $\mu_m \geq 1$ is the nest parameter. The first term of equation (3) is the probability of choosing alternative i conditional on choosing nest m , and the second term is the probability of choosing nest m . Larger values of μ_m indicate greater correlation among the unobserved utilities of the alternatives in nest m , and therefore greater substitution among them; when $\mu_m = 1$ for all nests, the NL model reduces to the MNL model. Alternatives that are not grouped with others form their own nest, with $\mu_m = 1$. Readers are referred to Ben-Akiva and Lerman (1985), Koppelman and Bhat (2006) and Train (2009) for a full treatment.

3.4.2. Use of Multiple Sources in Travel Choice Modeling

As discussed in Section 2.6, the estimation of choice models using multiple data sources relies on the recognition that the scale of the unobserved utility may differ across datasets (Ben-Akiva & Lerman, 1985; Swait & Louviere, 1993). We apply this approach at two levels, as illustrated in Figure 3. First, the Travel Needs model combines RP and SP choices from the same respondents. SP-specific constants are added to the utilities of the SP alternatives (dial-a-ride, bus and walk) to capture systematic differences in mode preferences between the hypothetical SP tasks and the actual RP trips:

$$V_{ni}^{SP} = V_{ni} + \delta_i^{SP} \quad (5)$$

where δ_i^{SP} is the SP-specific constant for alternative i . A separate SP scale parameter is often used to capture data-specific error variance; in our tests, the SP-specific constants fit the data better, so the SP scale was not retained in the final specifications.

Second, the Joint model combines the Travel Needs (satellite) and MiCounts (core) samples. Because the two surveys differ in design, timing and the precision with which travel attributes are measured, the variance of the unobserved utility may differ between them. The utilities of the MiCounts observations are therefore multiplied by a relative scale parameter, λ , estimated jointly with the other parameters, while the scale of the Travel Needs observations is normalized to one:

$$V_{ni}^{MC} = \lambda \beta' x_{ni} \quad (6)$$

All parameters are estimated simultaneously by maximizing the joint log-likelihood of the two samples:

$$LL(\beta, \mu, \lambda) = \sum_{n \in TNS} \sum_{i \in C_n} y_{ni} \ln P_{ni}(\beta, \mu) + \sum_{n \in MC} \sum_{i \in C_n} y_{ni} \ln P_{ni}(\lambda \beta, \mu) \quad (7)$$

where y_{ni} equals 1 if traveler n chose alternative i and 0 otherwise, and P_{ni} is given by equation (2) or (3). A value of λ greater than one indicates that the MiCounts choices contain less unexplained variation than the Travel Needs choices. Parameters can be shared across the two samples (such as the travel time parameter) or specified as dataset-specific (such as the alternative-specific constants and selected demographic parameters), and likelihood ratio tests are used to determine whether pooling a parameter across samples is supported by the data (Section 4.2.2). Because the parameters of the three models are estimated on different scales, we compare them using ratios of parameters, such as values of time, rather than the parameters themselves (Swait & Louviere, 1993; Louviere et al., 2000).

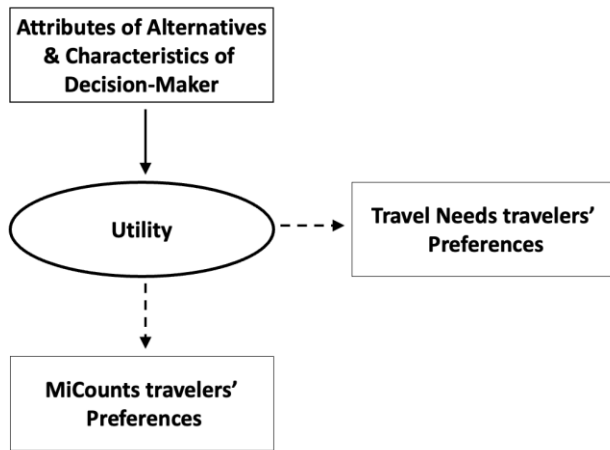


Figure 3. Multi-sample satellite-core estimation framework

4. Survey and Analysis Results

4.1.Descriptive Statistics for Travel Needs and MiCounts Surveys

Table 4. Descriptive Statistics of Person-level Demographics

Variable	Category	TNS			MiCounts (n=788)	2015 ACS
		TNS RP (n=114)	TNS SP (n=105)	RP+SP (n=122)		
age	15 + Younger	0.00%	0.00%	0.00%	0.00%	28.30%
	16-17 years	1.82%	2.04%	1.74%	0.00%	7.6%*
	18-64 years	90.00%	88.78%	88.70%	75.83%	58.7%**
	65 + Older	8.18%	9.18%	9.57%	24.17%	8.50%
gender	female	69.30%	70.19%	69.42%	56.01%	53.46%
	male	30.70%	29.81%	30.58%	43.99%	46.54%
race and ethnicity	Black/African American	77.19%	78.10%	77.05%	—	83.15%
	White/European	19.30%	17.14%	18.85%	—	7.46%
	Native American	1.75%	0.95%	1.64%	—	0.32%
	Hispanic	1.75%	1.90%	1.64%	—	5.13%
	Other	2.63%	1.90%	2.46%	—	3.94%
employment /status	Working (full-time)	24.78%	22.12%	23.33%	61.58%	42.99%
	Working (part-time)	22.12%	23.08%	21.67%	—	
	Working (self-employed)	0.00%	0.00%	0.00%	—	
	Not working (temporary layoff)	1.77%	1.92%	1.67%	0.13%	13.47%
	Not working (searching)	9.73%	10.58%	10.83%	1.78%	43.54%
	Not working (retired)	9.73%	10.58%	10.00%	23.41%	
	Not working (disabled)	20.35%	21.15%	21.67%	6.23%	
	Not working (student)	3.54%	2.88%	3.33%	2.29%	
	Not working (other)	7.96%	7.69%	7.50%	4.58%	
education	Elementary	6.42%	7.00%	6.90%	3.08%	29.40%
	High School / GED	66.06%	69.00%	66.38%	34.87%	37.90%
	Associate's, Technical, or Trade	20.18%	18.00%	19.83%	13.72%	27.60%
	Undergraduate	7.34%	6.00%	6.90%	29.49%	2.80%
	Graduate	0.00%	0.00%	0.00%	18.85%	2.20%

Notes: Shares are person-level. TNS columns are the respondents in the model dataset (RP = respondents with revealed-preference trips; SP = respondents who completed the stated-preference experiment). Race and ethnicity shares use all respondents as the denominator and can sum to more than 100% because respondents could select more than one category; race and ethnicity are not available in the MiCounts data. MiCounts employment does not separate full-time, part-time and self-employed workers, so all MiCounts workers are shown in the full-time row. MiCounts includes adults (18 and older) only. ACS age categories differ: * ages 15 to 19; ** ages 20 to 74. ACS employment status is from table DP03 (2011–2015 5-year estimates, population 16 and older): employed (shown across the working rows), unemployed (shown across the temporary layoff and searching rows) and not in the labor force (shown across the remaining not working rows).

Table 5. Descriptive Statistics of Household-level Demographics

Variable	Category	TNS			MiCounts	2015 ACS
		TNS RP (n=114)	TNS SP (n=105)	RP+SP (n=122)	adults (n=788)	
# hh members	1	27.52%	24.75%	26.72%	18.02%	37.70%
	2	32.11%	35.64%	34.48%	50.76%	24.30%
	3	17.43%	17.82%	17.24%	13.32%	16.40%
	4+	22.94%	21.78%	21.55%	17.89%	21.70%
# hh workers	0	36.36%	39.81%	38.46%	24.87%	19.90%
	1	35.45%	32.04%	34.19%	35.91%	55.40%
	2+	28.18%	28.16%	27.35%	39.21%	24.70%
# hh automobiles	0	36.61%	37.50%	36.97%	4.31%	19.10%
	1	38.39%	40.38%	39.50%	22.21%	44.90%
	2	18.75%	15.38%	17.65%	46.83%	21.50%
	3 or more	6.25%	6.73%	5.88%	26.65%	14.50%
hh income	Less than \$29,999	76.32%	81.90%	77.05%	25.63%	73.90%
	\$30,000 - \$74,999	15.79%	13.33%	14.75%	26.78%	21.70%
	\$74,999 +	2.63%	1.90%	2.46%	35.79%	4.30%
	missing	5.26%	2.86%	5.74%	11.80%	—
mode share (% of choices)	Drive	53.14%	51.39%	51.88%	85.12%	73.70%
	Carpool	20.50%	—	5.76%	10.36%	13.30%
	Bus	2.09%	9.82%	7.65%	1.99%	2.60%
	Dial-a-ride	21.34%	32.41%	29.29%	0.75%	—
	Walk	2.93%	6.38%	5.41%	1.78%	7.10%
# choices		239	611	850	2,916	2,923

Notes: Household shares are person-level (each respondent counted once). MiCounts income categories differ from the TNS and ACS: less than \$35,000, \$35,000–\$74,999 and \$75,000 or more. Mode shares are shares of choices: TNS RP = 239 reported trips; TNS SP = 611 stated-preference choice tasks (carpool was not offered); MiCounts = 2,916 trips by adults. ACS mode shares are commute trips only, for workers 16 and older who do not work at home (table B08301, 2011–2015 5-year estimates, Benton Harbor city); the ACS has no dial-a-ride category, and the remaining 3.4% (taxicab, motorcycle, bicycle and other) is not shown.

The Travel Needs (TNS) survey data used in our models include 122 Benton Harbor residents: 114 respondents who reported revealed preference (RP) trips (239 trips) and 105 respondents who completed the stated preference (SP) experiment (611 choice tasks), while the sample from MDOT's MiCounts survey includes 788 adult (18 and older) Benton Harbor respondents, who reported 2,916 trips. Descriptive statistics for these samples are presented in Tables 4 and 5, and compared with population statistics for Benton Harbor, based on the 2015 American Community Survey (U.S. Census Bureau, 2016). Because the TNS RP, SP and combined RP+SP samples have very similar characteristics, we focus on the TNS RP respondents below.

At the person level (Table 4), we find that despite the small sample size, the TNS reflects the expected population demographics (as indicated by the ACS statistics) well, with the exception of a few characteristics. The TNS respondents are more likely to be of working age (18-64), relative to the ACS (90.00% vs. 58.70%), while the share of respondents older than 65 is similar (8.18% vs. 8.50%). This is in part driven by the intentional targeting of working aged

adults, for the Travel Needs survey respondents. The TNS respondents are also more likely to be women, with nearly 70% women respondents (69.30%), vs. approximately 53% in the ACS. Regarding race and ethnicity, the TNS respondents reflect a higher proportion of white respondents (19.30% vs. 7.46%) and a lower proportion of Black (77.19% vs. 83.15%) and Hispanic (1.75% vs. 5.13%) respondents, relative to the ACS. Regarding employment status, the TNS respondents differ notably for each specific employment category. However, the estimates are comparable when aggregated; for working respondents (24.78% + 22.12% = 46.90% vs. 42.99%), for temporarily unemployed or searching respondents (1.77% + 9.73% = 11.50% vs. 13.47%), and for remaining unemployed respondents (9.73% + 20.35% + 3.54% + 7.96% = 41.58% vs. 43.54%). Regarding education level, TNS respondents are more likely to be at the high school or GED (66.06% vs. 37.90%), and undergraduate (7.34% vs. 2.80%) levels, relative to the ACS.

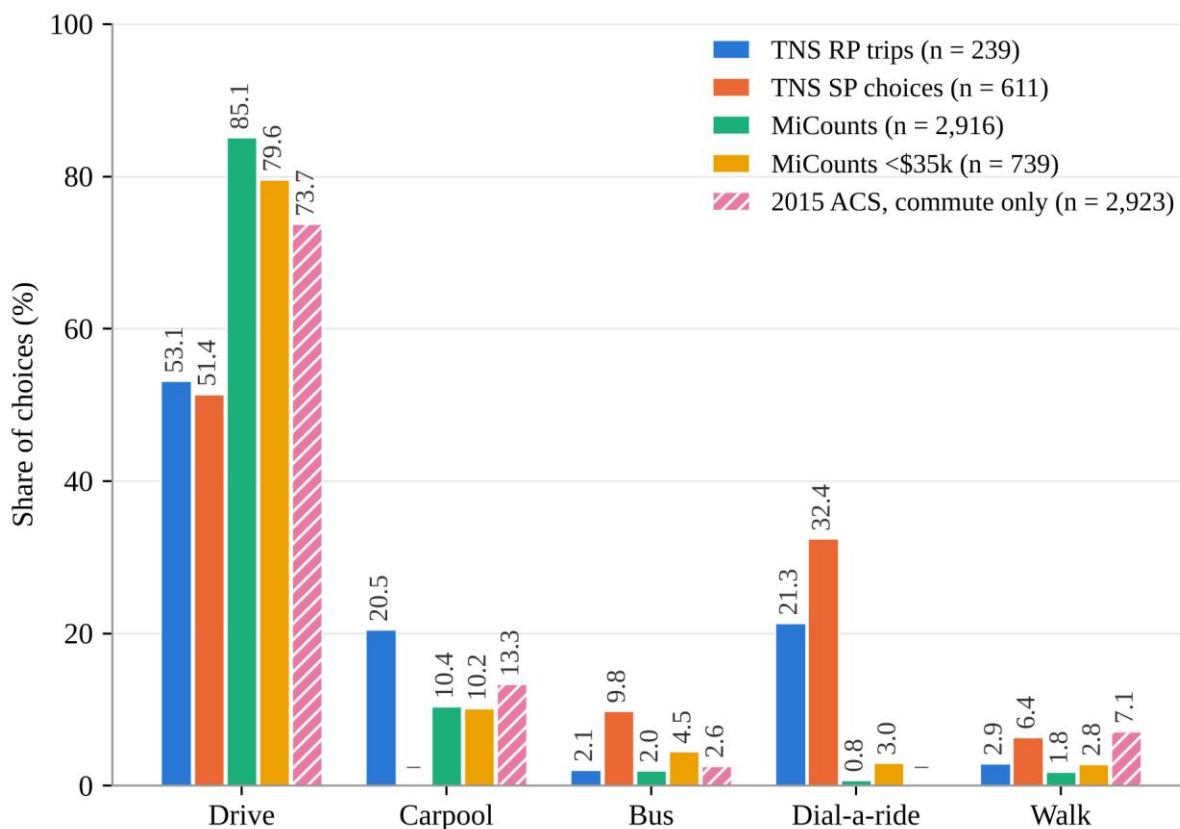
At the household level (Table 5), TNS respondents are less likely to be in 1-person households (27.52% vs. 37.70%), and more likely to be in 2-person households (32.11% vs. 24.30%). TNS respondents are also considerably more likely to live in zero-worker households (36.36% vs. 19.90%) and zero-automobile households (36.61% vs. 19.10%). Regarding household income, TNS respondents also have a similar distribution of income levels, with 76.32% earning less than \$30,000 (vs. 73.90% in the ACS), although 5.26% of respondents did not report their income.

When compared to the Benton Harbor sample of MDOT's MiCounts survey, respondents' characteristics differ from the TNS and ACS in notable ways. MiCounts respondents are more likely to be over the age of 65 (24.17%), relative to the TNS (8.18%) as well as the ACS (8.50%), and substantially more likely to hold undergraduate and graduate degrees (29.49% and 18.85%, respectively), relative to the TNS (7.34% and 0.00%) as well as the ACS (2.80% and 2.20%). MiCounts respondents are also more likely to live in 2-person households (50.76%), and slightly less likely to live in households with 3 members or 4+ members (13.32% and 17.89%, respectively), relative to the TNS (17.43% and 22.94%) as well as the ACS (16.40% and 21.70%). Very few MiCounts respondents live in zero-automobile households (4.31%), relative to the TNS (36.61%) and the ACS (19.10%). Finally, MiCounts respondents are considerably less likely to be low income, with 25.63% earning less than \$35,000, relative to the 76.32% of TNS respondents and 73.90% of ACS households earning less than \$30,000.

Regarding mode choices, we find that the recorded differences in subgroup representation for the travel surveys coincide with differences in mode choice behaviors (Table 5 and Figure 4). For their reported (RP) trips, TNS respondents are much less likely to drive (53.14% vs. 85.12%), and considerably more likely to carpool (20.50% vs. 10.36%) and to use dial-a-ride (21.34% vs. 0.75%), while bus (2.09% vs. 1.99%) and walk (2.93% vs. 1.78%) shares are low in both samples. In the SP experiment, where carpool was not offered, TNS respondents chose bus (9.82%), dial-a-ride (32.41%) and walk (6.38%) more often than in their RP trips. The 2015 ACS reports commute trips only, for workers 16 and older (U.S. Census Bureau, 2016), and is therefore not directly comparable to either survey, which include trips for all purposes; however, Benton Harbor commuters drive alone (73.70%) at a rate between the TNS and MiCounts samples, carpool at a similar rate to MiCounts respondents (13.30%), and have the highest walk share (7.10%), while public transit accounts for only 2.60% of commute trips. While we do not include comparisons of other travel behaviors (e.g. origin-destination patterns, activity patterns, etc.), this suggests that the travel behaviors and preferences of vulnerable travelers missing from conventional surveys may differ considerably from those of vulnerable travelers included in such

surveys. When we sub-sample the MiCounts survey for adult Benton Harbor respondents earning less than \$35,000 annually (n = 202 respondents, 739 trips; shown in Figure 4), we find that these mode choice differences are persistent, with low-income MiCounts respondents being much more likely to drive (79.57%), relative to TNS respondents, and much less likely to use dial-a-ride (2.98%). This further motivates investigation of potential differences in travel behavior, for TNS respondents relative to MiCounts respondents.

Overall, we find important differences in TNS vs. MiCounts respondents, for some key demographic subgroups. Specifically, MiCounts respondents are much more likely to hold undergraduate and graduate degrees, considerably more likely to live in smaller households (with 2 members or less), have access to at least one household automobile, and earn \$35,000 or more annually. This suggests that respondents to the MiCounts survey are less likely to be subject to barriers that pose constraints on travel accessibility.



Note: "-" = mode not available (carpool was not offered in the SP experiment; the ACS has no dial-a-ride category). ACS shares are commute trips by workers 16 and older (table B08301); the remaining 3.4% (taxicab, motorcycle, bicycle and other) is not shown.

Figure 4. Comparison of Mode Shares for Travel Needs and MiCounts Survey Respondents

4.2. Mode Choice Model Estimation Results

In this section, we discuss the results of two sets of mode choice models; (1) attributes-only models for income- and education-based subgroups, and (2) full model specifications with all relevant characteristics. The attributes-only models are used to explore the implications of demographic over- or under-representation on choice model results, while the full models reflect the specifications offering the best statistical fit, for each of the three datasets. The Travel Needs model is based on responses from the Travel Needs Survey, the MiCounts model is based on responses from the MiCounts survey (restricted to Benton Harbor residents), and the Joint model is estimated using both datasets. The models are estimated using Python Biogeme (Bierlaire, 2023), and the final specifications for each model reflect utility and nesting structures that provide the best balance of statistical fit and behavioral interpretability. Each model is the result of multiple iterations, incorporating both formal and informal statistical testing to arrive at the presented results.

4.2.1. Subgroup Model Results

Table 6. Subgroup Definitions

Group	Definition
Low Inc.	TNS: household income < \$45,000. MiCounts: household income < \$50,000
Higher Inc.	TNS: household income $\geq$ \$45,000. MiCounts: household income \$50,000–\$99,999 (households at \$100,000+ have no cost term)
HS, Tech. (level 1)	Education = High School/GED, Associate's, or Technical Certificate/Degree (MiCounts: High School/GED, Some College, or Associate's)
UG, Grad. (level 2)	Education = Undergraduate, Master's, or PhD/Professional Degree

Here we examine whether the model sensitivity to travel time and cost differs across income, and the degree to which the two datasets capture these differences. The model utilities include alternative-specific constants and travel time and cost, with the time and cost coefficients estimated separately for each subgroup. Further, the mode utilities are intentionally specified such that differences between subgroups can be distinguished as differences in travel behavior preferences rather than artifacts of how each sample was collected.

The TNS model combines revealed preference (RP) with stated preference (SP) choices and includes separate SP constants for dial-a-ride, bus and walk. These constants capture systematic differences in mode preferences between the hypothetical SP tasks and the actual RP trips (for example, due to the framing of the experiment). In this way, the time and cost coefficients are identified from trade-offs that respondents make in both settings rather than reflecting differences between the two survey formats. Further, the two models are compared using values-of-time (VOT) rather than direct comparisons of the model parameters, given that the scale cancels out when the ratio of the time and cost coefficients is calculated. The results for the income subgroup models are shown in Table 7.

Table 7. Estimation Results for Income Subgroups

Parameter Name	Travel Needs		MiCounts	
	Utility	Estimate (t-stat)	Utility	Estimate (t-stat)
Constants	Drive	—	Drive	—
	Carpool	-1.88 (-9.44)	Carpool	-2.64 (-26.93)
	Dial-a-ride	RP -1.70 (-8.30); SP -1.12 (-9.16)	Dial-a-ride	-5.24 (-18.23)
	Bus	RP -4.09 (-8.68); SP -2.33 (-13.50)	Bus	-3.14 (-16.76)
	Walk	RP -3.50 (-8.08); SP -2.08 (-8.46)	Walk	-2.84 (-18.29)
Time	All	—	Drive, Carpool, Bus	-0.2128 (-6.24)
Time (Low Inc.)		-0.0039 (-3.62)	Dial-a-ride, Walk	-0.0610 (-8.12)
Time (Higher Inc.)		-0.0503 (-2.68)	Dial-a-ride, Walk	-0.0884 (-6.67)
Cost (Low Inc.)		-0.0322 (-2.08)	All (exc. Walk)	0.0459 (0.37)
Cost (Higher Inc.)		-0.1050 (-1.95)	All (exc. Walk)	-0.3212 (-3.82)
N		850		2916
Rho-bar-squared		0.33		0.71
LL(0)		-1128.78		-4405.79
LL(β)		-740.65		-1255.91
Low Inc. VOT (\$/hour)		\$7.29		—
Higher Inc. VOT (\$/hour)		\$28.74		\$39.76 (Drive, Carpool, Bus); \$16.52 (Dial-a-ride, Walk)

In the Travel Needs income model, the RP and SP constants differ significantly, with the RP constants roughly 1.5 to 1.8 times the magnitude of the corresponding SP constants. If the underlying mode preferences were the same in both settings, this pattern would be consistent with an SP scale of about 0.6 relative to the RP scale; that is, a standard deviation of the SP error about $1/0.6 \approx 1.7$ times that of the RP error. This is consistent with the literature, suggesting that hypothetical choice data may carry more unexplained variation than actual trips (Ben-Akiva et al., 1994).

Regarding the travel time and cost parameters, the TNS model shows that higher-income travelers are about 13 times more sensitive to travel time than low-income travelers (-0.0503 vs. -0.0039 per minute) and about three times more sensitive to cost (-0.105 vs. -0.032 per dollar). This results in an estimated \$7.29 value-of-time (VOT) for low-income travelers, relative to a \$28.74 VOT for higher-income travelers.

The MiCounts income model results show a distinct pattern of preferences relative to the TNS income model. First, a time parameter for motorized modes (drive, carpool and bus) is significant (generic across income classes), while the travel time parameter for dial-a-ride and walk is income specific. This suggests that the time spent walking or riding dial-a-ride is perceived differently from in-vehicle time on faster modes. The cost parameter is specified as income specific on all motorized modes. While higher-income travelers are highly cost sensitive, the low-income cost parameter is positive and insignificant. No alternative cost specification was

found to be significant, so a low-income VOT cannot be estimated from MiCounts. The higher-income cost parameter and generic travel time parameters imply VOTs of \$39.76 per hour for drive, carpool and bus and \$16.52 for dial-a-ride and walk. It is important to note, however, that no higher-income MiCounts travelers made bus or dial-a-ride trips, so part of their cost parameter likely reflects avoidance of those modes, rather than cost sensitivity to bus or dial-a-ride fares.

Overall, the two models, as expected, show that higher-income travelers are significantly more time sensitive than low-income travelers. Yet the models differ in their reflection of travelers' cost sensitivity: although approximately 40% of MiCounts trips are made by low-income travelers, the MiCounts model cannot identify a low-income cost effect. The TNS sample, which targeted lower-income travelers, does find a significant cost effect for low-income travelers.

Table 8. Estimation Results for Education Subgroups

Parameter Name	Travel Needs		MiCounts	
	Utility	Estimate (t-stat)	Utility	Estimate (t-stat)
Constants	Drive	—	Drive	—
	Carpool	-1.86 (-9.38)	Carpool	-2.58 (-28.44)
	Dial-a-ride	RP -1.74 (-8.45); SP -1.14 (-9.53)	Dial-a-ride	-4.37 (-19.55)
	Bus	RP -4.11 (-8.72); SP -2.34 (-13.80)	Bus	-3.62 (-24.99)
	Walk	RP -3.56 (-8.22); SP -2.20 (-9.31)	Walk	-2.18 (-10.67)
Time (HS or Tech.)	All	-0.0035 (-3.30)	All	-0.0653 (-6.87)
Time (UG or Graduate)	All	-0.0296 (-1.93)	All	-0.0814 (-6.15)
Cost (HS or Tech.)	All (exc. Walk)	-0.0252 (-1.62)	—	—
Cost (UG or Graduate)	All (exc. Walk)	-0.1659 (-2.39)	—	—
Cost (Income < \$50k)	—	—	All (exc. Walk)	0.0588 (0.50)
Cost (Income \$50-100k)	—	—	All (exc. Walk)	-0.2449 (-3.04)
N	850		2916	
Rho-bar-squared	0.33		0.71	
LL(0)	-1128.78		-4405.79	
LL(β)	-744.40		-1257.41	
HS or Tech. VOT (\$/hour)	\$8.35		Income: \$50-100k	\$15.99
UG or Graduate VOT (\$/hour)	\$10.70		Income: \$50-100k	\$19.93

The education models in Table 8 follow the same approach as the income subgroup models. The models for both datasets are specified to capture differences in travel time and cost sensitivity across education: high school and technical degree holders (level 1) compared to bachelor's and graduate degree holders (level 2). The TNS education model uses the same structure as the TNS income model, with RP and SP specific constants, and education specific time and cost parameters. The model identifies significant travel time parameters for both education levels, with level 2 travelers being more sensitive to travel time (approximately eight times larger than that of level 1 travelers). Cost parameters are also identified for both groups, yet the level 1 cost parameter is only weakly significant ($t = -1.62$; an 89.5% confidence level), while the level 2 cost parameter is significant ($t = -2.39$) and the level 2 time parameter is marginally significant ($t = -1.93$; a 94.6% confidence level). Despite their weak significance levels, a likelihood ratio test of whether the level 1 and 2 cost parameters equal one another (i.e., whether cost should be specified as generic across education groups) motivates our education-specific specification ($p \approx 0.036$). As a result, the implied VOTs are \$8.35 per hour for level 1 and \$10.70 for level 2 travelers.

In the MiCounts education model, travel time is split by education, but no significant education-specific, nor generic cost parameter is identified. Instead, cost is specified by income rather than education, and similar to the MiCounts income subgroup results, no low-income cost parameter is identified. For this reason, the level 1 and 2 VOTs reflect travelers with incomes of \$50,000 to \$100,000 only. The MiCounts results show level 2 travelers to be somewhat more sensitive to travel time than level 1 travelers (-0.0814 vs. -0.0653 per minute), with VOTs of \$19.93 and \$15.99 per hour respectively, using the \$50,000 to \$100,000 cost coefficient.

Because education does not explain cost sensitivity in the MiCounts model beyond income, MiCounts education-specific VOTs reflect only differences in time sensitivity and are not directly comparable to the TNS education-specific VOTs. However, the TNS and MiCounts level 2 VOTs (for travelers with a bachelor's degree or higher) are \$10.70 and \$19.93, respectively. This suggests that the MiCounts data captures level 2 travelers with a relatively higher willingness to trade off higher costs for shorter travel times. Overall, the education results point in a similar direction as the income subgroup model results where the differences in education-specific time and cost sensitivity between the two models reflect apparent differences in travel behavior among the two data samples. Further, these results reinforce that the MiCounts sample, which underrepresents low-income and less-educated travelers, is limited in reflecting their travel behaviors, most clearly their sensitivity to travel cost. This motivates combining the targeted TNS data with the MiCounts data, which is examined in the next section.

4.2.2. Full Model Comparison Results

Table 9. Mode Choice Model Results

Parameter Name	Travel Needs		MiCounts		Joint	
	Utility	Estimate (t-stat)	Utility	Estimate (t-stat)	Utility	Estimate (t-stat)
Constants	Drive	–	Drive	–	Drive	–
	Carpool	-2.54 (-5.08)	Carpool	-3.46 (-21.40)	Carpool	TNS -2.33 (-5.70); MiCounts -0.132 (-3.40)
	Dial-a-ride	RP -1.72 (-8.28); SP -1.14 (-9.43)	Dial-a-ride	-5.14 (-18.00)	Dial-a-ride	TNS RP -1.68 (-8.32), SP -1.05 (-8.62); MiCounts -0.174 (-3.19)
	Bus	RP -4.32 (-9.08); SP -2.64 (-13.00)	Bus	-3.37 (-20.50)	Bus	TNS RP -3.47 (-7.60), SP -2.07 (-7.84); MiCounts -0.155 (-3.22)
	Walk	RP -4.02 (-6.57); SP -2.54 (-5.18)	Walk	-1.79 (-4.66)	Walk	TNS RP -3.31 (-6.28), SP -2.01 (-4.79); MiCounts -0.051 (-2.18)
Travel Time	All	-0.0051 (-4.27)	All	-0.0885 (-5.48)	All (shared)	-0.0037 (-3.78)
Travel Cost (generic)	All (exc. Walk)	-0.033 (-2.16)	–	–	–	–
Travel Cost (Low income)	–	–	Drive, Carpool	-0.200 (-2.36)	All (exc. Walk)	-0.032 (-2.05)
Travel Cost (Higher income)	–	–	All (exc. Walk)	-0.433 (-6.42)	All (exc. Walk)	-0.012 (-2.62)
Commute travel	–	–	Drive, Walk	1.16 (5.04)	MiCounts: Drive, Walk	0.039 (2.69)
Women	Drive, Bus, Dial-a-ride	1.10 (4.24)	Carpool, Bus, Dial-a-ride	1.39 (8.22)	TNS: Drive, Bus, Dial-a-ride; MiCounts: Carpool, Bus, Dial-a-ride	TNS 0.91 (4.19); MiCounts 0.052 (3.21)
Job seeker	Carpool, Bus	1.23 (4.52)	Carpool	0.79 (2.89)	TNS: Carpool, Bus; MiCounts: Carpool	TNS 0.83 (3.25); MiCounts 0.035 (2.07)
Low education	Carpool, Walk	1.41 (2.82)	–	–	TNS: Carpool, Walk	1.10 (2.65)
μ (nest)	–	–	Carpool, Bus	4.51 (2.97)	Walk, Bus, Dial-a-ride	1.45 (6.89)
Scale (MiCounts)	–	–	–	–	MiCounts	26.6
N	850		2916		3766	
Rho-bar-squared	0.35		0.731		0.653	
LL(0)	-1128.78		-4405.79		-5534.57	
LL(β)	-721.98		-1172.99		-1897.64	
VOT (\$/hour)	\$9.15		–		–	
Low Income VOT (\$/hour)	–		Drive, Carpool	\$26.55	\$6.92	
Higher Income VOT (\$/hour)	–		\$12.26		\$18.31	

Table 9 presents the estimation results for the full mode choice models for each of the three datasets: the Travel Needs (TNS) model, the MiCounts model (restricted to Benton Harbor adults), and the Joint model, which is estimated using both datasets. Unlike the attributes-only subgroup models, the full models include demographic and trip characteristics to examine more heterogeneity across groups, improve statistical fit, and explore how these vary across the data

samples. These models are developed to reflect the utility and nesting structures that provide the best balance of statistical fit and behavioral interpretability for each dataset. As with the subgroup models, the full models are compared using values-of-time (VOT) rather than direct comparisons of the model parameters, given that each dataset has a different scale.

The TNS model is a multinomial logit (MNL) model that follows a similar structure as the TNS subgroup models, with separate SP constants for dial-a-ride, bus and walk. The travel time and cost parameters are identified as generic across groups, and we find notable heterogeneity across gender, employment status and education level. In particular, women are more likely to drive, take the bus, or use dial-a-ride, while unemployed travelers searching for a job are more likely to carpool or take the bus. Travelers with less education are more likely to carpool or walk. The resulting parameter estimates here imply an overall VOT of \$9.15 per hour.

The MiCounts model is a nested logit model, where carpool and bus share a nest ($\mu = 4.51$). This suggests that the two modes share unobserved characteristics, such as relying on someone else to drive, and are closer substitutes for one another than for driving alone, dial-a-ride or walking. Consistent with the MiCounts subgroup models, travel cost is specified as income specific, though the low-income cost parameter is identified for the drive and carpool modes only.

The travel behaviors of MiCounts travelers vary in terms of preferences among commuters, women, and unemployed job seekers. Commuters are more likely to travel by driving and walking, women prefer carpool, bus, or dial-a-ride, and unemployed job seekers are more likely to carpool. The low-income MiCounts travelers show virtually no significant sensitivity to transit fares. As a result, the low-income VOT (\$26.55 per hour) reflects automobile travel only. Interestingly, the higher-income VOT is \$12.26 per hour. It is important to note that the low-income VOT is larger than the higher-income VOT, which runs counter to expectations; however, they are not directly comparable, given that low income VOT reflects their behavior for auto modes, whereas the higher-income VOT reflects their behavior (cost sensitivity) across all modes. This further reflects the limited ability of the MiCounts data to capture the cost sensitivity of low-income travelers.

Table 10. Likelihood Ratio Tests: Separate vs. Pooled parameters

Parameters tested	LL (separate)	LL (pooled)	LR statistic	Degrees of freedom	p-value
Women (drive, carpool, bus, dial-a-ride)	-1894.58	-1905.13	21.1	4	0.0003
Job seeker (carpool)	-1895.94	-1900.85	9.82	1	0.0017
Women and job seeker (jointly)	-1893.48	-1908.11	29.27	5	< 0.0001

Note: LL = log-likelihood. Each test compares a version of the final Joint model with dataset-specific parameters to one with the parameters pooled across the two datasets. Because the parameters for women are specified for drive, carpool, bus and dial-a-ride in both datasets in the test models, the log-likelihoods differ slightly from that of the Joint model reported in Table 9.

The Joint model combines both datasets, with a scale parameter estimated for the MiCounts data (26.6). The large MiCounts scale indicates that the MiCounts choices reflect considerably less unexplained variation than the TNS (RP and SP) choices. The Joint model

includes dataset-specific constants and demographic parameters, a jointly estimated travel time parameter, income-specific cost parameters, and a car-free nest for walk, bus and dial-a-ride ($\mu = 1.45$).

Regarding travel costs, the low-income cost parameter is identified from the TNS data only, while the higher-income cost parameter is jointly estimated across both datasets. The implied VOTs are \$6.92 per hour for low-income travelers and \$18.31 per hour for higher-income travelers. In this way, the Joint model draws on the strengths of each dataset: the TNS data identifies low-income cost sensitivity, while the larger MiCounts sample strengthens the identification of higher-income cost sensitivity.

Mode choice preferences also vary by traveler and trip characteristics. Both the TNS- and MiCounts-specific parameters for women indicate that they are more likely to use bus and dial-a-ride, and less likely to walk, relative to men. However, in the TNS women are also more likely to drive (relative to carpool and walk), and MiCounts women are more likely to carpool (relative to driving alone and walk). Job seekers (unemployed and looking for work) are more likely to carpool in both models, yet in the TNS model, job seekers also have a preference for bus. These behavioral differences for women and job seekers (for the TNS and MiCounts samples) are confirmed by using likelihood ratio tests to determine whether pooled parameters (across data samples) in the joint model offer greater explanatory power, compared to the data-specific parameters. As shown in Table 10, we reject the null hypothesis that these parameters are equal across the two datasets, indicating that the parameters for women and job seekers should be data specific.

Similar to the subgroup model results, the full model results reinforce the presence of heterogeneity in travel behavior that is data specific. The TNS and MiCounts models reflect different travel preferences, both in how travelers trade off time and cost and in how traveler characteristics describe their mode choices. The MiCounts model, despite its larger sample size and better statistical fit, is unable to represent critical behaviors for low-income travelers, such as cost sensitivity, while the TNS model, based on a sample targeting lower-income travelers, provides a more reliable estimate of low-income travel behavior. By combining the targeted TNS data with the MiCounts data, the Joint model produces parameters and VOT estimates that more clearly reflect differences across income groups, with higher-income travelers valuing travel time at roughly 2.6 times the rate of low-income travelers (\$18.31 vs. \$6.92 per hour).

4.3. Elasticities and Comparison of Model Sensitivities

Direct elasticities are useful because they reflect the percentage change in demand (the choice probability) that results from a 1% increase in an attribute (Train, 2009). In this case, we calculate elasticities of travel time and travel cost for the three models to compare the implied sensitivities across the models. The standard formula for calculating direct elasticities for multinomial logit models is given in formula (8):

$$E_{iC_{ni}} = \beta_C C_{ni} (1 - P_{ni}) \quad (8)$$

where $E_{iC_{ni}}$ is the elasticity of the probability of travel mode i with respect to cost attribute C for individual n , β_C is the utility parameter for cost and P_{ni} is the probability of travel mode i for individual n . For modes within a nest (the MiCounts and Joint models), the elasticity includes an additional term reflecting substitution within the nest (Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006):

$$E_{iC_{ni}} = \beta_C C_{ni} [(1 - P_{ni}) + (\mu - 1)(1 - P_{ni|m})] \quad (9)$$

where μ is the nest parameter and $P_{ni|m}$ is the probability of mode i given nest m (for modes outside a nest, formula (9) reduces to formula (8)). Travel time elasticities are calculated in the same way, using the travel time parameter β_T and travel time T_{ni} .

Given the differences in scale and model structure between the TNS and MiCounts models, it is necessary to adjust calculation of elasticities for consistency. Recall that each model's parameters are scaled by the variance of its unobserved utility. As a result, elasticities calculated directly from the MiCounts model are inflated relative to those of the Travel Needs model. To account for data-specific scale differences, we evaluate the model elasticities using two scale adjusted approaches: (1) within-mode elasticity ratios, and (2) standard direct elasticities rescaled, using the relative scale estimated from a joint (pooled) model (Swait & Louviere, 1993; Louviere et al., 2000). Further, because the travel cost parameters are income specific in the MiCounts and Joint models, all elasticities are summarized by income group, as the mean of the individual elasticities over the observations for which the mode is available:

$$\bar{E}_{iC} = \frac{1}{N_i} \sum_{n=1}^{N_i} E_{iC_{ni}} \quad (10)$$

where N_i is the number of observations in the income group for which mode i is available.

Travel Cost-to-Time Elasticity Ratios

The first scale-adjusted comparison (Table 11) is the ratio of the mean cost elasticity to the mean travel time elasticity for the same mode, within each model:

$$R_i = \frac{\bar{E}_{iC}}{\bar{E}_{iT}} = \frac{\sum_n \beta_C C_{ni} A_{ni}}{\sum_n \beta_T T_{ni} A_{ni}} \quad (11)$$

where $A_{ni} = (1 - P_{ni}) + (\mu - 1)(1 - P_{ni|m})$ is the probability term shared by the cost and time elasticities (with $\mu = 1$ for the Travel Needs model and for modes outside a nest). Since the scale enters the numerator and denominator in the same way, it cancels out, and the ratio can be calculated from each model's estimated parameters. For an individual trip, the ratio reduces to

$$\frac{\beta_C C_{ni}}{\beta_T T_{ni}} = \frac{C_{ni}}{VOT \times T_{ni}} \quad (12)$$

where $VOT = \beta_T / \beta_C$ is the value of time (in dollars per minute when travel time is measured in minutes). The ratio is therefore the money cost of the trip divided by the dollar value of its travel time.

Table 11. Ratio of cost elasticity to travel time elasticity, by mode

Model	Income group	Drive	Carpool	Bus	Dial-a-ride
Travel Needs	All	2.65	0.60	0.29	0.59
	Low income (<\$45k)	2.67	0.60	0.29	0.60
	Higher income (\$45k+)	2.43	0.60	0.26	0.52
MiCounts	All	0.62	0.20	0.09	0.12
	Low income (<\$50k)	0.51	0.20	—	—
	Higher income (\$50k–\$100k)	1.11	0.44	0.27	0.39
	\$100k+ or missing	—	—	—	—
Joint: TNS	Low income (<\$45k)	3.54	0.79	0.39	0.81
	Higher income (\$45k+)	1.22	0.30	0.13	0.27
Joint: MiCounts	Low income (<\$50k)	—	—	—	—
	Higher income (\$50k–\$100k)	0.74	0.30	0.20	0.26
	\$100k+ or missing	—	—	—	—

Notes: Walk has no cost. “—” indicates that the group has no cost parameter for that mode: the MiCounts low-income cost parameter applies to drive and carpool only, there is no cost parameter for MiCounts households earning \$100,000 or more, and in the Joint model, the low-income cost parameter is identified from the TNS data only.

A ratio of 1 indicates that the money cost and the monetized travel time carry equal weight in the trip’s generalized cost, while a ratio above 1 indicates that cost dominates, so that a 10% increase in cost reduces the mode’s demand more than a 10% increase in travel time. A ratio below 1 indicates that travel time dominates.

The cost-to-time ratios in Table 11 show that TNS travelers respond more strongly to travel costs relative to travel times than MiCounts travelers, for every mode. For example, the Travel Needs ratio for driving is 2.65, compared with 0.62 for MiCounts travelers (1.11 for the MiCounts higher-income group), and the Travel Needs ratios for bus (0.29) and dial-a-ride (0.59) are roughly two to five times those of the MiCounts model. In the Joint model, the ratios for TNS low-income travelers (0.39 to 3.54) are about three times those of higher-income travelers in either dataset, consistent with the lower values of time for low-income travelers.

Scale-Adjusted Elasticities

The second scale-adjusted comparison (Table 12) calculates the MiCounts elasticities with all MiCounts utility parameters divided by the relative MiCounts scale estimated in the Joint model ($\lambda = 26.6$), so that the MiCounts and Travel Needs elasticities reflect the same amount of unexplained variation:

$$\tilde{E}_{iC_{ni}} = \frac{\beta_C}{\lambda} C_{ni} [(1 - \tilde{P}_{ni}) + (\mu - 1)(1 - \tilde{P}_{ni|m})] \quad (13)$$

where $\tilde{P}_{ni}$ and $\tilde{P}_{ni|m}$ are the choice probabilities calculated with the rescaled utilities (V_{ni}/λ), and μ is unchanged. For the Joint model, the MiCounts observations are calculated with the Joint model parameters without the MiCounts scale (λ is set to 1), which places them on the TNS scale. The TNS and Joint (TNS) elasticities are calculated with formulas (8) and (9), since they

are already on the TNS scale. The scale-adjusted elasticities are then averaged by income group using formula (10).

Table 12. Scale-normalized elasticities (MiCounts parameters on the TNS scale)

Model	Income group	N	Time: Drive	Time: Carpool	Time: Bus	Time: Dial-a- ride	Time: Walk	Cost: Drive	Cost: Carpool	Cost: Bus	Cost: Dial-a- ride
Travel Needs	All	850	-0.024	-0.047	-0.136	-0.118	-1.031	-0.065	-0.028	-0.039	-0.069
	Low income (<\$45k)	758	-0.024	-0.045	-0.134	-0.117	-1.021	-0.065	-0.027	-0.039	-0.070
	Higher income (\$45k+)	67	-0.026	-0.064	-0.157	-0.132	-1.063	-0.064	-0.038	-0.040	-0.069
MiCounts	All	2,916	-0.017	-0.059	-0.128	-0.050	-0.159	-0.009	-0.012	-0.011	-0.006
	Low income (<\$50k)	1,105	-0.016	-0.051	-0.116	-0.043	-0.145	-0.008	-0.010	–	–
	Higher income (\$50k– \$100k)	836	-0.019	-0.064	-0.138	-0.055	-0.171	-0.021	-0.029	-0.038	-0.022
	\$100k+ or missing	975	-0.018	-0.062	-0.132	-0.053	-0.165	–	–	–	–
Joint: TNS	Low income (<\$45k)	758	-0.018	-0.033	-0.136	-0.099	-1.055	-0.063	-0.026	-0.052	-0.080
	Higher income (\$45k+)	67	-0.017	-0.048	-0.160	-0.113	-1.105	-0.021	-0.014	-0.020	-0.030
Joint: MiCounts	Low income (<\$50k)	1,105	-0.018	-0.017	-0.052	-0.068	-0.237	–	–	–	–
	Higher income (\$50k– \$100k)	836	-0.021	-0.022	-0.061	-0.088	-0.280	-0.016	-0.006	-0.011	-0.023
	\$100k+ or missing	975	-0.020	-0.021	-0.058	-0.086	-0.269	–	–	–	–

Note: Mean of individual elasticities over observations for which the mode is available, formulas (10) and (13). MiCounts elasticities are calculated with the MiCounts utility parameters divided by the MiCounts scale estimated in the Joint model (26.6); Joint (MiCounts) elasticities are calculated without the MiCounts scale. Travel Needs and Joint (TNS) elasticities are unadjusted, since they are on the TNS scale. Walk has no cost. The Travel Needs model has a single (generic) cost parameter; its income groups exclude 25 observations with missing income. “–” indicates that the group has no cost parameter for that mode (see Table 11 note).

Regarding the scale-adjusted travel time elasticities (Table 12), all three models exhibit higher sensitivity to walk and transit travel times, relative to auto modes (drive and carpool), which is expected (Wardman, 2004). While the MiCounts time elasticities are similar to the Travel Needs elasticities for drive, carpool and bus (-0.13 vs. -0.14 for bus), the elasticities are considerably smaller for dial-a-ride (-0.05 vs. -0.12) and walk (-0.16 vs. -1.03), relative to the TNS model. These patterns are similar for low- and higher-income travelers within each model. The Joint model produces time elasticities for the TNS sample that are close to those of the Travel Needs model, while the elasticities for the MiCounts sample are smaller than those for the TNS sample for every mode except driving, particularly for walking (-0.24 to -0.28 vs. -1.06 to -1.11).

Regarding travel cost elasticities, the Travel Needs travelers are relatively more elastic to increases in drive and dial-a-ride costs, relative to carpool and bus. While the elasticities are small (for example, a 1% increase in the bus fare would decrease the bus choice probability of Travel Needs travelers by only about 0.04%), the MiCounts cost elasticities are considerably smaller. Low-income travelers in the MiCounts sample are approximately 8 times less elastic to drive costs, while higher-income MiCounts travelers are 3 times less elastic, compared to TNS travelers. Cost elasticities for bus and dial-a-ride are not available, given that no significant low-income transit cost parameter was identified in the MiCounts model. In the Joint model, TNS low-income travelers have cost elasticities comparable to the Travel Needs model (-0.03 to -0.08), and roughly three times larger than those of TNS higher-income travelers (-0.01 to -0.03) and MiCounts higher-income travelers (-0.006 to -0.023). It is important to note, however, that the Joint model does not identify a cost parameter for MiCounts low-income travelers, given that the low-income cost parameter is identified from the TNS data only.

Summary of Results on Elasticities

Overall, the scale-adjusted elasticity comparisons suggest that TNS travelers are at least as sensitive to travel time, and more sensitive to travel cost, than MiCounts travelers. This implies that the MiCounts model alone would not capture low-income and transit sensitivities well. In absence of jointly estimating with TNS data, travel models based on standard data collection practices (like the MiCounts data) may understate how strongly travelers, and low-income travelers in particular, respond to transportation changes.

5. Implications for representativeness of vulnerable travelers in Mode Choice Models

This study integrated two complementary efforts: (1) the collection of a targeted travel survey designed to capture the behaviors of vulnerable travelers who are less likely to participate in conventional household travel surveys, and (2) the assessment of the technical benefits of jointly estimating travel demand models using multiple datasets, to enrich the representation of travel behaviors across subgroups. Together, these efforts were motivated by the goal of extending the capacity of travel demand models to support meaningful equity analyses of regional transportation plans.

The Travel Needs survey conducted in Benton Harbor, although a small sample, provided valuable insights into the travel behaviors of vulnerable populations. The mixed-methods data collection approach resulted in a final sample of 122 respondents and 850 revealed- and stated-preference mode choices (239 reported trips and 611 stated-preference choice tasks), with much higher shares of low-income households, zero-vehicle households, and individuals with high school or technical certification education levels, compared to the adult Benton Harbor

respondents of MDOT's 2015 MiCounts survey. Importantly, comparisons of mode shares between the two surveys suggest that the travel behaviors of groups often missing from conventional surveys can differ significantly from those of similar groups that are recorded in such surveys. Even among low-income MiCounts respondents, nearly 80% of trips were made by driving alone and 3% by dial-a-ride, compared with 53% and 21% of the trips reported by Travel Needs respondents. This raises important concerns about the adequacy of conventional data collection methods for informing transportation equity outcomes.

To evaluate these issues in practice, we estimated a series of mode choice models using (1) the Travel Needs survey (2017–2019), (2) the MiCounts survey (2015), and (3) a joint model estimated from both datasets. This approach reflects a rare demonstration of the core–satellite data fusion framework for multi-sample model estimation (Goulias et al., 2013; Li et al., 2025). We compared the results of these models with respect to heterogeneity across income-based and education-based subgroups, as well as for the full models that include a range of traveler and trip characteristics. The results highlight clear differences in mode choice preferences. The MiCounts data could not identify a significant cost sensitivity for low-income travelers in either the subgroup or the full models, and the resulting low-income value of time in the full MiCounts model (\$26.55/hour, for auto modes only) was larger than the higher-income value of time (\$12.26/hour). In contrast, the Travel Needs model, based on a sample targeting lower-income travelers, identified a significant cost sensitivity, with a value of time of \$9.15/hour. By combining the two datasets, the Joint model identified low-income cost sensitivity from the Travel Needs data and higher-income cost sensitivity from both datasets, resulting in values of time of \$6.92/hour for low-income travelers and \$18.31/hour for higher-income travelers. Likelihood ratio tests also rejected pooling the low-income cost, women, and job seeker parameters across the two datasets, indicating that the preferences of these groups differ significantly across the two samples. The nesting structures also varied, with carpool and bus sharing a nest in the MiCounts model and walk, bus and dial-a-ride forming a car-free nest in the Joint model, suggesting that certain modes play distinctly different roles across traveler groups.

An analysis of the model elasticities further showed that, in the absence of the targeted sample of Travel Needs respondents, a model estimated on the MiCounts survey alone may understate travelers' responses to transportation changes. Once differences in scale are taken into account, Travel Needs respondents weigh travel costs more heavily relative to travel times than MiCounts respondents for every mode and are more sensitive to travel costs and to dial-a-ride and walk travel times. Moreover, the MiCounts model provides no estimate of how low-income travelers respond to transit and dial-a-ride fares. These findings suggest that the underrepresentation of vulnerable travelers in survey data can produce models that mischaracterize behavioral responses, potentially constraining or skewing equity assessments of transportation plans and misguiding investment decisions.

While further research is needed to assess the broader policy implications of travel demand models with improved representation of vulnerable communities, this study underscores the value of targeted data collection and data fusion methods for advancing equity-focused transportation planning. Building models on datasets that more accurately reflect the travel behaviors of vulnerable populations offers the potential to produce more reliable forecasts and estimates of equity-related transportation outcomes.

5.1.Implications for Equity Analysis and Planning Practice

The results from this study imply critical ramifications for equity analysis. This is because the measures of transportation equity outcomes often rely on transportation attributes such as travel times and costs. Further, utility-based accessibility and consumer surplus measures are computed from similar choice utilities and parameters as estimated in this study (Bills & Walker, 2017; Bills, 2024). Models that underrepresent vulnerable travelers and understate their cost and time sensitivities may conclude that a fare change has negligible equity impacts, when it would in fact impose a meaningful burden on the travelers, which equity analyses are intended to detect. Similar concerns apply to the evaluation of transit service changes and to accessibility and consumer surplus (logsum) measures, which inherit any misrepresentation of the time and cost sensitivities of vulnerable travelers from the models used to calculate them. Importantly, decisions may be wrongly guided to make transportation changes inconsistent with critical transportation needs – or worse – invest in transportation projects that cause more harm to already vulnerable communities.

For this reason, it is recommended that transportation agencies consider the use of data collection techniques that specifically target the collection of underrepresented subgroups, as a supplemental data source. The approach can be integrated into regional modeling practice with modest changes to existing workflows. As agencies periodically conduct household travel surveys to update their models, a targeted satellite survey can be fielded alongside the core survey, focusing on groups found to be underrepresented when the core survey is compared with census benchmarks (as in Tables 4 and 5).

5.2.Limitations and Future Research

Several limitations of this work should be noted. First, while the Travel Needs Survey offers important information on the travel behaviors of underrepresented subgroups, it is certainly desirable to have a larger sample size, as smaller samples can limit the precision of model estimates and the number of subgroup effects that can be identified. In this case, the 122 respondents to the Travel Needs survey and their combined 850 RP and SP choices were adequate for estimating the main time, cost and demographic effects that were targeted in the sample. Yet, the sample size is admittedly too small for further subgroup segmentation or offering precise population estimates on its own. Second, most of the Travel Needs observations are stated preference choices, which may be subject to a degree of hypothetical bias, although they are anchored to revealed choices through SP-specific constants. Third, the level-of-service attributes of revealed preference trips were constructed from trip distances and average mode speeds and costs rather than from network skims, which can introduce a degree of measurement error, making the time and cost attributes less precise. Fourth, the MiCounts survey does not include race or ethnicity, preventing comparisons along this important dimension that is often a focus of transportation equity analyses in the United States. Finally, Benton Harbor is a small city with a distinctive socioeconomic profile and transit system, and the magnitude of the differences found here may not generalize to other regions. However, the underlying mechanism, in which conventional surveys under-sample the travelers who face the greatest mobility constraints, has been documented across many U.S. household travel surveys (Lubitow et al., 2021; Esekhaigbe et al., 2026), suggesting that the approach is expected to have relevance elsewhere. Future research should test the approach in larger regions and with larger satellite samples, examine how satellite samples can best be designed and integrated with core survey

samples, and evaluate how improved representation changes the equity conclusions drawn from complete travel demand model systems.

6. Acknowledgements

This work could not have been possible without the direct efforts of students, community partners, local transportation agencies, and the broader Benton Harbor community. The author would like to recognize and thank Tian Tian, a former graduate student at the University of Michigan, who was instrumental in the collection and curation of the Travel Needs survey dataset. Special thanks to Chris LeFlore, a former student at the University of Michigan, and Dr. Eronmonsele Esekhaigbe, a former PhD student at Wayne State University, for their support with community engagement and data collection. Gratitude is also extended to Vahid Bahrami, a former graduate student at Wayne State University, for his work on the development of the initial Travel Needs and MiCounts models, and to Kailong Ji, a PhD student at UCLA, for his contributions to processing and analyzing the Travel Needs and MiCounts surveys.

The author also thanks the dedicated staff of the Twin Cities Area Transportation Authority (TCATA), including Alex Little and Ellis Mitchell, and the team at Kinexus, including Ryan Thyfault, in Benton Harbor, Michigan, for their critical work and support in recruiting Travel Needs participants and facilitating community engagement. Finally, sincere thanks go to the residents of Benton Harbor for their support and willing participation. Thank you.

Finally, this material is based upon work supported by the National Science Foundation under Award No. 1831347.

7. References

- American Public Transportation Association (APTA). (2019). 2019 public transportation fact book. Washington, DC.
- Beauregard, R. A. (2009). Urban population loss in historical perspective: United States, 1820–2000. *Environment and Planning A*, 41(3), 514–528.
- Beimborn, E. (2006). A transportation modeling primer. Center for Urban Transportation Studies, University of Wisconsin–Milwaukee.
- Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., & Rao, V. (1994). Combining revealed and stated preferences data. *Marketing Letters*, 5(4), 335–349.
- Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.
- Bhat, C. R. (1997). An endogenous segmentation mode choice model with an application to intercity travel. *Transportation Science*, 31(1), 34–48.
- Bierlaire, M. (2023). A short introduction to Biogeme. Technical report TRANSP-OR 230620. Transport and Mobility Laboratory, ENAC, EPFL.
- Bills, T. S., & Walker, J. L. (2017). Looking beyond the mean for equity analysis: Examining distributional impacts of transportation improvements. *Transport Policy*, 54, 61–69.
- Bills, T. S. (2024). Advancing the practice of regional transportation equity analysis: a San Francisco bay area case study. *Transportation*, 51(3), 911–936.
<https://doi.org/10.1007/s11116-022-10355-z>

- Bills, T. S., Sall, E. A., & Walker, J. L. (2012). Activity-based travel models and transportation equity analysis: Research directions and exploration of model performance. *Transportation Research Record*, 2320(1), 18–27.
- Bills, T. S., Twumasi-Boakye, R., Broaddus, A., & Fishelson, J. (2022). Towards transit equity in Detroit: An assessment of microtransit and its impact on employment accessibility. *Transportation Research Part D: Transport and Environment*, 109, 103341.
- Bowman, J. L., & Ben-Akiva, M. E. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, 35(1), 1–28.
- Cabello, M., Hyland, M., & Marantz, N. (2025). From state of the practice to state of the art: Improving equity analysis in regional transportation plans. *Transportation*, 52(3), 791–826. <https://doi.org/10.1007/s11116-023-10439-4>
- Castiglione, J., Bradley, M., & Gliebe, J. (2015). Activity-based travel demand models: A primer (SHRP 2 Report S2-C46-RR-1). Transportation Research Board.
- Castiglione, J., Hiatt, R., Chang, T., & Charlton, B. (2006). Application of travel demand microsimulation model for equity analysis. *Transportation Research Record*, 1977, 35–42.
- Chen, Z., & Li, X. (2021). Unobserved heterogeneity in transportation equity analysis: Evidence from a bike-sharing system in southern Tampa. *Journal of Transport Geography*, 91, 102956. <https://doi.org/10.1016/j.jtrangeo.2021.102956>
- Deakin, E., & Harvey, G. (1996). *Transportation pricing strategies for California: An assessment of congestion, emissions, energy and equity impacts* (Final report, Contract 92-316). California Air Resources Board.
- Deschaintres, E., Morency, C., & Trépanier, M. (2024). Combining a regional household survey and passive data streams for longitudinal monitoring purposes. *Transportation Research Procedia*, 76, 397-408.
- Di Ciommo, F., & Shifan, Y. (2017). Transport equity analysis. *Transport Reviews*, 37(2), 139-151.
- Duthie, J., Cervenka, K., & Waller, S. T. (2007). Environmental justice analysis: Challenges for metropolitan transportation planning. *Transportation Research Record*, 2013(1), 8–12.
- Esekhagbe, E., Bills, T. S., & Broaddus, A. (2026). Group representation of vulnerable travelers in household travel surveys: An assessment of 43 U.S. surveys. *Transportation*. <https://doi.org/10.1007/s11116-026-10795-x>
- Executive Order 12898. (1994). Federal actions to address environmental justice in minority populations and low-income populations. *Federal Register*, 59(32), 7629–7633.
- Executive Order 13985. (2021). Advancing racial equity and support for underserved communities through the federal government. *Federal Register*, 86(14), 7009–7013.
- Executive Order 14148. (2025). Initial rescissions of harmful executive orders and actions. *Federal Register*, 90.
- Executive Order 14173. (2025). Ending illegal discrimination and restoring merit-based opportunity. *Federal Register*, 90.
- Federal Transit Administration (FTA). (2019). National Transit Database 2019 annual agency profile: Twin Cities Area Transportation Authority (NTD ID 50132). U.S. Department of Transportation.

- Federal Transit Administration (FTA). (2021). *National Transit Database 2021 annual agency profile: Twin Cities Area Transportation Authority (NTD ID 50132)*. U.S. Department of Transportation.
- Fitzpatrick, K., Brewer, M. A., & Turner, S. (2006). Another look at pedestrian walking speed. *Transportation Research Record*, 1982(1), 21–29.
- Gaker, D., & Walker, J. L. (2013). Revealing the value of “green” and the small group with a big heart in transportation mode choice. *Sustainability*, 5(7), 2913–2927.
- Goodspeed, R., Yuan, M., Krusniak, A., & Bills, T. (2021). Assessing the value of new big data sources for transportation planning: Benton Harbor, Michigan case study. In S. Geertman, C. Pettit, R. Goodspeed, & A. Staffans (Eds.), *Urban informatics and future cities* (pp. 127–150). Springer. https://doi.org/10.1007/978-3-030-76059-5_8
- Goulias, K. G., Pendyala, R. M., & Bhat, C. R. (2013). Keynote—Total design data needs for the new generation large-scale activity microsimulation models. In J. Zmud, M. Lee-Gosselin, M. Munizaga, & J. A. Carrasco (Eds.), *Transport survey methods: Best practice for decision making* (pp. 21–46). Emerald Group Publishing. <https://doi.org/10.1108/9781781902882-002>
- Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, 37(8), 681–698.
- Hensher, D. A., & Bradley, M. (1993). Using stated response choice data to enrich revealed preference discrete choice models. *Marketing Letters*, 4(2), 139–151.
- Hensher, D. A., & Greene, W. H. (2002). Specification and estimation of the nested logit model: alternative normalisations. *Transportation Research Part B: Methodological*, 36(1), 1–17.
- Hensher, D. A., Rose, J. M., & Greene, W. H. (2008). Combining RP and SP data: biases in using the nested logit ‘trick’—contrasts with flexible mixed logit incorporating panel and scale effects. *Journal of Transport Geography*, 16(2), 126–133.
- Hensher, D., Louviere, J., & Swait, J. (1998). Combining sources of preference data. *Journal of Econometrics*, 89(1–2), 197–221.
- Herald-Palladium. (2025, May 29). Benton Harbor Dial-A-Ride raises its fares. *The Herald-Palladium*. https://www.heraldpalladium.com/communities/benton_harbor/benton-harbor-dial-a-ride-raises-its-fares/article_f2498870-2c01-5b27-a938-00503154ca6c.html
- Himelein, K. (2014). Weight Calculations for Panel Surveys with Subsampling and Split-off Tracking. *Statistics and Public Policy*, 1(1), 40–45.
- Internal Revenue Service (IRS). (2017). Notice 2018-03: 2018 standard mileage rates. U.S. Department of the Treasury.
- Johnston, R. A., Rodier, C., Abraham, J., & Hunt, J. (2001). Applying an integrated model to the evaluation of travel demand management policies in the Sacramento region: Year two (Report 01-08). Mineta Transportation Institute, San Jose, CA.
- Karner, A., & Niemeier, D. (2013). Civil rights guidance and equity analysis methods for regional transportation plans: A critical review of literature and practice. *Journal of Transport Geography*, 33, 126–134.
- Karner, A., Bills, T., & Golub, A. (2023). Emerging perspectives on transportation justice. *Transportation research part D: transport and environment*, 116, 103618.

- Klein, N. J. (2007). Spatial methodology for assessing distribution of transportation project impacts with environmental justice framework. *Transportation Research Record*, 2013(1), 46–53.
- Koppelman, F. S., & Bhat, C. (2006). A self instructing course in mode choice modeling: Multinomial and nested logit models. U.S. Department of Transportation, Federal Transit Administration.
- Koppelman, F. S., & Wen, C. H. (1998). Alternative nested logit models: structure, properties and estimation. *Transportation Research Part B: Methodological*, 32(5), 289-298.
- Lawson, C. T., Krans, E., Rentz, E. G., & Lynch, J. (2023). Emerging trends in household travel survey programs. *Social Sciences & Humanities Open*, 7(1), 100466.
- Li, M., Wang, K., & Nurul Habib, K. (2025). Investigating recall & proxy bias in household travel surveys under the core-satellite fusion paradigm. *Transportation*.
<https://doi.org/10.1007/s11116-025-10654-1>
- Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). Stated choice methods: Analysis and applications. Cambridge University Press.
- Lubitow, A., Liévanos, R. S., Carpenter, E., & McGee, J. A. (2021). Transformative transportation survey methods: Enhancing household transportation survey methods for hard-to-reach populations. *Transportation Research Part D: Transport and Environment*, 98, 102953.
- Lucas, K., Martens, K., Di Ciommo, F., & Dupont-Kieffer, A. (Eds.). (2019). Measuring transport equity. Elsevier.
- McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5), 447–470.
- McGuckin, N., & Fucci, A. (2018). *Summary of travel trends: 2017 National Household Travel Survey* (Report No. FHWA-PL-18-019). U.S. Department of Transportation, Federal Highway Administration.
https://nhts.ornl.gov/assets/2017_nhts_summary_travel_trends.pdf
- McNally, M. G. (2007). The four-step model. In D. A. Hensher & K. J. Button (Eds.), *Handbook of transport modelling* (2nd ed., pp. 35–53). Elsevier.
- Metropolitan Transportation Commission, & Association of Bay Area Governments (MTC & ABAG). (2026). Final Plan Bay Area 2050+ equity analysis report.
https://planbayarea.org/sites/default/files/documents/2026-04/Final_Plan_Bay_Area_2050_Plus_Equity_Analysis_Report.pdf
- Metropolitan Transportation Commission (MTC). (2001). *The 2001 regional transportation plan: Equity analysis and environmental justice report*. Metropolitan Transportation Commission, Oakland, CA.
- Metropolitan Transportation Commission (MTC). (2013). Plan Bay Area: Equity analysis report. Metropolitan Transportation Commission, Oakland, CA.
- Miami Valley Regional Planning Commission (MVRPC). (2026). 2050 long-range transportation plan.
https://www.mvrpc.org/sites/default/files/lrtp2026_report_final_compressed_1.pdf
- Michigan Department of Transportation (MDOT). (2016). *MI Travel Counts III household travel survey: Final methodology report* (prepared by Westat).
https://www.michigan.gov/documents/mdot/MTC_III_Methodology_Report_554340_7.pdf

- Miller, E. J., Srikukenthiran, S., & Chung, B. (2018). Workshop Synthesis: Household travel surveys in an era of evolving data needs for passenger travel demand. *Transportation Research Procedia*, 32, 374-382.
- Mills, G. S., & Neuhauser, K. S. (2000). Quantitative methods for environmental justice assessment of transportation. *Risk Analysis*, 20(3), 377-384.
- Mishra, S., Welch, T. F., & Chakraborty, A. (2014). Experiment in megaregional road pricing using advanced commuter behavior analysis. *Journal of Urban Planning and Development*, 140(1), 04013007.
- Nahmias-Biran, B. H., & Shiftan, Y. (2020). Using activity-based models and the capability approach to evaluate equity considerations in transportation projects. *Transportation*, 47(5), 2287-2305.
- National Academies of Sciences, Engineering, and Medicine (NASEM). (2004). *Effective methods for environmental justice assessment*. The National Academies Press.
- National Academies of Sciences, Engineering, and Medicine (NASEM). (2024). *Elevating equity in transportation decision making: Recommendations for federal competitive grant programs* (TRB Special Report 348). The National Academies Press. <https://doi.org/10.17226/27439>
- National Academies of Sciences, Engineering, and Medicine (NASEM). (2025). *An assessment of data, tools, and metrics for equity in decisions about surface transportation investments*. The National Academies Press.
- Newman, J. P., Lurkin, V., & Garrow, L. A. (2018). Computational methods for estimating multinomial, nested, and cross-nested logit models that account for semi-aggregate data. *Journal of choice modelling*, 26, 28-40.
- Ortúzar, J. de D. (1983). Nested logit models for mixed-mode travel in urban corridors. *Transportation Research Part A: General*, 17(4), 283-299.
- Ortúzar, J. de D., & Willumsen, L. G. (2011). *Modelling transport* (4th ed.). John Wiley & Sons.
- Pereira, R. H. M., Schwanen, T., & Banister, D. (2017). Distributive justice and equity in transportation. *Transport Reviews*, 37(2), 170-191.
- Qualtrics. (2017). *Qualtrics* [Computer software]. Qualtrics. <https://www.qualtrics.com>
- Rezaei, N., Todd-Blick, A., Fujita, K. S., Popovich, N., Needell, Z., Poliziani, C., ... & Spurlock, C. A. (2024). At the nexus of equity and transportation modeling: Assessing accessibility through the Individual Experienced Utility-Based Synthesis (INEXUS) metric. *Journal of Transport Geography*, 115, 103824.
- Rodier, C. J., Abraham, J. E., Dix, B. N., & Hunt, J. D. (2009). *Equity analysis of land use and transport plans using an integrated spatial model*. Institute of Transportation Studies, University of California, Davis.
- Sall, E., Bent, E., Koehler, J., Charlton, B., & Erhardt, G. D. (2010). *Evaluating regional pricing strategies in San Francisco: Application of the SFCTA activity-based regional pricing model*. Paper presented at the 89th Annual Meeting of the Transportation Research Board, Washington, DC.
- Sharp, J., & Murakami, E. (2004). *Travel survey methods and technologies resource paper*. Paper presented at the 7th International Conference on Travel Survey Methods, Playa Herradura, Costa Rica.
- Swait, J., & Louviere, J. (1993). The role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of Marketing Research*, 30(3), 305-314.

- Swait, J., Louviere, J., & Williams, M. (1994). A sequential approach to exploiting the combined strengths of SP and RP data: Application to freight shipper choice. *Transportation*, 21(2), 135–152.
- Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.
- Twin Cities Area Transportation Authority (TCATA). (2020). *TCATA fixed route schedule and fares* [Rider brochure, February 2020].
https://www.mywaythere.org/downloads/2_2020_tcata_routes.pdf
- Twin Cities Area Transportation Authority (TCATA). (2025). *Fare increase notice* [Public notice, May 28, 2025].
https://www.mywaythere.org/downloads/fare_increase_notice_52825.pdf
- U.S. Census Bureau. (2016). 2011–2015 American Community Survey 5-year estimates, Tables B08301 and DP03. U.S. Department of Commerce.
- U.S. Census Bureau. (2026). 2020–2024 American Community Survey 5-year estimates, Data Profiles DP03 and DP04: Benton Harbor city and Michigan. U.S. Department of Commerce.
- U.S. Department of Transportation (USDOT). (2000). *Transportation and environmental justice case studies* (Report No. FHWA-EP-01-010). Federal Highway Administration and Federal Transit Administration.
- van Wee, B., & Mouter, N. (2021). Evaluating transport equity. In N. Mouter (Ed.), *New methods, reflections and application domains in transport appraisal* (Advances in Transport Policy and Planning, Vol. 7). Academic Press.
- Verreault, H., & Morency, C. (2018). Integration of a phone-based household travel survey and a web-based student travel survey. *Transportation*, 45(1), 89–103.
- Waddell, P. (2002). UrbanSim: Modeling urban development for land use, transportation, and environmental planning. *Journal of the American Planning Association*, 68(3), 297–314.
- Wang, K., Hossain, S., & Habib, K. N. (2022). A hybrid data fusion methodology for household travel surveys to reduce proxy biases and under-representation of specific sub-group of population. *Transportation*, 49(6), 1801–1836.
- Wardman, M. (2004). Public transport values of time. *Transport Policy*, 11(4), 363–377.
- Williams, K., & Golub, A. (2017). Evaluating the distributional effects of regional transportation plans and projects (NITC-RR-862). Transportation Research and Education Center, Portland State University.