Improving Destination Choice for Work Trips in Travel Demand Modeling

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Full Name	Student ID
Yasaman Eslamijadidi	2219867

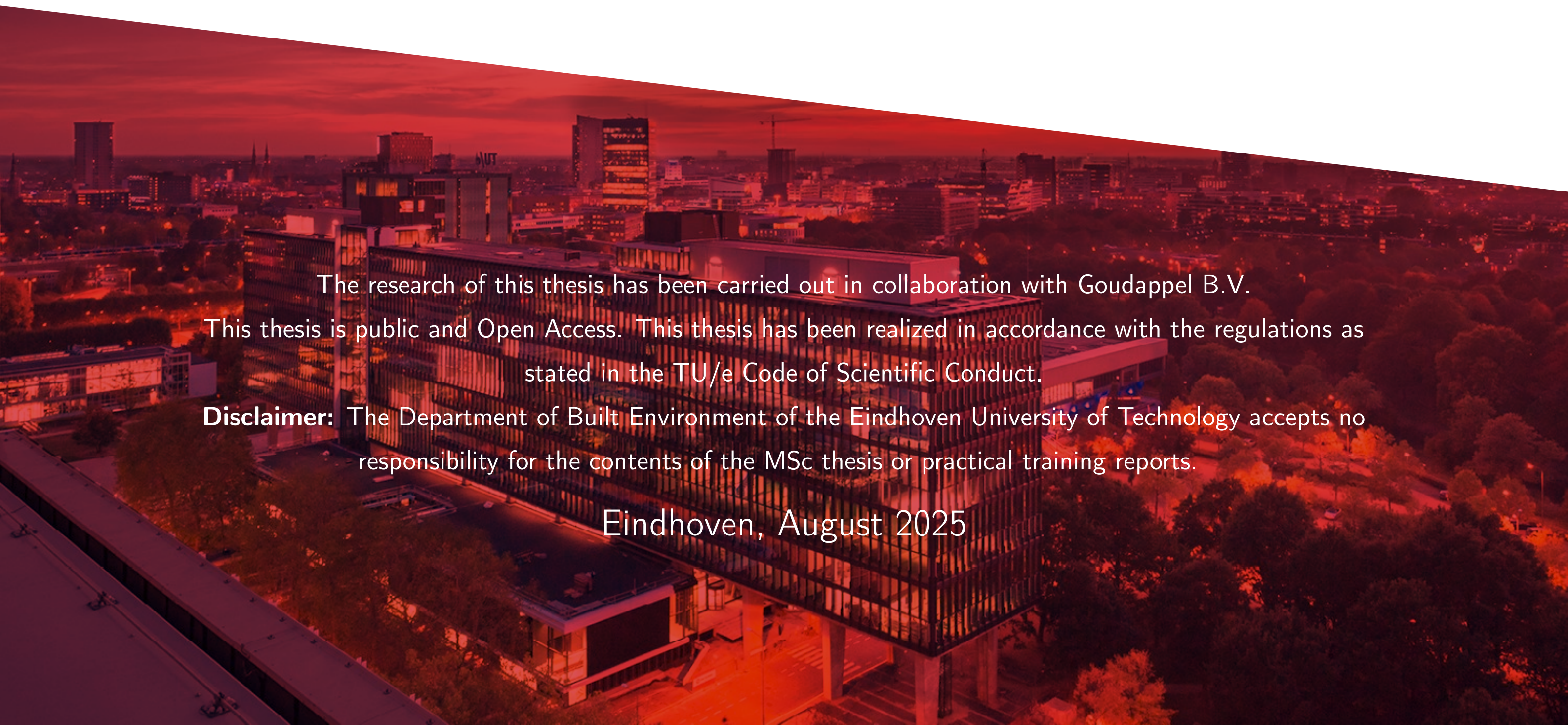
Supervisors

Prof. Dr. Soora Rasouli

Dr. Valeria Caiati

Tanja Hardt

Dr. Johan Los



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Preface

This thesis is the result of my efforts to improve destination choice modeling for work trips within Octavius, a modeling framework developed by Goudappel, a consultancy in the Netherlands. The work tackles real-world challenges that arise in practical transport projects, challenges that often reveal the need for more structural and sometimes even radical reforms. Understanding the root of these problems and identifying where to apply more strategic approaches has been central to this research.

First, I would like to sincerely thank my supervisors. I thank Dr. Soora Rasouli, whose ability to quickly grasp complex concepts has been invaluable, especially during theoretical and technical challenges. I also thank Dr. Valeria Caiati, whose experience with travel demand models guided me at crucial moments and helped me stay on the right path.

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Lastly, I am deeply grateful to my parents, who supported my decision to study abroad and never doubted my ability to do it. I also thank my close friends and my boyfriend for being there through difficult times, giving me strength and encouragement when I needed it most.

Working on this project has been both challenging and rewarding. Every obstacle brought doubts, but ultimately taught me to trust the process and grow through it.

Executive Summary

This report investigates how destination choice models for car-based work trips, the main commuting mode for work trips in the Netherlands, can be improved through refined variable specification and effective data integration strategies. This study aims to increase predictive accuracy while preserving operational feasibility within large-scale transportation planning systems. The research addresses a critical limitation of existing destination choice models, which rely predominantly on aggregate employment size and basic socio-demographic variables. This reliance overgeneralizes employment attractiveness, risks mispredicting commuting flows, and overlooks sector-specific job opportunities and behavioral heterogeneity that fundamentally influence workplace destination choices.

The study used Dutch national survey data (LRO) at the PC4 postal code level to develop and estimate two multinomial logit (MNL) model specifications using a comparative modeling framework. The base model incorporates standard variables such as total employment count per PC4, travel time, basic demographic interactions with travel time, and closely mimics the current operational framework. The enhanced model expands this specification by integrating sector-specific job share variables, individual characteristics such as work flexibility and household composition, and allowing the model to freely estimate the effect of total jobs. In addition, the enhanced model applies a more advanced approach to choice set formation, further improving its behavioral realism. Both models were estimated using maximum likelihood estimation, with comprehensive validation through in-sample and out-of-sample testing procedures.

Key findings indicate that the enhanced model achieves substantial performance improvements across multiple evaluation criteria: a **24.3%** improvement in the rho-squared goodness-of-fit criterion (from 0.247 to 0.307) compared to the base model, with Top-1 predictive accuracy increasing from 7.4% to 10.8% in-sample (a **45%** relative improvement) and from 7.3% to 9.2% out-of-sample (a **26%** relative improvement). Sector-specific variables reveal significant behavioral heterogeneity, with people working in education showing the strongest sensitivity to sectoral job concentrations, while travel time interactions demonstrate that workers with the option of working remotely show greater tolerance for longer commutes, and workers with children prioritize shorter travel distances. Additionally, the enhanced model better captures the empirical travel data by generating more realistic spatial distributions of probabilities assigned to destination choices.

In conclusion, these findings show that by carefully integrating sector-specific employment variables and demographic heterogeneity indicators, destination choice models can achieve significant behavioral realism and improvements in predictive accuracy while retaining computational viability for operational implementation. The results confirm the importance of matching worker characteristics with spatial job opportunities in destination choice modeling, challenging con-

ventional practices that rely only on aggregate employment counts and revealing the potential for enhanced behavioral representation within existing transportation planning frameworks.

Based on these conclusions, it is recommended that transportation planning agencies, better to consider incorporating sector-specific employment data and behavioral heterogeneity indicators into the destination choice models, while recognizing that the most substantial future improvements may require implementing more strategic refinements, such as using nested logit structures to relax restrictive substitution assumptions and exploring mixed logit formulations to capture unobserved heterogeneity. Practically, these results suggest opportunities for improving existing operational models through targeted variable additions, while future efforts can also focus on implementing employment capacity-constrained formulations and developing hybrid data-driven approaches that combine discrete choice foundations with machine learning components to better support transportation planning and policy evaluation.

1 Introduction

1.1 Background and Motivation

The Netherlands faces significant challenges in transportation planning driven by urbanization, economic growth, and evolving travel patterns. As one of the most densely populated countries in the world, with more than 18 million residents (Statistics Netherlands (CBS), 2025), the need for advanced analytical tools to accurately capture individual travel decisions and their aggregate effects on the transport system has become increasingly critical for effective policy and infrastructure planning.

Traditional transportation planning approaches, largely based on aggregated four-step models developed in the mid-20th century, have served the planning community well but increasingly show limitations in addressing contemporary policy questions. Their reliance on zonal aggregation and uniform behavioral assumptions prevents them from fully representing heterogeneous travel behavior, land use–transport interactions, and new mobility trends.(Ortúzar & Willumsen, 2011; Timmermans, 2003)

In response to these limitations, agent-based microsimulation models have emerged as a promising alternative, offering the capability to represent individual travelers as decision-making agents. These models simulate travel behavior at the disaggregated level, allowing for a more realistic representation of various preferences, complex activity patterns, and the dynamic interactions that shape travel demand. By modeling each individual's choices explicitly, agent-based approaches can better capture the behavioral mechanisms underlying aggregate travel patterns and provide more nuanced insights for policy evaluation (Bernardin et al., 2018).

The Octavius Modeling Framework

This research is conducted within Octavius, a demand modeling framework within the OmniTRANS Multi-Modal Transportation Planning package, developed by Goudappel, a leading Dutch transportation consultancy. Octavius represents an implementation of agent-based travel demand modeling, incorporating complex microsimulation techniques to forecast transport demand and traffic flows across large-scale networks. The system is widely used by governmental agencies, regional authorities, and private consultancies throughout the Netherlands for strategic mobility planning, infrastructure investment analysis, and policy evaluation.

The Octavius framework, within the OmniTRANS package, employs a comprehensive four-stage modeling framework: population synthesiser, tour generation, destination choice, and mode choice. These stages differ from the traditional four-step model by incorporating agent-based microsimulation principles. Each stage utilizes discrete choice models estimated from national travel survey data, ensuring that simulated travel behavior reflects empirically observed patterns. The system's agent-based architecture allows for detailed representation of individual characteristics, household interactions, and spatial constraints, making it particularly well-suited for analyzing complex transportation scenarios and policy interventions.

Despite these advanced modeling capabilities, several components of the current Octavius implementation rely on simplified behavioral representations that may limit the system's accuracy and policy relevance. Of particular concern is the destination choice modeling component, which is a crucial link between travel purposes and spatial flow patterns. Destination choice is important because it determines where trips go across the network. This choice directly affects predicted traffic flows, accessibility measures, and the evaluation of transportation policies. Existing models often overestimate the attractiveness of certain areas by relying mainly on total employment as the only size variable. This approach leads to assigning too many trips to already popular zones. It misrepresents actual commuting patterns and may direct planners toward poor infrastructure investments, zoning decisions, or congestion management strategies. By improving destination choice modeling through sector-specific employment, behavioral differences, and better variable specifications, this study aims to create more realistic destination predictions. These predictions, when aggregated, are vital for making informed and effective transportation planning decisions.

1.2 Problem Statement and Research Gaps

The current destination choice models implemented in Octavius, while computationally efficient and operationally practical, suffer from several theoretical and empirical limitations that may compromise their behavioral realism and predictive accuracy. First, destination attractiveness is typically measured using aggregate indicators such as total employment or number of inhabitants per zone, without consideration of sector-specific job opportunities or qualitative workplace characteristics. This aggregation overlooks the fundamental insight from labor economics that job search and workplace selection are inherently sector-specific processes, with workers primarily considering opportunities within their field of expertise.

Second, the models employ limited individual-level heterogeneity in destination preferences, often restricting person-specific variables to basic demographic characteristics such as age and gender. This approach fails to capture important behavioral differences related to household composition, work arrangements, income levels, and lifestyle preferences that significantly influence destination choice patterns. Recent studies in travel behavior have shown that such factors play crucial roles in shaping spatial choices, particularly for work trips where commuting patterns reflect complex trade-offs between career opportunities, housing preferences, and family responsibilities.(Auld & Mohammadian, 2011; Gupta et al., 2015)

These limitations manifest themselves in several practical modeling challenges. The current Octavius models tend to over-concentrate simulated trips in highly attractive zones, leading to unrealistic flow patterns that diverge from observed travel behavior. This concentration effect is particularly problematic for work trips, where the diversity of employment sectors and workplace types should naturally distribute demand more evenly across the urban landscape. Furthermore, the models may inadequately capture emerging trends in work arrangements, such as flexible working, remote work capabilities, and changing preferences for work-life balance, which have become increasingly important determinants of workplace location choice.

1.3 Research Objectives and Questions

This research addresses the limitations of current destination choice modeling approaches by developing enhanced specifications that incorporate more complex behavioral representations while maintaining computational feasibility for large-scale applications. The overarching research question guiding this study is:

Research Question: How can destination choice models for car-based work trips be improved, through refined variable specification, enhanced behavioral representation, and effective data integration strategies, to increase predictive accuracy while preserving operational feasibility in large-scale transportation planning systems?

To address this central question, the following specific research objectives are pursued:

1. **Variable Identification:** Determine which explanatory variables best improve destination choice models for car-based work trips, particularly incorporating sector-specific employment data and examining how demographic characteristics and flexible work arrangements influence travel behavior.

2. **Model Specification:** Reformulate destination choice models to better represent the observed choices while maintaining operational feasibility, exploring appropriate functional forms for travel impedance and effective methods to represent sectoral matching between workers and job opportunities.

3. **Data Integration:** Develop strategies to address data limitations, e.g., sector matching and zonal aggregation challenges, while ensuring robust model estimation.

4. **Performance Evaluation:** Assess the improvements achieved through enhanced variable specification by comparing goodness-of-fit measures and evaluating how the enhanced models perform in reproducing observed spatial patterns of commuting flows.

These objectives are designed to improve destination choice modeling within operational transportation planning systems through systematic enhancement of behavioral representation and practical implementation strategies.

1.4 Case Study Context

The research focuses specifically on car-based work trips, representing the most significant component of commuting demand in the Netherlands and the travel segment with the greatest potential for model improvement through enhanced destination choice specifications. While the methodological approach developed in this study could be extended to other trip purposes and travel modes, the current scope provides a focused context for detailed model development and validation.

This research is implemented and validated using the Dutch transportation planning context, with particular focus on car-based work trips within the Octavius modeling framework. The Netherlands provides an ideal setting for this analysis due to its extensive transportation data infrastructure, widespread use of agent-based modeling in planning practice, and well-documented travel behavior patterns.

The study utilizes data from multiple sources, including the LRO (Landelijk Reizigersonderzoek) national travel survey, CBS employment statistics, and detailed spatial datasets at the PC4 postal code level. This data foundation enables comprehensive analysis of destination choice behavior while ensuring compatibility with existing operational modeling systems used throughout the Netherlands.

The methodological approach and implementation details are presented in the following sections, with results evaluated through statistical performance measures, predictive accuracy metrics, and analysis of predicted spatial commuting patterns to ensure both analytical validity and practical relevance for transportation planning applications.

2 Theoretical and Modeling Framework

In travel demand modeling, destination choice represents a fundamental component that determines where individuals travel to fulfill their activity needs. This section establishes the theoretical foundation for destination choice modeling, reviews the evolution from aggregated to disaggregated approaches, and examines the application of these models to work trip analysis. The framework developed here guides the methodological approach and model specifications used in this research.

2.1 Overview of Travel Demand Prediction Models

Travel demand prediction models seek to forecast how many trips will be made, where they will begin and end, which modes will be used, and how traffic will be assigned across a transportation network (Oregon Department of Transportation, n.d.). Over the past half-century, two broad modeling paradigms have emerged:

- **Four-Step Aggregated Models**. First, estimating trip *productions* and *attractions* at each zone (trip generation), these sequential models were developed in the 1950s and 1960s. They then involved a discrete choice of travel mode (mode choice), an equilibrium assignment of trips onto the network (traffic assignment), and a distribution of trips between zones via spatial interaction (trip distribution) (Cascetta, 2001). In many planning organizations, they are the industry standard due to their ease of use and dependence on easily accessible zonal summaries.

- **Disaggregated Choice-Based Models**. Since the 1970s and 1980s, growing computer power and improved statistical methods have made it possible to simulate travel behavior at the individual level. These disaggregated models estimate a person's choice of destination, travel mode, and sometimes route, using a random utility framework. Commonly used approaches, such as multinomial and nested logit models, take into account the specific characteristics of the trip and the individual differences between travelers. These models are typically estimated using data from household surveys or travel diaries (Ben-Akiva & Lerman, 1985; Cascetta & Papola, 2001). Building on the idea that travel is part of a person's daily activity pattern, **activity-based models** were later developed. These models simulate full schedules (or "tours") of activities and trips for each person, rather than treating each trip separately. This allows them to capture inter-dependencies between different trips, as well as constraints related to time and personal resources. As a result, they can better reflect how people make decisions about when, where, and how to travel (Arentze & Timmermans, 2005; Bowman & Ben-Akiva, 2001; McNally, 2000).

Each paradigm trades off operational efficiency against behavioral realism (Cascetta, 2001;

Ortúzar, 2010). Aggregated models are still widely used for large-scale forecasting due to their lower data requirements and computational efficiency (Cascetta, 2001; Ortega-Tong, 2013). Disaggregate choice models offer a richer representation of traveler preferences and can accommodate emerging policies (e.g., flexible working hours, congestion pricing) (Ben-Akiva & Lerman, 1985; Hensher et al., 2005). Activity-based frameworks provide the most detailed description of travel behavior, supporting a fine-grained analysis of time-of-day impacts, joint travel, and emerging mobility services (Arentze & Timmermans, 2005; Bhat, 2008; Bowman & Ben-Akiva, 2001; H. J. Miller, 2005).

Contemporary practice increasingly blends these approaches—using aggregate models where appropriate, choice models for mode and route, and agent–based components for nuanced temporal and demographic effects—thus leveraging the strengths of each to improve the accuracy and policy relevance of travel demand forecasts (Bradley et al., 2010; Cascetta, 2001; McNally, 2000).

2.2 Aggregated Models

Aggregated trip-distribution models originated in the post–World War II era, when growing urban car ownership and the availability of large-scale computing made it feasible to go beyond simple counts of existing trips. Early growth-factor methods, such as the uniform-factor and Fratar procedures, were among the first techniques to project future travel flows. These methods start with a base-year origin–destination (O–D) matrix, recording trips between all pairs of zones during a specific period (Fratar, 1954). Future travel demand is estimated by applying growth factors reflecting expected changes in trip production (originating trips) and attractions (destination trips). In the Fratar method, an iterative balancing procedure adjusts the matrix so that row and column totals match projected productions and attractions, while preserving the original spatial distribution of trips as closely as possible (Cascetta, 2001).

Although computationally straightforward, these approaches are purely arithmetic and do not account for individual decision-making. They rely on aggregate flows, meaning that zero entries in the base O–D matrix permanently exclude certain origin-destination pairs at the neighborhood level from projections, and they impose homogeneous choice sets across all travelers within a zone, ignoring intra-zone differences in accessibility, preferences, or information. Moreover, when significant new destinations emerge, such as major employment centers, manual adjustments to balancing factors or distance-decay parameters are required, undermining model consistency (Cascetta et al., 2007).

By the 1950s, two dominant conceptual approaches to trip distribution emerged. The gravity model links flows to origin and destination activity, inversely weighted by travel cost or distance, drawing analogies to Newtonian physics and entropy-maximization principles (Wilson, 1970). In contrast, the intervening-opportunities model emphasizes the sequence of opportunities encountered, prioritizing proximity to alternative destinations rather than absolute distance (Schneider, 1959; Stouffer, 1960). Recognizing the complementary strengths of both, hybrid gravity–opportunity models incorporate distance-decay and intervening-opportunity factors, often achieving superior fit to observed O–D flows (Almeida & Gonçalves, 2001).

Despite their widespread use, aggregated trip-distribution models have inherent limitations stemming from their theoretical foundations in spatial interaction principles. The classic four-step travel demand model, for example, predicts travel demand through sequential sub-models: trip generation, trip distribution, mode choice, and traffic assignment (Ortúzar & Willumsen, 2011). While effective for system-level analysis, these models treat zones rather than individuals as the unit of analysis. Trip generation predicts the total number of trips originating in a zone based on land-use and socio-demographic characteristics, while trip distribution assigns trips to destinations according to production-constrained spatial interaction models. These models assume that trip probabilities are proportional to destination attractiveness, inversely proportional to travel time or distance, and inversely proportional to competing alternatives (Rasouli & Timmermans, 2013).

The limitations of aggregated approaches, particularly their inability to capture individual heterogeneity, flexible choice sets, or responses to new destinations, have motivated the development of disaggregated, behaviorally realistic models.

2.3 Disaggregated Models

Disaggregated models represent a fundamental shift from zone-based to individual-based travel behavior analysis. At the heart of these models lies destination choice modeling, the process of predicting where individuals will travel for specific purposes such as work, shopping, or leisure activities. Destination choice models have emerged as a central component of modern transport demand forecasting because they directly capture the spatial dimension of travel decisions and can incorporate detailed behavioral factors that influence individual location preferences (Louviere et al., 2000; Train, 2009).

The development of destination choice models has been driven by the recognition that spatial choices are inherently complex, involving trade-offs between accessibility, activity opportunities, travel costs, and personal preferences. Unlike aggregated approaches that treat all travelers within a zone homogeneously, destination choice models can capture heterogeneity in individual preferences, choice set formation processes, and the multidimensional nature of destination attractiveness (Fotheringham & O'Kelly, 1989; Pellegrini et al., 2005).

This individual-level approach has proven particularly valuable for work trip analysis, where destination choice is constrained by employment opportunities, commuting preferences, and household responsibilities. The ability to model these choices at the disaggregate level enables more accurate prediction of travel flows and better understanding of how policy interventions or land-use changes might affect travel behavior (Waddell, 2002).

2.3.1 Destination choice models

These models incorporate a range of factors, including generalized travel costs, accessibility, personal characteristics (e.g., age, income), and trip purposes (Ben-Akiva & Lerman, 1985; McFadden, 1974; B. J. Vitins et al., 2016).

A major advancement in this field was the shift from aggregate to disaggregate models, such as the multinomial logit models (MNL), which are based on random utility theory (Akiva & Lerman, 1985). These models simulate decisions at the individual level, incorporating detailed variables beyond simple attraction or impedance measures. By doing so, they can more accurately reflect heterogeneity in traveler preferences and how choice sets vary across people and contexts (Rasouli & Timmermans, 2013).

2.3.2 Random Utility Concept

At the core of discrete destination choice modeling lies the random utility theory, which assumes that individuals choose the alternative offering the highest perceived utility (Ben-Akiva & Lerman, 1985). The theoretical foundation builds on the premise that decision-makers evaluate alternatives based on both observable characteristics and unobserved factors, with the alternative providing the highest total utility being selected.

This framework allows destination choice models to incorporate various factors, such as travel time, cost, and destination attractiveness, and to be estimated using revealed or stated preference data. The utility function is typically linear in attributes, but alternative forms like Box-Cox transformations or random coefficients can capture population heterogeneity and improve model fit (Gaudry & Dagenais, 1979).

While powerful, these models face challenges such as the treatment of spatial correlation (McFadden, 1974) among alternatives, capacity constraints at destinations, and computational complexity for large-scale applications (Nerella & Bhat, 2004; B. J. Vitins et al., 2016). The most widely used model is the MNL model, derived under the assumption that the error terms are independently and identically distributed (IID) with a Type I extreme value distribution (Ortúzar, 2010). To address this limitation, nested logit models are commonly used. These models group similar alternatives into hierarchical "nests," which allows correlation within groups of similar choices in a nest (Wen & Koppelman, 2001). Ignoring such correlations can bias results: the model may predict that travelers see very different destinations as close substitutes, while failing to capture the stronger substitution that actually occurs between similar, nearby alternatives. In contrast, a nested logit structure allows individuals to first choose a broader category (e.g., city center, suburbs) where substitution is more likely, and then select a specific destination within that category. This hierarchical structure improves behavioral realism by relaxing the Independence of Irrelevant Alternatives (IIA) assumption within nests (Hammadou et al., 2008).

2.3.3 Choice Set Formation

One of the assumptions of destination choice models is that individuals select a destination from a finite set of distinct alternatives, but in large-scale models, using the full universal set is impractical. This makes sampling essential, yet challenging, as poor sampling can introduce bias and violate assumptions like the IIA, especially in spatially correlated contexts. To address this, researchers have developed methods to estimate choice models consistently using carefully constructed subsets of alternatives. This section reviews key strategies for defining and sampling destination choice sets (Pagliara & Timmermans, 2009).

Individuals are thought to construct destination choice sets not merely by geography or cost but also through cognitive and psychological heuristics. Early work in marketing distinguished awareness, evoked (consideration), and choice sets, emphasizing how people select alternatives that fail simple "must-have" or "must-avoid" criteria (e.g. (Wright & Barbour, 1977)). In transportation, Swait and Ben-Akiva (Swait & Ben-Akiva, 1987) formalized this via random constraint models, positing that each alternative is included only if its unobserved "threshold" criteria (e.g., threshold for travel time, threshold for perceived safety) are met. Gillbride and Allenby (Gillbride & Allenby, 2004) extended this by embedding conjunctive and disjunctive screening rules directly into utility models, so alternatives violating a user's psychological cut-offs have zero choice probability. Cantillo and Ortúzar (Cantillo & de D. Ortuzar, 2006) later showed that ignoring such thresholds biases both parameter estimates and predictions, and they proposed estimating threshold distributions jointly with utility parameters to capture heterogeneity in individual cut-offs.

While screening models address *which* alternatives are even considered, sampling-based approaches tackle *how many*. Nerella and Bhat (Nerella & Bhat, 2004) used numerical experiments with MNL models to show that too small a sampled choice set inflates variance and biases, recommending at least 12.5%–25 % of the universal set for reliable estimation. Pagliara and Timmermans's review (Pagliara & Timmermans, 2009) further argued that, for non-spatial attributes, simple random sampling of alternatives often suffices, but spatial attributes (e.g. distance, accessibility) demand more careful choice-set construction to avoid mis-estimating distance decay and substitution patterns.

A complementary strand leverages *time-space prisms* to bound choice sets by individuals' temporal budgets and travel speeds. Based on Hägerstrand's time geography, a prism determines all the points that can be reached between two fixed activities, given a maximum travel speed and the available time window. Scott and He (Scott & He, 2012) and Chen and Kwan (Chen & Kwan, 2012) showed that projecting these prisms onto geographic space restricts destination alternatives to those that are feasible, improving predictive accuracy.

2.4 Application of Destination Choice Models to Work Trips

The selection of explanatory variables in destination choice models is fundamental to accurately capturing the determinants of individual travel decisions. These variables are typically grouped into three categories: size or attraction variables, impedance or friction factors, and constants. Size or attraction variables represent the magnitude of opportunities available at each destination, such as the number of jobs or the amount of retail floor area. Impedance or friction factors capture the cost or time required to reach each destination, while constants account for unobserved influences on choice behavior (Bernardin et al., 2018).

Among the early studies addressing the complexity of size variables in destination choice models, Daly (1982) made a significant contribution by demonstrating how multiple attractiveness variables, such as zone-level job counts segmented by sector, can be properly incorporated into choice models. This work was particularly important because it addressed a fundamental challenge: when there are multiple variables representing the size of different opportunity groupings, the coefficients of these variables appear in an intrinsically non-linear way, requiring the development of alternative estimation algorithms beyond standard Newton-Raphson procedures (Daly, 1982).

Sector-mix log-sum extension: Daly's approach introduces attractiveness variables via a generalised inclusive value term. Denoting $S_{j,k}$ as the number of jobs in sector k at zone j, one defines the composite size variable

$$\theta \, \log\Bigl(\sum_{k=1}^{K} S_{j,k} \, \exp(\gamma_k)\Bigr)$$

where each γ_k is an unconstrained parameter (so that $\exp(\gamma_k) > 0$), and θ scales the overall effect. This formulation ensures that the probability of choice is directly proportional to these size variables, making the model essentially independent of the groupings of elementary alternatives, a crucial property for geographical zoning systems where zone boundaries may be somewhat arbitrary. The logarithmic form imposes diminishing marginal returns; doubling every sector's jobs increases attraction by only $\theta \ln 2$, while the estimated sector weights $\exp(\gamma_k)$ allow the model to learn which job sectors are most influential for destination choice. The parameter θ can be interpreted as reflecting the difference in sensitivity between the aggregate destination choice level and the lower-level choice among elementary alternatives within each zone, with values between 0 and 1 indicating that zone boundaries have behavioral meaning for travelers. Daly's algorithm accommodates this form via an expanded estimation procedure, ensuring consistent, unbiased parameter estimates even when multiple "size" attributes enter nonlinearly (Daly, 1982).

Building on these foundational insights, subsequent work has refined the application of employment variables in work trip models. For instance, Mishra et al. (2013) estimated a detailed destination choice model for home-based work (HBW) trips, where travel impedance was captured through a flexible distance specification, including linear, squared, and logarithmic terms, along with distance band constants. Mode choice logsums (the overall accessibility or utility across all available transportation modes) were used to incorporate accessibility, while size terms were segmented by employment type (e.g., retail, office, industrial) and household presence. The model also included contextual indicators, such as intrazonal dummies, bridge crossing penalties, and regional fixed effects, along with interactions between income levels and distance, capturing heterogeneity in travel preferences across socioeconomic groups (Mishra et al., 2013).

Gupta et al. (2015)[1] extend the MNL framework by embedding it within an agent-based simulation that enforces capacity constraints via "shadow prices." They aimed to integrate individual choices with system-level feasibility, ensuring that workplace allocations remain consistent with limited spatial capacities. They developed a mode-specific MNL model for workplace choice, where the systematic utility U_{ijn} for individual n choosing zone j from origin i is specified as:

$$U_{ijn} = \underbrace{\ln\big(S_{o(n)j}\big)}_{\substack{\text{industry-segmented}\\ \text{job counts}}} + \alpha\, L_{ij} + \sum_{m} \beta_m\, D_{m,ij}(c_{ij}) + \sum_{z} \gamma_z\, D_{z,n} + C_j\,.$$

Here, $S_{o(n)j}$ is the number of jobs in worker n's occupation at zone j with a coefficient being set to one, as a normalization that reflects the assumption that each job opportunity within a worker's occupation contributes equally to destination attractiveness, L_{ij} is the mode-choice accessibility logsum that captures the ease of reaching destination j by aggregating utilities from different transport modes into a single accessibility index, $D_{m,ij}$ terms represent nonlinear distance decay of generalized cost c_{ij}, $D_{z,n}$ capture personal attributes (e.g., income, household size), and C_j corrects for sampling. (Gupta et al., 2015).

This work models workplace-location choices of both members of two-worker households simultaneously, incorporating industry-specific employment size, generalized travel-cost logsums, and intra-household interaction terms (such as the product of commuting distances, inter-workplace distance, and the angle formed at home between the two workplaces). Contrary to the hypothesis of distance trade-offs, they find that workers do not compensate for one partner's longer commute with a shorter one; instead, significant effects arise from the distance and angular relationship between workplaces, with sharper angles (i.e., more aligned commutes) in high-accessibility areas, for full-time and lower-income households. Their results across four

[1] The initial version of this model appeared as a conference paper in 2012, with significant expansion and refinement published in 2015.

U.S. regions show that industry-segmented job counts and the log-sum term significantly improve model fit, and that nonlinear distance-decay parameters vary by socio-demographic group.

Vitins et al. (2016) developed a comprehensive destination choice model for workplace choice in Singapore's transport model that incorporates multiple dimensions of destination attractiveness and individual heterogeneity. The deterministic utility includes nonlinear travel-time decay parameters by car-ownership class, sectoral number of workplaces derived separately through reported travel patterns and destinations' designated land use types, and a competing-destination gravity term. Individual characteristics are captured through income differentials $\ln(\frac{\text{inc}_n}{\overline{\text{inc}}_j})$, where inc_n is the income of individual n and $\overline{\text{inc}}_j$ is the average income in group j, and demographic similarity measures, while accessibility effects are represented through mode-choice log-sums.

Building on these approaches, Van Lent et al. (2025) show how job flexibility and sector-specific employment characteristics affect work-trip patterns in the Dutch context. Workers with greater telework options experience substantially higher accessibility (30% by car on average), though these gains diminish when job market competition is considered (van Lent et al., 2025). Their findings highlight the importance of including flexible work arrangements and sectoral heterogeneity in destination choice models to reflect contemporary labor-market dynamics.

A key innovation found in studies of Vitins et al. (2016, 2023) is the integration of capacity constraints through iteratively estimated shadow prices λ_j that penalize oversaturated zones. This mechanism addresses the common problem of unrealistic over-assignment to highly attractive destinations in standard MNL models. The shadow price framework improves model realism by incorporating supply-side constraints that reflect real-world capacity limitations at workplaces.

Auld & Mohammadian (2011) frame destination choice as a balance between travel impedance, socio-demographic affinity, land-use/employment attractiveness, and competition among alternatives. Zones farther from home or with larger income or racial gaps impose greater disutility, while the cumulative size of land-use areas and employment sectors enhances overall utility through a log-sum formulation. Additional terms adjust for the presence of competing destinations and correct for survey sampling probabilities, ensuring that the model captures both individual preferences and structural data artifacts (Auld & Mohammadian, 2011).

2.4.1 Summary of Variables in Work Trip Studies

Table 1 details the key variable types used in selected destination choice models.

Table 1: Model specifications in selected work-trip destination choice studies

Study	**Size (attraction) variables**	**Agent / contextual variables**
Mishra et al. (2013)	Employment by sector (retail, office, industrial, other) Regional indicators (CBD, suburban, semi-urban)	Mode-choice logsum Distance (linear, squared, cubed, log) Intrazonal dummy Income-distance interactions Regional dummies Bridge-crossing indicator Binned distance constants
Gupta et al. (2015)	Industry-segmented job counts Mode-choice log-sum	Income Household size Sampling correction
Vitins et al. (2016)	Number of work places by sector Competing-destination gravity	Car-access class Income-workplace count interaction Intra-household interaction terms Shadow prices
Auld et al. (2011)	Land-use areas by type Employment by sector (logsum)	Travel time Income-difference disutility Race-difference disutility Competing-destination effects Sampling weight

2.4.2 Criticisms and Limitations

Disaggregate destination-choice models provide a richer representation of travel behavior than aggregated approaches, but several **limitations** are notable in the literature. First, standard multinomial logit (MNL) frameworks treat workers as if choosing jobs independently, ignoring the “two-sided” nature of workplace allocation, where both employers and employees influence final assignments. Joint models in previous studies have shown that residential and workplace locations are interdependent, and ignoring these interactions can bias predictions (Paleti et al., 2013).

Second, capacity constraints at destinations are typically not enforced in basic MNL models. This can result in unrealistic over-concentration of workers in highly attractive zones. (B. Vitins & Erath, 2023; B. J. Vitins et al., 2016) address this issue using *shadow prices*, iteratively penalizing oversaturated destinations to reflect real-world limits on job availability. Without such adjustments, simulated flows may diverge from observed patterns.

Third, the Independence of Irrelevant Alternatives (IIA) assumption inherent in MNL models treats all alternatives as equally substitutable. In reality, geographically or functionally similar zones are closer substitutes, which nested logit models can capture (Wen & Koppelman, 2001). However, implementing a full nested structure for a large set of zones (over 1,000) requires detailed hierarchical definitions and substantially more data, complicating estimation. Given the objectives and data constraints of this study, a single-level MNL model was chosen for transparency and computational feasibility.

Fourth, the construction of explanatory variables and zone definitions can introduce further limitations. Spatial aggregation can mask intra-zone heterogeneity, while the specification of employment-attraction variables (e.g., total jobs versus sector-specific counts) and impedance measures requires balancing model detail with tractability (Auld & Mohammadian, 2011; Daly, 1982; Gupta et al., 2015; Mishra et al., 2013; B. J. Vitins et al., 2016).

Building on this literature, the present study adopts an MNL destination choice model enhanced with sector-specific employment counts and personal attributes. While not addressing all theoretical limitations (e.g., two-sided matching or nested alternatives), this approach captures key determinants of work-trip destination choice and remains compatible with the existing Octavius modeling framework. The following methodology chapter details the model specification, estimation procedure, and data used, bridging the theoretical insights to practical implementation.

3 Methodology

This chapter presents the methodological framework for enhancing destination choice models within the Octavius modeling system. The existing Octavius model structure is described to establish the context for the proposed contributions. The modeling approach involves estimating two model variants: a *base model* that replicates the current framework using the available dataset, and an *enhanced model* that incorporates new explanatory variables and the refinement of the current variables within the base model. Along with that, in this chapter, the contribution to the existing framework and model specifications is described.

3.1 Research Design and Approach

A comparative modeling approach is used to isolate the impact of introducing disaggregated variables into work-trip destination choice. The original destination choice module in Octavius was estimated using the Dutch national travel survey (OViN), which is different from the available dataset for this study. To ensure a valid comparison with the performance of the existing model, a *base model* is first established that replicates the current modeling framework using the LRO dataset. This baseline controls for dataset-specific differences when evaluating improvements.

By extensively comparing the estimation results of the base and enhanced models, this study aims to clearly assess how the extensions and new specifications improve model fit and better capture observed travel patterns.

The methodological framework is grounded in discrete choice theory and multinomial logit modeling, following established practices in transport demand modeling. Model estimation utilizes maximum likelihood procedures with appropriate sampling strategies to handle large choice sets computationally. Both statistical significance and behavioral plausibility of parameter estimates are evaluated to ensure model validity.

Model performance is assessed through multiple criteria, including goodness of fit measures, predictive accuracy at different levels, and behavioral realism of predicted travel patterns. Particular attention is given to the spatial distribution of predicted travel time and its correspondence with observed travel time patterns. This comprehensive evaluation framework enables robust assessment of model improvements and their potential for practical implementation.

3.2 Existing Model Structure - Octavius

The Octavius model simulates daily travel behavior using a four-stage agent-based framework: population synthesis, tour generation, destination choice, and mode choice. Each stage relies on discrete choice models estimated from national survey data, as explained in detail. Presenting the full Octavius framework is important because it provides a holistic view of how the stages interact, which in turn clarifies the limitations of the current model and informs the interpretation of the proposed methodological enhancements.

Population Synthesizer:

The Population Synthesizer generates individual agents for each zone based on a set of 2,459 distinct household/person level segments. These types are constructed to simultaneously match CBS neighborhood (Buurt-level) demographic margins (Centraal Bureau voor de Statistiek (CBS), n.d.) at both person and household levels. Figure 1 illustrates this process with a flowchart of the population synthesis methodology.

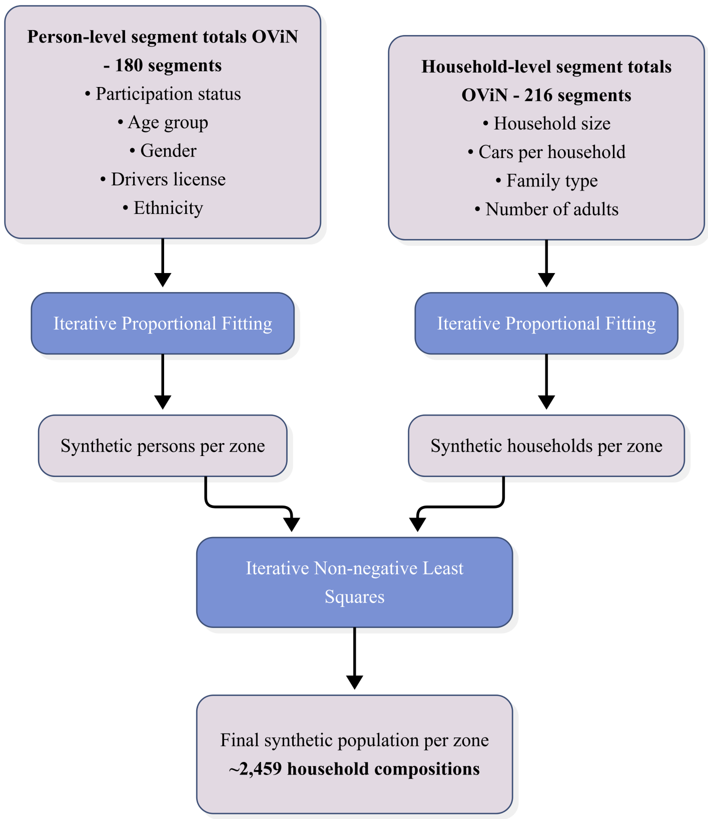

Figure 1: Population synthesizer flowchart.

At the person level, the synthesizer captures key sociodemographic attributes including social status (employed, student, other), age category (0–17, 18–29, 30–44, 45–64, 65+), gender, driver's license possession, and ethnicity (Dutch, western immigrant, non-western immigrant). The multiplication of these categories creates 180 distinct person types. Currently, household-level characteristics are synthesized to comply with zonal margins for household size (1–6+ persons), car ownership (0–3+ cars), and household composition type (single, with/without children) and number of adults (1–3+) in the household. These household attributes combine to form 216 distinct household types.

For employed individuals, additional work-related attributes need to be synthesized to support the destination choice modeling application central to this research. These include flexible workplace arrangements (whether physical presence in the workplace is required every day), and the sector of employment (mapped to the seven-sector classification described in Section 4.3). The method for synthesizing additional attributes is not reported on this project, as is considered out of scope.

The resulting synthetic population provides a representative agent database that serves as input to subsequent modeling stages, particularly the destination choice components that are the focus of this research (Goudappel internal documentation, confidential).

Tour Generator:

The Tour Generator predicts, for each individual, the number of tours undertaken per day (ranging from zero to three), the primary and, if applicable, secondary purposes of those tours, as well as the internal sequence of trips within each tour. A tour is defined as a chain of trips that starts and ends at the individual's place of residence. Figure 2 illustrates this structure.[2]

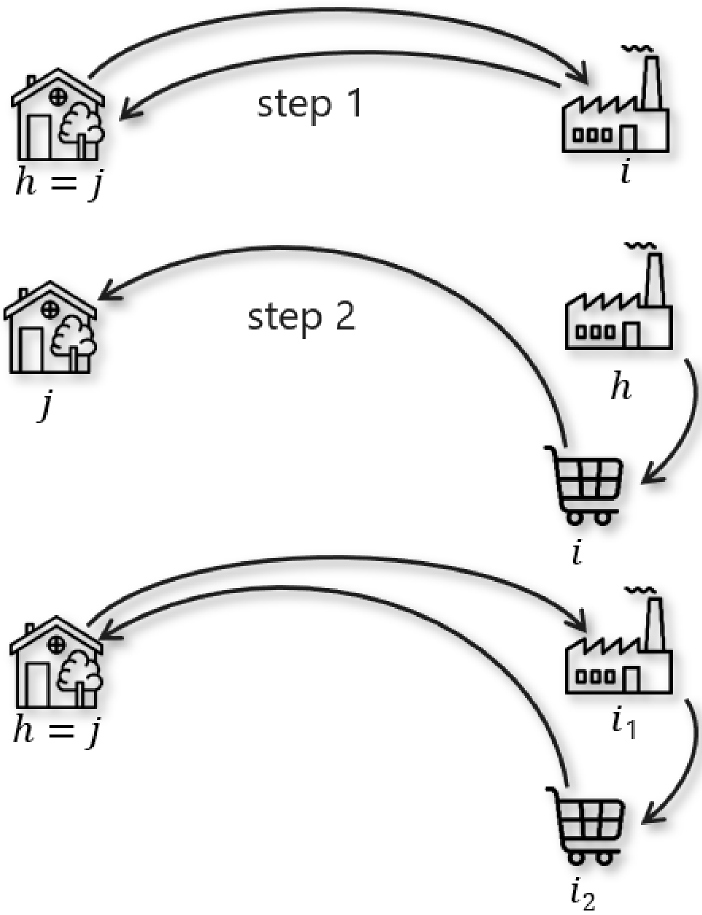

Figure 2: Illustration of the tour structure.

Seventy-nine MNL models, estimated using the Dutch national travel survey OViN (2010–2017), are employed to model tour frequency and structure. The number 79 corresponds to the total combinations of tour types, purposes, and patterns considered in the model. These com-

[2]The illustrations are borrowed from Goudappel's Octavius model documentation.

binations arise from six primary tour purposes (e.g., work, school, shopping, leisure), four travel modes, and additional variations for secondary activities and combined-mode cases. The models rely on explanatory variables such as urbanization level, gender, age, household car ownership, household size, and social participation. For each tour, the generator produces an ordered sequence of purposes, such as work, school, shopping, or leisure and any associated secondary activities. This sequence serves as the input for subsequent modules, including destination and mode choice.

In this study, the focus is limited to tours with a main and only destination of work (home-based work trips). As a result, the choice of the work destination is assumed to be independent of other secondary destinations. At this stage, the model is assumed to have already determined "work" as the primary purpose of the tour, and the next step involves selecting the specific work location through the destination choice model.

Destination Choice: The Destination Choice module assigns specific geographic zones as destinations for each trip, conditional on origin, tour type, and mode of the trip. In total, 26 “main” destination choice models (four modes × six purposes, plus two combined mode cases) are estimated; an additional 108 “secondary” models (detailed purpose combinations) are beyond the scope of this study. The model for forecasting destination choice for work trips as the main purpose of the tour with the mode car is specified with variables including travel time for mode car, gender (woman and man), age group (four categories), total job count per zone, and cost of car mainly the fuel cost, which inspired the base model specified in detail in the following section.

Mode Choice: The Mode Choice module selects the travel mode for each tour using another MNL model. The total utility of each mode is determined by combining socio-demographic factors with the average accessibility of possible destinations when using that mode, commonly represented by a “logsum” variable, which reflects the spatial opportunity associated with that mode. Once a specific tour is constructed (e.g., home → work → shopping → home), the model proceeds to identify the most suitable travel mode based on both the structure of the tour and the individual’s profile. In practice, a separate discrete choice model is estimated for each combination of tour purpose and trip pattern. Because two-trip and three-trip tours involve different sequences of activities, the model includes multiple specifications, six for two-trip tours and seventeen for three-trip tours, to adequately capture variation in mode preferences.

In this study, the focus is exclusively on the destination choice component for car travel; mode-choice models are not estimated. However, the new estimates would be incorporated in this structure and be passed on to the selection of the actual mode by the agents.

3.3 Contributions to the Existing Model Framework

To operationalize these enhancements in both practical applications and simulation phases, it would be necessary to implement modifications in both the population synthesis and destination choice modules. Nevertheless, given the time constraints and the defined scope of this research, the present study is limited to the estimation phase within the destination choice module.

- **Population Synthesizer Enhancement**: Extension of person-level attributes to include employment sector classification, work flexibility indicators (including remote work capabilities). This may also involve re-structuring the levels of household composition and age categories to comply with the destination choice model specification.

- **Destination Choice Module Refinement**: Implementation of an enhanced destination choice model that integrates sector-specific job accessibility and behavioral variables, as developed in this research. The refined model specification incorporates interaction terms between individual employment sector and zonal sectoral job shares, as well as work flexibility and household composition effects. This approach enables the utility function to reflect both general agglomeration benefits (total jobs) and sectoral clustering, while accounting for heterogeneity in travel time sensitivity by demographic and behavioral characteristics.

3.4 Theoretical Foundation

The destination choice module in this study is grounded in the random utility maximization (RUM) framework (Akiva & Lerman, 1985; McFadden, 1974), which is widely used in discrete choice modeling for travel behavior analysis (discussed in Chapter 2). In this framework, it is assumed that each individual n evaluates a finite set of alternatives C_n and selects the alternative j that provides the highest utility. Formally, individual n chooses alternative j if and only if $U_{nj} \geq U_{nk}$ for all $k \in C_n$, where U_{nj} denotes the total utility associated with alternative j.

The utility U_{nj} is composed of two parts:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

where V_{nj} is the systematic (observable) component, typically specified as a linear function of explanatory variables, and ε_{nj} is the random (unobservable) component capturing factors not included in the model.

Assuming that the error terms ε_{nj} are independently and identically distributed (IID) with a Type I extreme value (Gumbel) distribution, the probability that individual n chooses alternative j is given by the MNL model:

$$P_{nj} = \frac{\exp(V_{nj})}{\sum_{k \in C_n} \exp(V_{nk})} \tag{2}$$

This formulation allows for the estimation of the influence of various explanatory variables on destination choice, including a size term. By estimating the coefficient of the size term, typically specified as the logarithm of the number of opportunities at a destination, this approach relaxes the assumption of homogeneity among all detailed alternatives (i.e., the exact workplaces) within each zone and the arbitrariness of zone boundaries. For example, if Zone A has 100 jobs and Zone B has 400, a fixed coefficient of 1 would assume Zone B is four times as attractive. By estimating the coefficient instead, the model can reveal a less-than-proportional relationship (e.g., only twice as attractive), capturing effects such as competition among alternatives within a zone. Instead of imposing a fixed coefficient of 1, the model allows the data to inform the extent to which destination size drives choice.

At the same time, the model accounts for unobserved heterogeneity through the random utility framework. The systematic utility V_{nj} can incorporate a wide range of factors, including travel impedance (e.g., travel time or cost), destination attractiveness (e.g., sectoral employment opportunities), and individual-specific characteristics, making the model both flexible and behaviorally meaningful.

Due to limited data, where many zones have very few observations, alternative-specific constants (ASCs) are not included. Consequently, the model attributes destination choice entirely to observed variables, capturing average effects rather than unobserved zone-specific preferences, since estimating ASCs requires sufficient variation across individuals for each alternative, which this dataset does not provide.

In the following sections, the model specifications used in this study will be explained, including the base and enhanced models. It will be described how the systematic utility functions are constructed to reflect both current practice and proposed methodological improvements.

3.4.1 Base Model Specification

The base model replicates the current Octavius framework structure as closely as possible using the available LRO dataset. The systematic utility function for individual n choosing the workplace destination j from the origin i is specified as:

$$V_{nj}^{\text{base}} = \underbrace{\ln(E_j)}_{\substack{\text{total job}\\ \text{opportunities}}} + \underbrace{(\beta_{\text{gender}} D_{n,\text{male}} + \sum_a \beta_a A_{na} + \beta_{\text{tt}}) \cdot TT_{nj}}_{\substack{\text{person-specific}\\ \text{travel impedance}}} + \beta_{\text{cost}} \ln(C_{nj}) + \sum_{u=2}^{5} \gamma_u \cdot U_{u,j} \quad (3)$$

where:

- E_j is the total employment (number of jobs) at destination j
- $D_{n,\text{male}}$ is gender dummy variable for individual n

- A_{na} are age category dummy variables where B = 18-29 years (reference), C = 30-44 years, D = 45-64 years, E = 65+ years
- TT_{nj} is the total travel time by car from individual n's home to destination j (minutes, round-trip)
- C_{nj} is the car cost from individual n's home to destination j (round-trip)
- $U_{u,j}$ are urbanity dummy variables for levels 2-5 (high urbanity to low, with level 1 as reference) at destination j
- β_{gender}, β_{tt}, β_{cost}, β_C, β_D, β_E and γ_u are parameters to be estimated.

Since this specification replicates the operational Octavius model, where the employment size term has a fixed coefficient of 1, this coefficient is kept fixed and not included among the estimated parameters.

3.4.2 Enhanced Model Specification

For the enhanced model, two highly different alternative specifications were tested to incorporate sector-specific employment effects. Daly's (1982) sector-mix log-sum approach and a variation of sector-specific job accessibility, based on Gupta et al. (2015).

Daly's approach employs a composite size variable of the form $\theta \cdot \log\Big(\sum_{s=1}^{S} E_{s,j} \cdot \exp(\gamma_s)\Big)$, where $E_{s,j}$ represents jobs in sector s at zone j, γ_s are sector-specific weights, and θ scales the overall employment effect. The detailed specification and model results for this approach can be found in the Appendix.

The selected specification incorporates sector-specific job shares through interaction terms between individual work sector and zonal employment composition, while retaining total employment to capture general agglomeration effects. This hybrid approach enables workers to exhibit different sensitivities to destination employment composition based on their sector affiliation. For example, office workers may value destinations with high office concentrations differently from healthcare workers, even when total employment is identical.

Additional variables identified in the literature but not included in this study due to data limitations from the LRO survey include individual and household income, ethnicity or migration background, education level, job contract type (permanent vs. temporary), and intra-household interactions (such as commuting patterns of other household members). These variables are recommended for future research as data availability improves.

The systematic utility function for the enhanced model is specified as:

$$
\begin{aligned}
V_{nj}^{\text{enhanced}} = & \underbrace{\sum_{s} \beta_s \cdot S_{s,j} \cdot I_{n,s}}_{\substack{\text{sector-specific job}\\ \text{share interactions}}} + \underbrace{\beta_{\text{jobs}} \ln(E_j)}_{\substack{\text{total job}\\ \text{opportunities}}} \\
& + \underbrace{\left(\beta_{\text{gender}} D_{n,\text{male}} + \beta_{\text{HH}} H_{nh} + \sum_{a} \beta_a A_{na} + \beta_{\text{flex}} F_n + \beta_{\text{tt}}\right) \cdot TT_{nj}}_{\substack{\text{person-specific}\\ \text{travel impedance}}} \\
& + \sum_{u=2}^{5} \gamma_u \cdot U_{u,j}
\end{aligned}
\tag{4}
$$

where the additional variables are:

- $S_{s,j} = E_{s,j}/E_j$ is the job share for sector s in zone j (proportion of total jobs in zone j that belong to sector s)
- $I_{n,s}$ is an indicator variable (1 if individual n works in sector s, 0 otherwise)
- H_{nh} is are household composition dummy variable (1 if a child exists in the household and 0 otherwise)
- F_n is a binary indicator for work flexibility arrangements (1 if individual n has a flexible work type, 0 otherwise)
- $\beta_s, \beta_{\text{jobs}}, \beta_{\text{gender}}, \beta_{\text{HH}}, \beta_a, \beta_{\text{flex}}, \beta_{\text{tt}}, \gamma_u$ are parameters to be estimated

Various travel time specifications will also be tested to identify the form that best represents behavioral sensitivity to travel time. While logarithmic transformations of travel time are often used to capture diminishing marginal disutility for longer trips (where small differences matter more for short trips than for long trips)(Bernardin et al., 2014), both linear and non-linear forms will be examined and will be considered to evaluate how they affect the prediction of commuting distances.

These model specifications, their estimation results, and comparative performance will be tested and discussed in detail in the following chapters, with particular attention to their ability to capture observed commuting patterns and behavioral heterogeneity.

Cost Variable Exclusion: Preliminary estimations indicated that the travel cost variable was not statistically significant and did not improve model fit in any of the models. This is consistent with the focus on car-based commuting, where fuel or monetary costs may be less relevant to destination choice than travel time or job availability. Travel time captured most of the variability, leaving little explanatory power for travel cost. As a result, the cost variable was excluded from the final model's specification. This streamlines estimation, avoids unnecessary complexity, and ensures that models focus on the most behaviorally relevant predictors.

Model Evaluation Metrics

To assess the predictive performance of the enhanced model, several evaluation metrics are reported for both in-sample (training) and out-of-sample (test) data (see Table 9). These metrics capture different aspects of prediction accuracy and robustness:

- **Top-1 Accuracy**: Measures the proportion of agents whose most likely predicted workplace exactly matches the observed destination. This provides a strict assessment of predictive power, especially relevant in large choice sets where exact matches are challenging.
- **Macro-Precision**: Computes precision for each alternative (the proportion of predicted positives that are correct) and averages across all alternatives. This gives equal weight to rare and common destinations, ensuring fairness in prediction.
- **Macro-Recall**: Calculates the proportion of actual positive cases correctly predicted for each alternative, averaged across alternatives. High macro-recall indicates that the model effectively captures true destinations, including less frequent ones.
- **Macro-F1 Score**: The harmonic mean of macro-precision and macro-recall. It balances false positives and false negatives, providing a single measure of overall predictive performance.
- **Top-5 / Top-10 Accuracy**: Measures the proportion of agents whose true destination is within the top 5 or top 10 predicted alternatives. This recognizes near-misses and is useful for practical applications where a shortlist of likely destinations is valuable.
- **City-level Accuracy**: Assesses whether the predicted and observed workplace fall within the same city, regardless of the exact postal code. This metric captures broader spatial patterns and is particularly relevant for regional planning or aggregate flow analysis.

These metrics collectively allow evaluation of both exact destination prediction and broader spatial patterns, ensuring that the model's performance is assessed comprehensively across multiple dimensions.

4 Data Preparation and Model Implementation

This section describes the data preparation process required for implementing the destination choice models. This step was crucial for model estimation, as the datasets were structured at different levels. Figure 3 illustrates the workflow, showing how multiple data sources were integrated at the PC4 postal code level.

The implementation utilized four primary data sources: (1) the LRO survey with individual travel behavior data at the PC4 level, (2) sectoral employment statistics by zone at the neighborhood level, (3) travel time matrices between origin-destination pairs at the neighborhood level, and (4) PC4 zoning boundaries for spatial reference.

A key challenge involved harmonizing data collected at different spatial scales. The process began with cleaning the LRO survey data, followed by processing sector-specific employment counts at the neighborhood-level (Buurt). Travel time matrices were transformed from the neighborhood level to the postal code (PC4) level. These datasets were then merged to create a comprehensive modeling framework linking individuals to their potential destinations.

The following subsections detail each component of this process, describing the datasets, their transformation, and the methods used to construct the final modeling database.

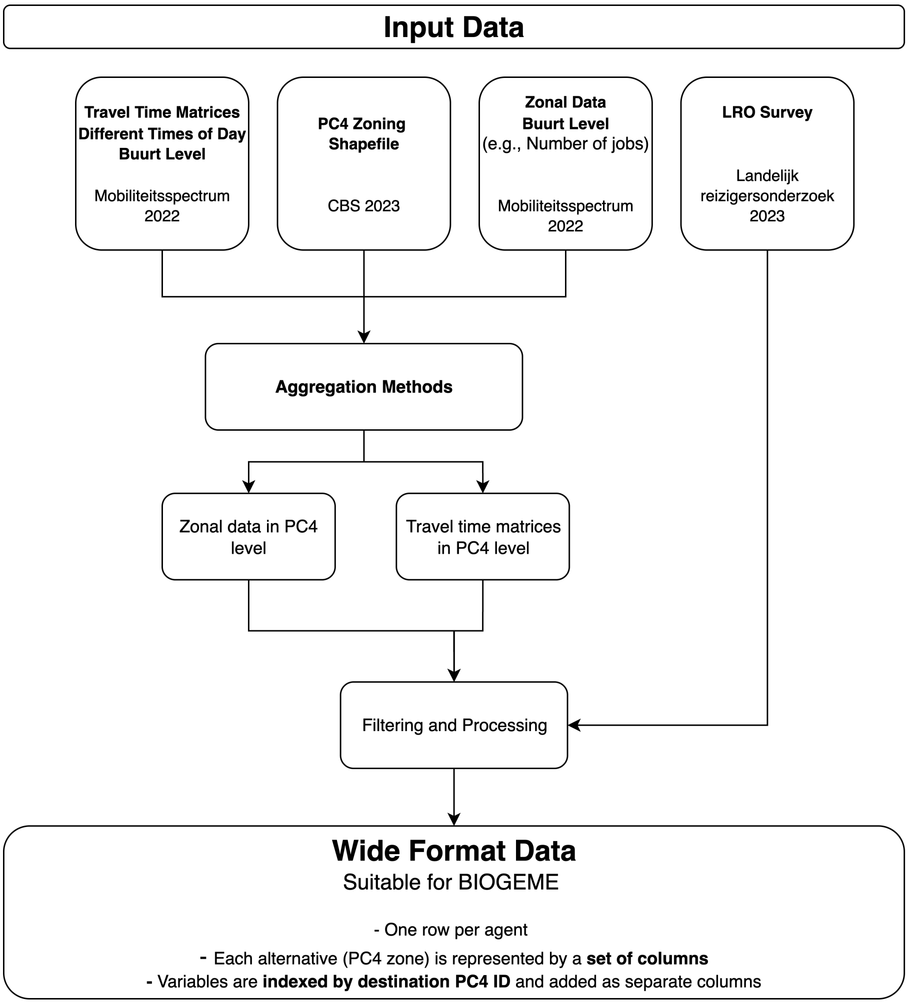

Figure 3: Data preparation and integration workflow.

4.1 LRO Survey Description

The analysis utilizes the LRO (Landelijk Reizigersonderzoek) data, a national travel survey conducted annually in the Netherlands since 2019. The 2023 iteration collected responses from 15,047 participants (which is the version used in this study), providing a representative sample of Dutch travel behavior. The survey is commissioned by the Ministry of Infrastructure and Water Management and conducted by Goudappel and I&O Research, adhering to ISO 27001 and ISO 20252 standards for information security and market research. The detailed questionnaire with all variable levels and response categories is publicly available in Dutch (van Essen et al., 2024).

The LRO employs a comprehensive modular structure that captures multiple dimensions of mobility behavior. Participants complete questionnaire sections covering: employment and work-related travel patterns (W-series variables), mobility resources and vehicle ownership (M-series), detailed commuting behavior including flexible work arrangements (T-series), mode choice factors (MB-series), shared mobility usage (DM-series), recreational travel (RR-series), and socio-demographic characteristics (A-series).

For work-related travel, the survey collects detailed information on employment sector (classified into 15 categories), work location addresses, and flexible working arrangements. Workplace locations are reported using 4-digit postal codes, with their spatial distribution shown in Figure 4, indicating a wide spread across the country and relatively lower concentration in Friesland (northern region). In addition, the survey records weekly work routines across different locations, arrival and departure times, and factors influencing commuting decisions, including infrastructure availability, travel costs, and environmental considerations. Importantly, the questionnaire distinguishes between employer-imposed remote work policies and individual preferences, allowing for the analysis of potential mismatches. In this project, work flexibility refers specifically to respondents whose employers provide the option to work remotely (from home), regardless of whether or not they choose to make use of this option.

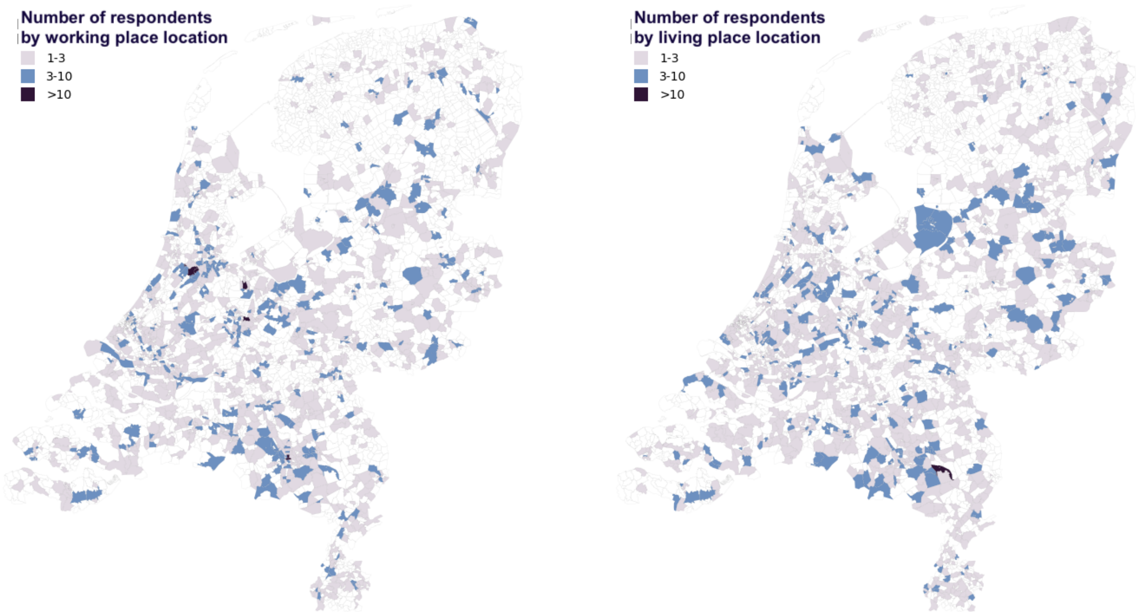

Figure 4: Spatial distribution of workplace locations and living locations at PC4 level.

Sample Selection and Filtering

The full dataset, consisting of 15,047 respondents, was filtered to include only employed individuals who commute by car at least once per week. The initial filtering process retained three employment categories:

1. Employed workers (full-time and part-time)
2. Self-employed without employees (e.g., freelancers)
3. Self-employed with employees

Address validation was performed for both home and work locations, with data geocoded to the PC4 level. After excluding participants with missing or invalid addresses, the dataset was reduced to **2,550** participants.

The selected characteristics from the extensive survey include basic sociodemographic attributes such as age, gender, household composition, and employment sector. In addition, variables related to flexible working arrangements were examined, including the availability of the option to work from home and whether respondents make use of this option. For the purposes of this study, the flexibility flag is assigned to all respondents whose workplace provides the option to work remotely, regardless of whether they actually choose to do so. These variables were incorporated to capture the evolving relationship between work practices and travel behavior.

Table 2 provides detailed information about all variables used in this study.

Table 2: Socio-demographic characteristics of respondents

Variable	**Classification**	**Number of cases**	**Percentage (%)**
Gender	Male	1206	47.5
	Female	1332	52.5
Age category	17–28	227	8.9
	29–43	920	36.3
	44–63	1235	48.7
	64+	166	6.5
Household composition	Without child	829	32.7
	Single	625	24.6
	With child <12	553	21.8
	With child >12	433	17.1
	Other people	110	4.1
Work flexibility	Flexible	1405	55.4
	Non-flexible	1133	44.6
Work type	Full-time	1331	52.4
	Part-time	1207	47.6
Work sector	Health and welfare	637	25.1
	Other services	385	15.2
	Industry	289	11.4
	Education	250	9.8
	Commerce	206	8.1
	Business services	154	6.1
	Public administration	128	5.0
	ICT	116	4.6
	Financial services	97	3.8
	Construction	89	3.5
	Transportation	79	3.1
	Hospitality	39	1.5
	Agriculture and fishery	38	1.5
	Culture	31	1.2
	Utilities	12	0.5

4.2 Employment Sector Data and Processing

This study employs a seven-category employment sector classification aligned with CBS (Statistics Netherlands) standards to ensure compatibility with national employment statistics to be able to capture the interaction of the relevant work sector share with the individual in the model specification:

1. **Industry & Construction**: Manufacturing, construction, and industrial activities
2. **Shop (Retail)**: Retail trade and commercial activities
3. **Hospitality, Culture & Sports**: Tourism, recreation, cultural activities, and personal services
4. **Office Services**: ICT, financial services, business services, and public administration
5. **Education**: Educational institutions and training services
6. **Care**: Health and welfare services
7. **Remaining**: Agriculture, transportation, utilities, and other services

The sector mapping with LRO (agent-declared categories) and CBS and zonal data is detailed in Table A10 in the Appendix.

Data Sources for Sectoral Employment

The zonal employment data for these sectors was sourced from the Mobility Spectrum, a comprehensive data resource developed by Dat.mobility and Goudappel. This integrated platform provides spatial data and mobility patterns for the entire Netherlands, offering insights into mobility across all transportation networks (Goudappel internal documentation, confidential).

The dataset combines information from two primary sources:

- **Basisregistratie Adressen en Gebouwen (BAG)**: The Dutch national building and address registry containing detailed information about all buildings in the Netherlands, including function, surface area, and precise location.
- **LISA (Landelijk Informatiesysteem van Arbeidsplaatsen)**: A business registry providing detailed employment information by sector and location at the municipal level.

To create spatially disaggregated employment data at the neighborhood level, a two-stage methodology was employed by Mobility Spectrum: First, building characteristics from the BAG database, specifically function (e.g., shop, office, education, etc.) and surface area, were extracted for each address. Second, these characteristics were used to distribute LISA employment data from the municipal level to specific locations within each municipality, creating a finer spatial resolution than would be possible with municipal-level data alone. Figure A12 in the Appendix illustrates the spatial resolution difference between municipality boundaries and PC4 postal code areas, highlighting the disaggregation challenge.

4.3 Travel Time Data and Processing

Travel Time Data Source

Travel time data was obtained from the Mobility Spectrum platform, provided in matrix format containing origin-destination pairs with corresponding travel times for different time periods: morning rush hour, evening rush hour, and off-peak periods. The data also included distance measurements for each origin-destination pair.

The travel times were originally calculated between neighborhood zone centroids, with each centroid determined as a weighted average of the x,y positions of all addresses within the zone. This weighting incorporated calculated production/attraction values per address to ensure centers reflected actual activity concentrations rather than simple geographic centroids.

For car traffic, routes were calculated using the HERE network, with speed profiles derived from GPS observations accounting for congestion patterns at different times of day. These profiles capture variations in travel speeds during peak and off-peak periods, enabling a more realistic representation of temporal traffic conditions. The travel times for different periods in a day were calculated by weighting hourly speed information according to the proportion of journeys occurring during each hour relative to the entire period, ensuring an appropriately proportional influence of each time segment. (Goudappel internal documentation, confidential)

Aggregation to PC4 Level.

The spatial resolution of the travel time data presented a significant processing challenge, as it was originally provided at the neighborhood (Buurt) level, that are intended for fine-grained local statistics rather than the PC4 level, which is an address/postcode aggregation used for postal and many address-based statistics, and it is the required level for this analysis. Converting between these levels required careful spatial processing to maintain accuracy while ensuring complete coverage. This transformation involved aggregating from 14,422 neighborhood zones to 4,071 PC4 zones (Centraal Bureau voor de Statistiek (CBS), 2024), a substantial reduction in spatial granularity that necessitated appropriate averaging methods to preserve travel time patterns.

To establish correspondence between neighborhood-level zones and PC4 zones, the following spatial analysis approach was implemented:

1. For each neighborhood zone, a centroid was calculated with a 1-kilometer buffer as a pragmatic compromise between avoiding false geometric assignments caused by tiny centroid shape and keeping the buffer small enough to reflect local neighborhood-scale conditions

2. PC4 zones were identified where the buffer was completely contained

3. For neighborhood zones intersecting multiple PC4 areas, the PC4 with the largest intersection area was selected

4. neighborhood zones that could not be assigned using geometric criteria were assigned to the PC4, containing their centroid

This process required manual validation using GIS software to correct the ambiguous cases, ensuring comprehensive coverage. After geographical correspondence was established, multiple travel times often existed for the same PC4 origin-destination pairs (because multiple neighborhood zones mapped to the same PC4 zone), as is visible on Figure 5. For each PC4 origin-destination pair, the average travel time was calculated across all constituent neighborhood pairs to reflect typical travel conditions.

The aggregation process resulted in 151 PC4 zones (approximately 2.3% of all postal code areas) that could not be matched with any neighborhood travel time data. These zones were consequently excluded from the analysis. Geographic analysis confirmed that excluded zones were scattered across the country rather than concentrated in specific regions, suggesting that the exclusions do not introduce systematic spatial bias. Importantly, none of the survey respondents claimed residence or work locations in the excluded zones, ensuring the analytical sample remains intact.

Figure 5 illustrates several spatial challenges encountered in the aggregation process using Zwolle as an example. The figure shows both the neighborhood (thin blue lines) and PC4 (black lines) boundaries, highlighting the complexity of administrative divisions. Several notable challenges are visible, such as discontinuous PC4 zones that span multiple distinct areas despite sharing the same code and size inconsistencies, where some neighborhood zones can fall into multiple PC4 zones, which violates nested relationships. These irregularities in administrative boundaries necessitated careful processing and resulted in the exclusion of zones with ambiguous or unresolvable spatial relationships.

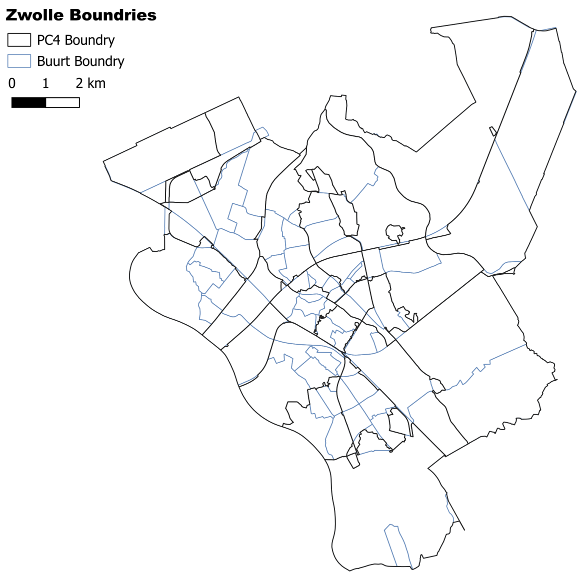

Figure 5: Comparison of neighborhood and PC4 boundaries for Zwolle.

4.4 Data Integration

The modeling dataset was constructed by merging multiple data sources into a wide-format structure suitable for BIOGEME discrete choice estimation. Each row represents an individual respondent from the LRO survey, with personal characteristics stored as individual-level variables and destination-specific attributes replicated across all potential workplace zones.

The wide-format structure includes:

- **Individual-level variables**: Socio-demographic characteristics (age, gender, household composition), employment sector, and work flexibility indicators stored as single columns per respondent

- **Alternative-specific variables**: For each PC4 zone, corresponding travel time (originating from agent's living place), sectoral job counts, total employment, and urbanity levels stored as separate columns with PC4 code suffixes (e.g., `travel_time_1011`, `total_jobs_1011`)

- **Availability indicators**: Binary variables for each PC4 zone indicating whether that destination is feasible for the specific individual, accounting for travel time constraints (see Section 4.4.1) and sector-specific job availability

- **Choice indicators**: Binary variables identifying the observed workplace destination, with exactly one zone coded as 1 (chosen) and all others as 0

This structure enables BIOGEME's estimation procedures to handle different available alternative sets for each agent while maintaining computational efficiency. The availability conditions allow the model to exclude infeasible alternatives on an individual basis, ensuring that each agent's choice set reflects realistic constraints based on their employment sector and acceptable commuting range.

4.4.1 Availability condition of Alternatives

The mirroring of zonal job sector classifications with agent employment sectors enables the construction of sector-specific choice sets. For each agent, destinations are considered available only if they contain relevant employment opportunities within the agent's specific sector. This matching process ensures that the choice set reflects realistic job search behavior, where workers primarily consider locations with opportunities in their field of expertise. Agents for whom no relevant job opportunities exist in their chosen destination are excluded from the analysis, which affected 71 agents among all agents. This exclusion occurred because of the approximation method used in the job data, as the employment counts are not sufficiently accurate to guarantee coverage across all sectors and zones. For each agent, the choice set includes:

1. **For both base and enhanced models**: The set of alternative destinations was restricted to PC4 zones with a round-trip travel time from the individual's residence not exceeding 160 minutes. This upper limit was determined based on the OViN survey data (2010–2017), corresponding to the 99th percentile of observed car-based work travel times. This travel time constraint reduces the universal choice set from 3,917 zones to an average of 1,465 zones per agent.

2. **For enhanced model only**: While retaining the travel-time feasibility limits, only zones with relevant job opportunities are included. Relevance is determined by matching the agent's employment sector with the zonal sector-specific job counts. This sector-specific filtering reduces the average choice set to 1,242 zones per agent (ranging from 103 to 2,473 zones), ensuring that destination alternatives reflect realistic job-search behavior, where workers mainly consider locations offering opportunities in their field.

4.4.2 Sector-Specific Job Share

For the enhanced model, sector-specific job share is operationalized through interaction terms that capture the alignment between an individual's employment sector and the sectoral composition of potential destinations. Rather than using absolute job counts, which would create scale dependencies and correlation with the total employment variable, the model employs sectoral job shares defined as $S_{s,j} = E_{s,j}/E_j$, representing the proportion of total jobs in zone j that belong to sector s.

The interaction mechanism works as follows: for individual n employed in sector s, the term $S_{s,j} \times I_{n,s}$ contributes to the utility of destination j only when the agent's sector indicator $I_{n,s} = 1$. This ensures that workers receive additional utility from destinations with high concentrations of employment opportunities in their own field, while remaining unaffected by sectoral concentrations in other fields. For instance, education workers derive extra utility from zones with high educational employment shares, whereas healthcare workers benefit specifically from healthcare job concentrations but not from educational clustering.

4.5 Travel Pattern Analysis

This section explores how commuting patterns vary across demographic and behavioral groups, with a focus on work flexibility, household composition, age, and gender. Table 3 summarizes key travel time statistics, with all values expressed as percentages for clarity.

Table 3: Descriptive statistics of two-way travel time by work flexibility, household composition, age category, and gender

	Travel Time (minutes)				
	Mean	**Std Dev**	**Count (%)**	**Max**	**Min**
Work Flexibility					
Flexible	45.3	26.8	55.1	119.1	3.3
Non-flexible	36.0	23.9	44.9	119.2	3.7
Household Composition					
With child	40.4	25.6	39.8	115.0	3.3
No child	41.6	26.2	60.2	119.2	3.7
Age Category					
18–29 (B)	40.73	27.00	8.9	114.92	3.94
30–44 (C)	42.17	26.04	36.3	118.90	3.26
45–64 (D)	40.57	25.88	48.7	119.24	3.94
65+ (E)	39.88	24.75	6.5	105.24	4.14
Gender					
Man	45.0	27.6	48.7	119.2	3.7
Woman	37.5	23.8	51.3	118.9	3.3

The results reveal clear behavioral differences. Workers with flexible arrangements have, on average, 26% longer commutes than those without flexibility (45.3 vs. 36.0 minutes). Men commute on average about 20% longer than women. Differences by household composition and age are less pronounced, but parents and older workers tend to have slightly shorter commutes.

Work flexibility is not evenly distributed across employment sectors (Table 4). For example, over 90% of ICT and public administration workers report flexible arrangements, compared to less than 10% in hospitality. These sectoral patterns highlight the need to jointly consider sector and flexibility in the destination choice model.

Table 4: Work flexibility distribution by employment sector (%)

Work Sector	**Flexible (%)**	**Non-flexible (%)**
Agriculture and fisheries	31.6%	68.4%
Business services	76.0%	24.0%
Commerce	42.7%	57.3%
Construction	66.3%	33.7%
Culture	74.2%	25.8%
Education	48.0%	52.0%
Financial services	84.5%	15.5%
Health and welfare	42.9%	57.1%
Hospitality	7.7%	92.3%
ICT	93.1%	6.9%
Industry	52.6%	47.4%
Other services	57.4%	42.6%
Public administration	90.6%	9.4%
Transportation	27.8%	72.2%
Utilities	75.0%	25.0%

To better understand the distributional properties of travel times, Figure 6 and Figure 7 show the empirical and suggested distributions. The raw travel times are highly right-skewed, with a long tail indicating that while most commutes are relatively short, a non-negligible proportion of workers travel much longer distances. This skewness is typical in commuting data and reflects the presence of both local and regional commuters within the sample.

To formally assess the fit of different statistical distributions to the observed travel times, explanatory tests were conducted for several candidate distributions, including the normal, log-normal, and gamma distributions. The results indicate that the Gamma distribution provides the best fit to the observed data, capturing both the central tendency and the heavy right tail more accurately than the alternatives. The log-normal distribution also performs reasonably well, but slightly underestimates the frequency of very long commutes.

To further examine the most appropriate transformation, a Box-Cox analysis was performed to identify the optimal power transformation for travel time (Gaudry & Dagenais, 1979). The Box-Cox method estimates a transformation parameter λ to best approximate normality and stabilize variance. The optimal value was found to be $\lambda = 0.42$, suggesting that a transformation between the square root ($\lambda = 0.5$) and the logarithmic form ($\lambda = 0$) would be most suitable. Although the Box-Cox transformation offers a statistically optimal adjustment, it is less interpretable in the context of discrete choice models. Therefore, both logarithmic and square root transformations will be tested as more interpretable approximations.

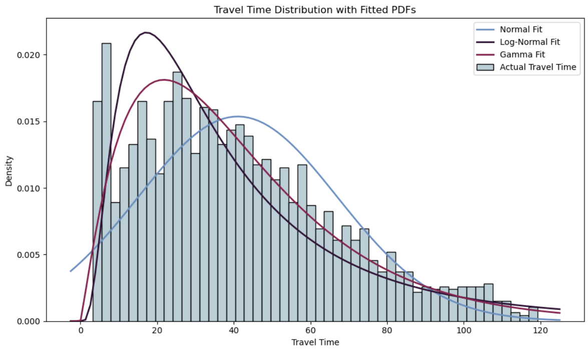

Figure 6: Distribution of travel times (minutes) for work trips.

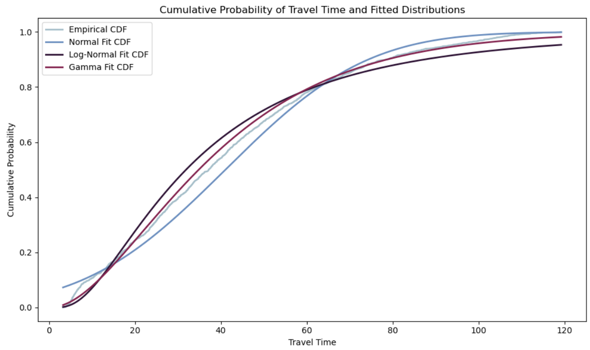

Figure 7: Distribution of log-transformed travel times for work trips.

4.6 Data Quality Assessment

Data quality assessment revealed good spatial coverage across the Netherlands, with survey respondents distributed throughout the country without systematic geographic bias. The exclusion of 151 PC4 zones due to missing travel time data represents approximately 2.3% of all postal code areas. Importantly, these excluded zones are scattered geographically rather than concentrated in specific regions, indicating that the exclusions do not introduce systematic spatial bias into the destination choice modeling framework.

After removing observations with missing values for any variables included in the analysis (no imputation was performed to avoid introducing bias), the final dataset comprises 2478 complete observations. Following the 80-20 split for model validation, the training set contains **1,983** agents while the test set contains **495** agents. This sample size provides sufficient statistical power for reliable parameter estimation while maintaining adequate data for out-of-sample validation.

5 Empirical Results and Model Performance

This chapter presents the empirical results from estimation and primary evaluation of the destination choice models specified in Section 4.3. Two model variants are analyzed: a base model that replicates the existing Octavius framework, and an enhanced model incorporating sector-specific employment variables and additional interaction effects on travel time.

The chapter systematically presents estimation procedures, parameter estimates, and performance comparisons between the two specifications. Results are reported objectively to provide the empirical foundation for subsequent discussion and interpretation of findings.

5.1 Model Specification and Estimation Procedures

Both models were estimated using maximum likelihood estimation in the BIOGEME software environment, which is specifically designed for large-scale discrete choice modeling. Several technical and methodological considerations were addressed to ensure robust estimation, model identification, and computational feasibility:

Scaling of Employment Variables: During estimation, total job counts were divided by 1,000 to address numerical stability issues. This scaling reduces the magnitude of the logarithmic size variable, preventing it from dominating the utility function and overwhelming the effects of other variables such as travel time or demographic indicators. Without this adjustment, the $\ln(E_j)$ term for large employment centers could reach values of 12–14, which would bias the optimization process and potentially lead to convergence failures or extreme predicted probabilities. After scaling, the employment variable remains interpretable, and the estimated coefficients retain their behavioral meaning.

Sector-Specific Job Share Normalization: In the enhanced model, one sectoral job category (the "remaining" sector) is fixed with a coefficient of 1.0, following the normalization convention recommended by Ben-Akiva & Lerman (1985). This approach anchors the utility scale and allows the other sector coefficients to be interpreted as deviations in attractiveness relative to this baseline. The normalization ensures that the sectoral size terms function as pure availability corrections, maintaining theoretical consistency and facilitating interpretation of the sectoral effects. Similarly, in the base model, the total employment coefficient is normalized to 1.0 rather than estimated, which is necessary for model identification when using employment as the size variable.

Computation Time and Resources: Model estimation was computationally intensive due to the large number of agents (1,983 in the training set), the high dimensionality of the choice set (average of 1,242 alternatives per agent), and the complexity of the enhanced utility specification (18 parameters). The enhanced model required up to 27 hours of computation time on a workstation with a 16-core processor and 32 GB RAM, while the base model required approximately 23 hours. The majority of computation time was spent evaluating the likelihood function across all agent-alternative pairs and updating parameter estimates. The initial creation of the BIOGEME object, which involves parsing the data and constructing internal data structures, also contributed significantly to total runtime, especially for the enhanced model with more alternative-specific variables.

Travel Time Transformation: Multiple functional forms of travel time were tested to determine the specification that best captures behavioral sensitivity to travel time while maintaining predictive accuracy. As shown in Table 5, linear, logarithmic, and square root transformations were evaluated using the enhanced model specification.

Table 5: Comparison of travel time specifications in the enhanced model

TT Specification	Initial LL	Final LL	ρ^2	AIC
Linear	-13,964.69	-9,676.962	0.307	19,389.92
Square root	-13,964.69	-9,724.551	0.303	19,481.10
Log	-13,964.69	-10,040.22	0.281	20,112.44

The linear specification achieved the best overall performance, with the highest log-likelihood (-9,676.962), highest rho-square (0.307), and lowest AIC (19,389.92). While logarithmic and square root transformations are theoretically appealing, as they reflect diminishing marginal disutility where small travel time differences matter more for short trips than long trips, they produced inferior model fit in this application.

More critically, the transformed specifications exhibited severe behavioral limitations. Both logarithmic and square root forms created much steeper travel time penalties, causing the model to become overly confident in assigning probabilities to nearby destinations while severely underestimating longer commutes (see Appendix B.2). This concentration effect essentially ignored the long tail of the empirical commute distribution, failing to capture the substantial share of workers who travel longer distances for work.

The logarithmic transformation, in particular, assigns disproportionate weight to differences between short-distance alternatives. For example, while the 4-minute difference between 6 and 10 minutes may indeed be more perceptually significant than the same difference between 26 and 30 minutes, this specification proved too restrictive for the national-scale choice set examined in this study. The resulting model concentrated nearly all predicted choices on very short commutes, contradicting observed travel patterns where many workers accept longer commutes for better job opportunities or other preferences.

The linear specification, while simpler, better preserved the behavioral realism of the full commute distribution and maintained the highest predictive accuracy across all evaluation metrics. This finding suggests that, at least for this dataset and spatial scale, the linear form provides the most appropriate balance between theoretical considerations and empirical performance.

5.2 Parameter Estimates

Tables 6 and 7 summarize the estimation results for the base and enhanced models, respectively. The base model incorporates standard socio-demographic variables (such as age and gender), travel time, urbanity level, and total job counts at each destination. The enhanced model extends this specification by including additional variables, such as a work flexibility indicator, and sector-specific job share interactions that capture the match between an individual's employment sector and the sectoral composition of jobs at each destination.

Parameter estimates are interpreted in terms of both behavioral realism and statistical significance. Positive coefficients indicate that an increase in the corresponding variable raises the probability of choosing a destination, while negative coefficients indicate a deterrent effect. For example, a negative coefficient for travel time reflects the expected disutility of longer commutes, while a positive coefficient for sectoral job share suggests that individuals are more likely to select destinations with a higher proportion of jobs in their own sector.

For each agent, the alternative with the highest predicted probability within their available choice set is selected as the predicted workplace destination. This enables a direct comparison between observed and predicted choices, supporting the evaluation of model accuracy and the effectiveness of the enhanced specification in replicating actual workplace destination patterns.

5.2.1 Base Model Results

As shown in Table 6, the base model estimation results demonstrate the expected behavioral meaning. The size variable (ln(Total jobs)) is normalized to 1.0 for direct proportionality purposes, implying that destinations with larger employment are inherently more attractive to commuters. Travel time has a negative and statistically significant coefficient (-0.047), reflecting the expected disutility of longer commutes. Among the interaction terms, only the interaction of gender with travel time is statistically significant (-0.014), indicating that women are more sensitive to travel time than men (the reference category). The age-based travel time interactions show directionally negative coefficients relative to the reference category (18-29 years) but are not statistically significant at the 5% level, though the 65+ group approaches significance ($p = 0.0599$), suggesting that older workers may be more sensitive to travel time than younger workers, which is an expected behaviour. Urbanity effects of the destination zones are significant and positive for levels 2-4 relative to the reference level (level 1, very highly urban), while the lowest level of urbanity (level 5) shows negative utility compared to very highly urban destinations. The model achieves reasonable fit statistics (Final LL = -10,059.21; $\rho^2 = 0.247$), providing a solid benchmark for evaluating the enhanced specification.

Table 6: Base model estimation results

Parameter	Value	Rob. Std Err	p-value
Size variables			
ln(Total jobs)	1.0	-	-
Travel time interactions			
Travel time (base)	−0.047***	0.00348	<0.001
Travel time × Age 30–44 (C)	−0.000961	0.00369	0.795
Travel time × Age 45–64 (D)	−0.00609*	0.00365	0.0955
Travel time × Age 65+ (E)	−0.00992*	0.00527	0.0599
Travel time × Woman	−0.014***	0.00196	<0.001
Urbanity level (ref: level 1)			
Level 2 (highly urban)	0.196**	0.0786	0.0125
Level 3 (moderately urban)	0.27***	0.0757	<0.001
Level 4 (low urban)	0.236**	0.0743	0.00146
Level 5 (not urban)	−0.409***	0.0881	<0.001
Model Statistics			
Sample size			1,983
Number of estimated parameters			9
Initial log-likelihood			$-13,354.14$
Final log-likelihood			$-10,059.21$
Rho-square			0.247
Adjusted Rho-square			0.246
Akaike Information Criterion			20,136.42
Bayesian Information Criterion			20,186.76

***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$

The ln(Total jobs) coefficient is fixed to 1.0; it is therefore not estimated (NaN standard error and p-value).

5.2.2 Enhanced Model Results

The enhanced model estimation results are presented in Table 7. Compared to the base model, the enhanced model incorporates sector-specific job share interactions, work flexibility, and household composition effects. The coefficients for sectoral job shares vary among different work sectors: Care (2.65), Education (4.42), Industry/Construction (1.72), and Office/Services (1.93) are positive and statistically significant, indicating that workers are more likely to choose destinations with higher concentrations of jobs in their own sector.

The relatively large values of the significant sectoral coefficients (ranging from 1.72 to 4.42) indicate utility gains relative to the normalized "Remaining" sector, whose coefficient is fixed at 1.0. For instance, the coefficient of 4.42 for Education means that education workers place 4.42 times more weight on increases in education-sector jobs than workers in the Remaining sector do for equivalent increases. Likewise, the coefficient of 2.65 for Care implies that care workers benefit 2.65 times more from concentrations of care-sector jobs than from equivalent concentrations in the Remaining sector.

The travel time coefficient is negative and significant (-0.0558), and its interactions reveal behavioral heterogeneity: men and older workers (45-64, 65+) are more sensitive to travel time, while workers with flexible arrangements are less sensitive (positive interaction coefficient of 0.0149), and those with children are more sensitive (negative interaction coefficient of -0.00621). These patterns align with behavioral expectations that flexible work arrangements allow workers to work from home occasionally, reducing the burden of longer commutes; parents prioritize shorter commutes to balance work and family responsibilities.

Urbanity effects remain positive and significant for levels 2-4, while level 5 (not urban) is not significant, indicating that workers generally prefer more urbanized destinations, likely due to better amenities, infrastructure, and job diversity. Overall, the enhanced model demonstrates substantially improved fit statistics (Final LL = -9,676.962; ρ^2 = 0.307) (see Table 8) and behavioral realism, supporting the value of integrating sectoral and behavioral variables into destination choice modeling.

Table 7: Enhanced model estimation results

Parameter	**Value**	**Rob. Std Err**	**p-value**
Size variables			
ln(Total jobs)	0.773***	0.0245	<0.001
Sector-specific job shares			
Share Care	2.65***	0.24	<0.001
Share Education	4.42***	0.384	<0.001
Share Hospitality/Culture/Sports	1.63	1.83	0.374
Share Industry/Construction	1.72***	0.216	<0.001
Share Office/Services	1.93***	0.246	<0.001
Share Shop	−0.114	1.02	0.91
Travel time interactions			
Travel time (base)	−0.0558***	0.00244	<0.001

Continued on next page

Table 7 – continued from previous page

Parameter	Value	Rob. Std Err	p-value
Travel time × Age 30–44 (C)	0.0000923	0.00354	0.979
Travel time × Age 45–64 (D)	−0.0047**	0.00208	0.024
Travel time × Age 65+ (E)	−0.0077*	0.00402	0.0553
Travel time × Woman	−0.0117***	0.00193	<0.001
Work flexibility			
Travel time × Flexible work	0.0149***	0.00204	<0.001
Household composition			
Travel time × With child	−0.00621**	0.00212	0.00336
Urbanity level (ref: level 1)			
Level 2 (highly urban)	0.327***	0.0814	<0.001
Level 3 (moderately urban)	0.415***	0.0796	<0.001
Level 4 (low urban)	0.326***	0.0807	<0.001
Level 5 (not urban)	0.0991	0.1	0.322
Model Statistics			
Sample size			1,983
Number of estimated parameters			18
Initial log-likelihood			$-13,964.69$
Final log-likelihood			$-9,676.962$
Rho-square			0.307
Adjusted Rho-square			0.306
Akaike Information Criterion			19,389.92
Bayesian Information Criterion			19,490.59

***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$

5.3 Comparative Performance Evaluation

5.3.1 Goodness-of-Fit Statistics

Table 8 presents a direct comparison of goodness-of-fit statistics between the base and enhanced models. The final log-likelihood indicates model fit, with higher (less negative) values representing a better fit. Rho-square (ρ^2) and its adjusted version measure the proportion of improvement over a null model, accounting for complexity in the adjusted form. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) balance model fit against the number of parameters, with lower values indicating a better trade-off between fit and efficiency.

Table 8: Goodness-of-fit comparison between base and enhanced models

Metric	Base Model	Enhanced Model
Number of parameters	9	18
Final log-likelihood	-10,059.21	-9,676.962
Rho-square (ρ^2)	0.247	0.307
Adjusted Rho-square	0.246	0.306
AIC	20,136.42	19,389.92
BIC	20,186.76	19,490.59

The enhanced model achieves a significantly higher rho-square (0.307 vs. 0.247) and lower AIC (19,389.92 vs. 20,136.42), indicating improved model fit that justifies the additional complexity. The improvement in log-likelihood (382.25 points) is significant for a discrete choice model with nearly 1,200 alternatives per agent. Part of this improvement in rho-square is attributed to estimating the total employment coefficient (0.773) rather than fixing it at 1.0 as in the base model, allowing the data to determine the optimal scaling of the size variable effect.

5.3.2 Predictive Accuracy Metrics

Table 9: Predictive accuracy comparison between base and enhanced models

Metric	In-sample		Out-of-sample	
	Base	Enhanced	Base	Enhanced
Average number of alternatives	1,465	1,242	1,255	1,255
Top-1 accuracy	0.0740	0.108	0.0738	0.0925
Top-5 accuracy	0.2275	0.238	0.2233	0.2375
Top-10 accuracy	0.320	0.340	0.3125	0.3405
City-level accuracy	0.2732	0.3089	0.2875	0.3010
Precision (macro)	0.0295	0.0570	0.0222	0.0479
Recall (macro)	0.0515	0.0784	0.0472	0.0514
F1 (macro)	0.0327	0.0575	0.0315	0.0470

The enhanced model demonstrates consistent performance improvements over the base model across all predictive accuracy metrics. Top-1 accuracy (exact postal code match) increases from 7.4% to 10.8% in-sample and from 7.3% to 9.2% out-of-sample, representing relative improvements of **45%** and **26%** respectively. While these absolute values may appear modest, they are significant given the extremely large choice set of approximately 1,200 alternatives per agent.

Top-5 accuracy shows similar patterns, improving from 22.2% to 23.8% in-sample, while Top-10 accuracy reaches 34% both in-sample and out-of-sample for the enhanced model. At the city level, accuracy achieves approximately 31% in-sample and 30% out-of-sample, indicating that nearly one-third of all predicted workplace destinations fall within the correct municipality. The enhanced model also demonstrates superior performance in precision (0.057 vs. 0.030), recall (0.078 vs. 0.051), and F1 score (0.057 vs. 0.032), providing more balanced prediction across both frequent and rare destinations. Importantly, the performance improvements remain consistent between in-sample and out-of-sample testing, with only minimal degradation in the test set, confirming the model's generalizability and robustness against overfitting.

5.3.3 Spatial Distribution of Predicted Travel Times

Figure 8 compares the predicted travel time distributions for both models against observed data. The enhanced model produces a distribution with a less truncated right tail and mean/median values closer to the empirical distribution compared to the base model.

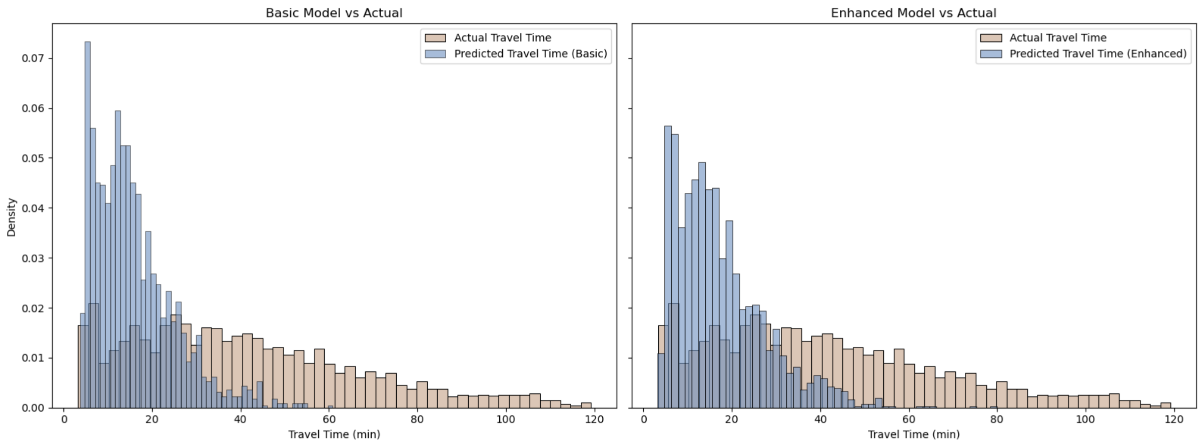

Figure 8: Distribution of predicted travel times for both models compared to observed data.

Both models, however, underestimate the frequency of very long commutes, but the enhanced model slightly improved behavioral realism in capturing the heterogeneity of commuting patterns across the full distribution. The base model's distribution peaks more sharply at shorter travel times (approximately 15-25 minutes) and declines more rapidly, failing to clearly represent medium to long-distance commuters. In contrast, the enhanced model's distribution exhibits a smoother decline and better preservation of the right tail beyond 40 minutes.

5.3.4 Predicted Workplace Destination Probabilities

To illustrate how the two models differ in distributing probabilities across PC4 zones, figure 9 visualizes the average predicted workplace destination probabilities across zones in the Overijssel province. The average probability for each zone is computed only for agents that zone is available in their choice set (i.e., those not excluded by sectoral job availability or travel time constraints). This ensures that the reported averages reflect only feasible alternatives.

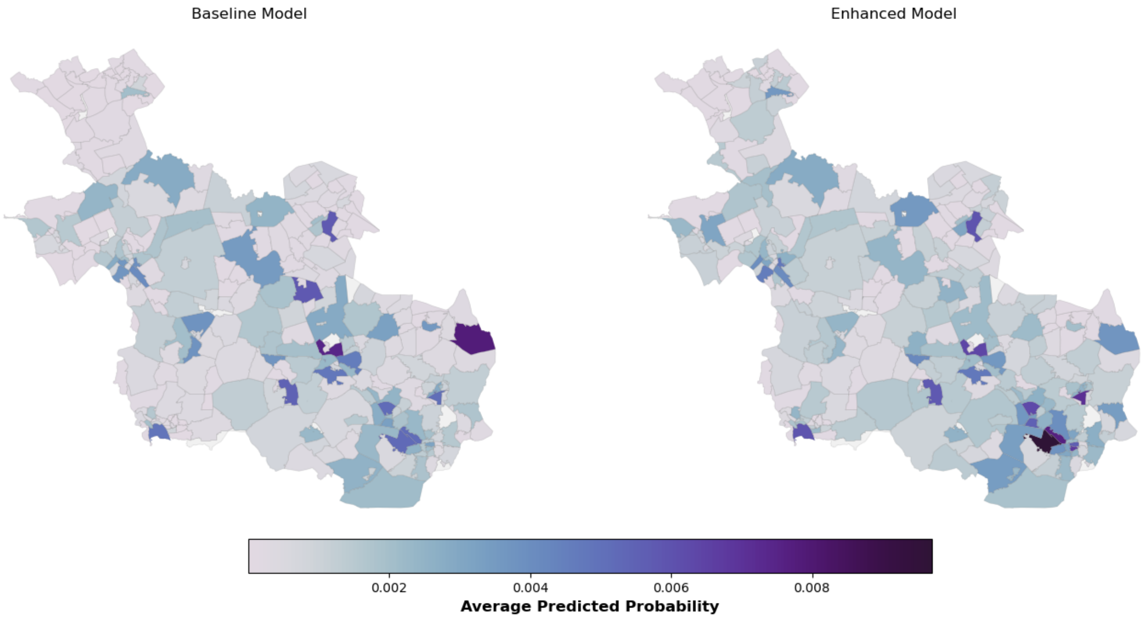

Figure 9: Predicted workplace destination probabilities for Overijssel Province.

The comparison between the base and enhanced models reveals several important differences. In both models, the highest probabilities are assigned to the main cities of Overijssel, consistent with the concentration of job opportunities in urban areas. However, the enhanced model distributes nonzero probabilities across a broader set of zones, including some that receive negligible or zero probability in the base model. This dispersion results from the inclusion of sector-specific job accessibility, which enables the model to recognize additional relevant opportunities for agents based on their employment sector.

As a result, the enhanced model produces a more realistic spatial pattern of probability assignment. While dominant employment centers remain prominent, it better captures the diversity of feasible workplace destinations, particularly for agents in sectors with more dispersed job opportunities. This improvement increases the model's usefulness for policy analysis and scenario evaluations in which probability assignment matters.

6 Discussion

This chapter discusses the key findings and implications of the enhanced destination choice model developed in this study. The discussion is organized around four main themes: the interpretation of model enhancements and their behavioral implications, the contributions to travel demand modeling theory and practice, the methodological limitations and constraints encountered, and directions for future research.

The discussion examines these findings in the context of existing literature, evaluates the practical significance of the improvements achieved, and identifies opportunities for further methodological advancement. While the enhanced model represents a meaningful step forward in behavioral realism, the analysis reveals that the most promising directions for future improvement may lie beyond utility specification refinements toward more fundamental changes in model structure and data integration approaches.

6.1 Interpretation of Model Enhancements

The enhanced destination choice model demonstrates notable improvements in both model fit and predictive accuracy. Incorporating sector-specific employment variables, demographic interactions, and introducing relaxed size term estimation increases the McFadden ρ^2 from 0.247 to 0.307 and reduces the AIC from 20,136.42 to 19,389.92. These gains are achieved despite a significant increase in the number of parameters, indicating that the added variables capture meaningful behavioral variation rather than overfitting.

Predictive accuracy improves across all hit-rate measures. The Top-1 hit rate (exact postal code) rises from 7.4% to 10.8% in-sample and from 7.3% to 9.2% out-of-sample. The Top-10 hit rate increases to approximately 34% both in-sample and out-of-sample. Accuracy at the municipality level also shows measurable improvement. While absolute values remain modest due to the large choice set (approximately 1,200 alternatives), these increases represent a meaningful enhancement in the model's ability to rank the observed workplace among the most probable alternative destinations.

Size Variable and Sector-Specific Job Shares: The enhanced model confirms that total jobs at a destination are a strong predictor of workplace choice, with an estimated coefficient of 0.773 that is both positive and statistically significant. In contrast, the base model fixes this coefficient at 1.0, making the total employment effect fully proportional. As shown in Figure 10, elasticity values for total employment cluster around 1.5 across all employment sectors, indicating high sensitivity to job agglomeration.

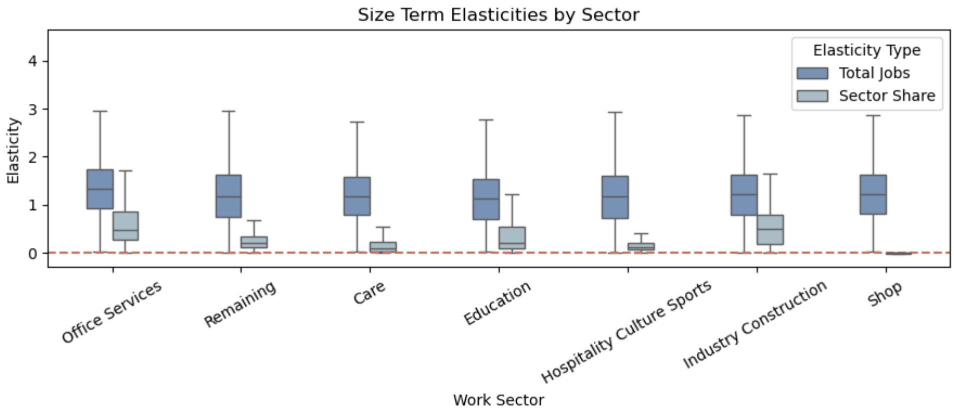

Figure 10: Elasticity of destination choice probability with respect to total employment and sectoral job share.

Elasticities quantify the percentage change in choice probabilities resulting from a **1% change** in key variables. For example, an elasticity of 1.5 for total employment implies that a 1% increase in jobs at a destination raises its choice probability by 1.5%. Mathematically, the elasticity of choice probability P_{nj} with respect to variable X_{nj} is:

$$\text{Elasticity}Xnj = \frac{\partial P_{nj}}{\partial X_{nj}} \cdot \frac{X_{nj}}{P_{nj}} = \beta_X \cdot X_{nj} \cdot (1 - P_{nj}) \tag{5}$$

where β_X is the estimated coefficient for X_{nj}, and the elasticity varies across alternatives depending on both the variable value and the predicted probability.

Total employment remains the dominant driver of destination choice, with workers responding strongly to zones with larger job concentrations. The slightly lower coefficient in the enhanced model (0.773) reflects a more nuanced relationship than the fixed proportional assumption in the base model, allowing for diminishing returns as employment scales up.

The enhanced specification distinguishes between two forces: the *mass effect*, captured by total employment, and the *matching effect*, captured by sector-specific job shares. Total jobs primarily concentrate choice probabilities on large, nearby employment zones, explaining why both models tend to under-predict very long commutes. Sector-specific shares refine the prediction by aligning workers with destinations that match their sectoral profile within these high-employment zones. Consequently, sectoral elasticities are smaller (mostly 0–1.8, Figure 10), and improvements in log-likelihood and ρ^2 remain modest despite statistical significance.

Differences in sectoral elasticity reflect both behavioral and structural factors. Education exhibits the highest responsiveness (4.42), due to the spatial concentration and size of educational jobs staffed by similarly qualified workers. Care shows moderate elasticity (2.65), reflecting partial clustering but tempered by irregular hours and part-time positions. Office/Services has lower elasticity (1.93) because it encompasses geographically dispersed and substitutable activities like business services, ICT, finance, and public administration. While sector-specific effects contribute to utility gains, they remain secondary to the overwhelming influence of total employment.

Travel Time Sensitivity: Both models penalize longer commutes, but the enhanced model exhibits a slightly stronger base travel time coefficient (-0.0558 vs. -0.047 in the base model), suggesting that controlling for sectoral heterogeneity reveals greater overall sensitivity to travel time. Figure 11 illustrates the combined elasticity effects across different demographic groups. Flexible workers without children show the lowest sensitivity to travel time, with a median elasticity of around -1.0, indicating a greater tolerance for long commutes. In contrast, non-flexible workers with children exhibit the highest sensitivity, reaching maximum elasticity values around -3.5, reflecting the combined constraints of rigid work schedules and family responsibilities. The other two groups (flexible with children and non-flexible without children) display intermediate sensitivities, illustrating how work flexibility and household composition independently influence commuting preferences.

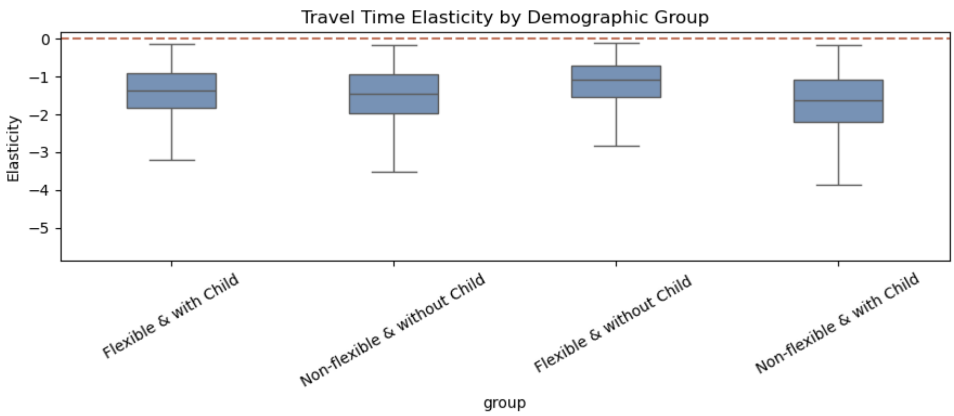

Figure 11: Travel time elasticity by demographic group for the enhanced model.

6.2 Sectoral effects and data limitations

Sectoral job shares reveal meaningful but comparatively modest effects on choice. The strong total-jobs term weakens the incremental explanatory power of sectoral composition, which helps explain why improvements in log-likelihood and ρ^2 are modest even when sectoral variables are significant.

Three practical data limitations reduce the measured effect of sectoral composition:

- **Unbalanced sectoral representation:** The dataset contains significantly different numbers of agents across employment sectors (e.g., 25.1% in Health and welfare versus only 1.5% in Hospitality), making it difficult to detect meaningful sectoral effects for underrepresented categories across such a large study area.

- **Loss of granularity through recategorization:** The original 15 LRO employment categories were consolidated into 7 broader sectors to comply with CBS classification standards, potentially obscuring more nuanced sectoral patterns. For example, diverse activities like retail shops, food stores, and supermarkets were grouped under "Shop," while distinct sectors like "Business services," "ICT," "Financial services," and "Public administration" were combined into "Office/Services," blurring important differences in workplace preferences.

- **Sectoral heterogeneity within categories:** Broad categories such as *Shop* or *Retail* combine heterogeneous establishments (e.g., bakeries and car dealers) that attract different commuting patterns, diluting estimated sectoral responses. This likely explains why the Shop interaction term was not statistically significant in the enhanced model. The internal diversity of retail establishments creates opposing destination preferences that cancel out when aggregated, preventing the detection of a sectoral effect, unlike the more homogeneous sectors such as Education or Care.

The interaction between an agent's own sector and the zone-level sectoral share is statistically significant and behaviorally meaningful, suggesting thick-market benefits (higher matching probabilities), sector-specific agglomeration economies, and potential wage/amenity premiums that accumulate where local opportunities match workers' skills. This cross-level interaction, therefore, captures nuances that simple sectoral shares by themselves cannot.

Despite these meaningful interactions, sectoral variables showed limited influence on overall utility. To further investigate this limitation, another alternative specification was compared that can be found in Appendix B. Daly's logsum formulation, where each sector contributes with its own parameter γ_k. Even with this theoretically stronger logsum specification, most sectors failed to reach statistical significance; only Education ($\gamma \approx 0.97$) and Industry ($\gamma \approx -0.90$) showed meaningful effects, while Care, Office, Shop, and Hospitality remained insignificant. This suggests that sectoral effects operate primarily through worker–sector matching rather than through generic sectoral attractiveness, and even with more sophisticated modeling approaches, the impact of sectoral variables remains constrained by limited variation, aggregation error, and measurement noise in the underlying data.

6.3 Limitations and methodological constraints

While this study successfully enhanced the destination choice model in ways that maintain compatibility with the Octavius framework, it is important to acknowledge the fundamental limitations inherent in the modeling approach. The primary goal was to develop enhancements that could be readily integrated into the existing operational pipeline without requiring structural modifications to the broader modeling system. This compatibility objective was achieved through careful specification choices and targeted variable additions. However, despite these improvements, significant structural constraints remain that limit the model's ability to fully capture observed travel patterns. These limitations are not merely implementation challenges but reflect deeper conceptual boundaries of the multinomial logit framework when applied to complex spatial choice problems.

The modeling exercise is subject to several important constraints:

Spatial and measurement. Using PC4 administrative zones may misalign model alternatives with how agents perceive or use space. Administrative boundaries often fragment functionally integrated areas, creating alternatives that look distinct in the model but not to decision-makers.

Model structure and IIA. The multinomial logit assumption of Independence of Irrelevant Alternatives (IIA) is particularly restrictive for spatial choices at the PC4 level. Consider three workplace destinations in the Netherlands: a PC4 zone in central Amsterdam (covering parts of the city center) with 5,000 jobs, and two adjacent PC4 zones in Utrecht (both covering Utrecht's central district) with 1,000 jobs each. Initially, each Utrecht zone attracts 20% of commuters while the Amsterdam zone attracts 60%. If one of Utrecht's zones improves its accessibility through better parking facilities, the MNL model with IIA would predict that its share increases proportionally from all alternatives, drawing equally from Amsterdam and the adjacent Utrecht zone.

In reality, however, the two Utrecht zones likely share unobserved characteristics (similar city functions, local amenities, transit connections) that make them closer substitutes for each other than for the Amsterdam zone. A more realistic model would predict that Utrecht draws disproportionately more commuters from Utrecht than from Amsterdam. This pattern cannot be captured by a single-level MNL model. A nested structure with cities as higher-level nests (Amsterdam, Utrecht) and PC4 zones as lower-level alternatives would better represent these substitution patterns, allowing for stronger competition between PC4 zones within the same city than between zones in different cities. Future research could expand upon the findings of this research by implementing nested logit structures that relax IIA assumptions through spatial clustering (urban core, suburban, rural nests) and exploring mixed logit formulations with random coefficients to capture unobserved heterogeneity in travel time sensitivity across the population.

No residential-workplace integration or household interactions. The model treats residential location as exogenous and fixed, ignoring the interdependence between living and workplace choices. In reality, households often make joint decisions about where to live and work, with residential location potentially serving as both a constraint on and a response to workplace opportunities. As Paleti et al. (2013) demonstrate, ignoring this endogeneity can lead to biased parameter estimates and unrealistic predictions of spatial patterns. Similarly, the model does not account for the influence of other household members' workplace locations on an individual's destination choice. In multi-worker households, members often coordinate their commuting patterns to minimize household-level travel costs or maintain proximity between workplaces. Gupta et al. (2015) found significant effects from inter-workplace distance and the angle formed at home between workplaces, suggesting that workers do not make destination choices independently of their partners' employment locations.

No capacity constraints / one-sided matching. The model treats destination attractiveness solely from the worker's perspective without considering capacity limits or employer choice processes. This one-sided approach can predict unrealistically concentrated flows to attractive but capacity-limited destinations.

While these limitations are primarily relevant for simulation applications rather than estimation, they represent important post-estimation considerations. For practical implementation in simulation frameworks, doubly-constrained formulations using *shadow prices* (Lagrangian multipliers) are often employed to adjust destination utility based on capacity constraints. This post-estimation procedure typically involves: (1) estimating the unconstrained model; (2) summing predicted flows to each destination; (3) comparing these to control totals C_j; (4) computing shadow prices $\lambda_j = \ln(C_j/\hat{T}_j)$; and (5) re-estimating with updated λ_j until convergence (Gupta et al., 2015; B. J. Vitins et al., 2016).

However, these post-estimation measures were not implemented in the current study due to:

- **Data limitations:** Reliable control totals (verified employment capacities) were unavailable at the required spatial resolution for all sectors.
- **Computational demands:** Iteratively updating shadow prices and re-estimating large-scale models is computationally intensive.
- **Study focus:** This research prioritized improving behavioral specification and variable selection rather than producing equilibrated forecasts under capacity constraints.

6.4 Future research directions

The analysis suggests several concrete, prioritized directions for future work. These are grouped by (A) model structure and estimation, (B) data and spatial definition, and (C) system-level and two-sided representations.

A. Model structure and estimation

- **Relax IIA with nested formulations:** Construct nests by spatial clusters (e.g., urban core, suburban belts, labor market regions) so choice decomposes into cluster choice and within-cluster choice. This reduces unrealistic substitution across geographically similar alternatives (Akiva & Lerman, 1985).

- **Capture unobserved heterogeneity with mixed logit (random parameters):** Allow coefficients (travel time, size, sectoral share) to vary randomly across agents to capture differing sensitivities. While mixed logit can approximate any substitution pattern and is well suited where respondents differ in travel-time tolerance (Train, 2009), their direct application at a national scale with thousands of alternatives is computationally enormous. Therefore, practical implementation requires strategic simplifications, choice set reduction, or advanced sampling methods to maintain computational feasibility without sacrificing behavioral richness.

- **Explore latent class segmentation:** Latent class models partition the sample into discrete behavioral segments (e.g., high vs low travel-time sensitivity) and estimate class-specific utilities. They are a useful complement or alternative when classes are conceptually meaningful (Train, 2009).

- **Constrained estimation / joint estimation with shadow prices:** Implement estimation routines that incorporate attraction constraints directly (rather than purely post-estimation calibration). Recent work demonstrates techniques for unbiased estimation of destination choice under attraction constraints and highlights the bias introduced by ignoring constraints during estimation (Bernardin et al., 2014).

- **Accessibility measures within richer structures:** Replace or augment simple size terms with accessibility indices (e.g., logsum-based or travel-time weighted opportunities) inside nested or mixed structures; prior work shows notable performance gains when accessibility is modeled carefully (Dong et al., 2006).

B. Data and spatial definition

- **Finer spatial units or functional clusters:** Where possible, move to smaller spatial units or define functional market clusters derived from commuting flows or travel time thresholds to reduce aggregation bias.

- **Richer sectoral disaggregation:** Obtain more detailed employment classifications to separate heterogeneous activities within aggregated categories (e.g., retail subtypes) that attract different trip types.

- **Use passively collected mobility data:** Integrate large-sample passive sources (mobile or vehicle traces) to better observe revealed destination patterns and validate or augment survey data. These data also support alternative sampling and choice-set construction approaches (Bowman & Ben-Akiva, 2001).

C. System-level realism and two-sided matching

- **Two-sided matching/employer choice:** Extend the model to incorporate employer preferences and capacities (a two-sided matching or assignment model). This could be implemented as a separate employer choice module, or by combining worker choice with an employer selection/assignment algorithm to ensure feasible matches.

- **Doubly-constrained or equilibrium formulations:** For forecasting and policy evaluation, integrate shadow pricing or equilibrium algorithms so that predicted destination allocations respect control totals. This is particularly important for applications that test land-use or employment shocks where capacity matters (Daly, 1982; Federal Highway Administration (FHWA), 2018).

- **Hybrid theory-driven / data-driven approaches:** Combine discrete-choice models with machine learning to capture complex, nonlinear patterns while keeping interpretability (Bhat, 2015). These methods can also better represent travel time variability and reliability effects, where travel time variance differs between congestion onset and offset despite similar averages, reflecting travelers' sensitivity to both mean and variability of travel times. (Van Cranenburgh et al., 2022)

- **Computational strategies:** Given the computation demands of iteratively estimating large-scale constrained models, explore parallelized estimation, surrogate models for iterative shadow price updates, or two-stage procedures that alternate rapid utility updates with occasional full re-estimation.

D. Applying the framework to other travel modes Although this study focused on car-based work trips, many elements of the enhanced specification are largely mode-independent and can be transferred to other travel modes with targeted adjustments. Sector-specific employment, worker–sector matching, and demographic interactions (work flexibility, household composition) capture demand-side preferences that should also influence destination choice for public transport, cycling, and walking; what changes across modes are the impedance measures, modal attributes, and capacity constraints that enter the utility function (Bowman & Ben-Akiva, 2001; E. Miller, 2020).

Practically, applying the framework to other modes requires three types of adaptation: (1) substitute mode-relevant attributes for travel-time and impedance (e.g., in-vehicle time, access time, transfers, waiting time, fares, parking cost and availability for park-and-ride) (Schakenbos et al., 2016; Zhao et al., 2019); (2) incorporate mode-specific availability and quality indicators (service frequency, network connectivity, bike lanes, sidewalk continuity) (Kohlrautz & Kuhnimhof, 2025; E. Miller, 2020); and (3) account for differing capacity and matching processes (public transport crowding, bike parking, employer parking allocation) (Kohlrautz & Kuhnimhof, 2025; Li & Hensher, 2011; Zhao et al., 2019).

This study has enhanced the modeling of destination choice for car-based work trips by explicitly incorporating sector-specific job shares, relaxing the estimation of total jobs, and including additional travel time interactions. The enhanced specification improves the behavioral realism of predicted flows while maintaining compatibility with the operational Octavius travel demand framework. Total employment remains the dominant driver of destination choice, but sectoral matching refines predictions and captures meaningful interactions that simple size measures cannot. Despite data and methodological limitations, the framework demonstrates flexibility and applicability across different travel modes, offering a foundation for future extensions such as nested or mixed logit structures, two-sided matching with employers, and mode-specific adaptations. Overall, the findings provide both theoretical and practical insights for transport planners seeking to better understand and forecast workplace destination patterns.

A Sector Classification

Table A10: Mapping work sector categories among all datasets

CBS	LRO	MPN	Mobility Spectrum
Care	Health and welfare	Health care	Healthcare jobs
Office/Services	Public administration	Public administration, security and justice	Office jobs
	Business services	Personnel, organization and strategy; Language, Media and Communication; Real Estate and Brokerage	
	ICT	Automation and ICT	
	Financial services	Financial services	
Industry/Construction	Construction Industry	Construction Technique; Industry and production	Industry jobs
	Transportation	Storage and Transportation	
Shop	Commerce	(Detail) trade	Retail shops; Food shops; Supermarkets

Continued on next page

Table A10 – continued from previous page

CBS	**LRO**	**MPN**	**Mobility Spectrum**
Hospitality/ Culture/Sports	Hospitality	Catering and housekeeping; Tourism and recreation; Sports and Personal Care	Sports facilities; Hotels
	Culture	Culture	Meeting venues
Remaining	Agriculture and fisheries	Agriculture, fishing and livestock	Residential; Parking; Farms; Combined functions
	Other services	Other	Other facilities; Cell function
	Utilities	Nature and environment	Distribution centers; Warehouses
Education	Education	Education and science	Education jobs

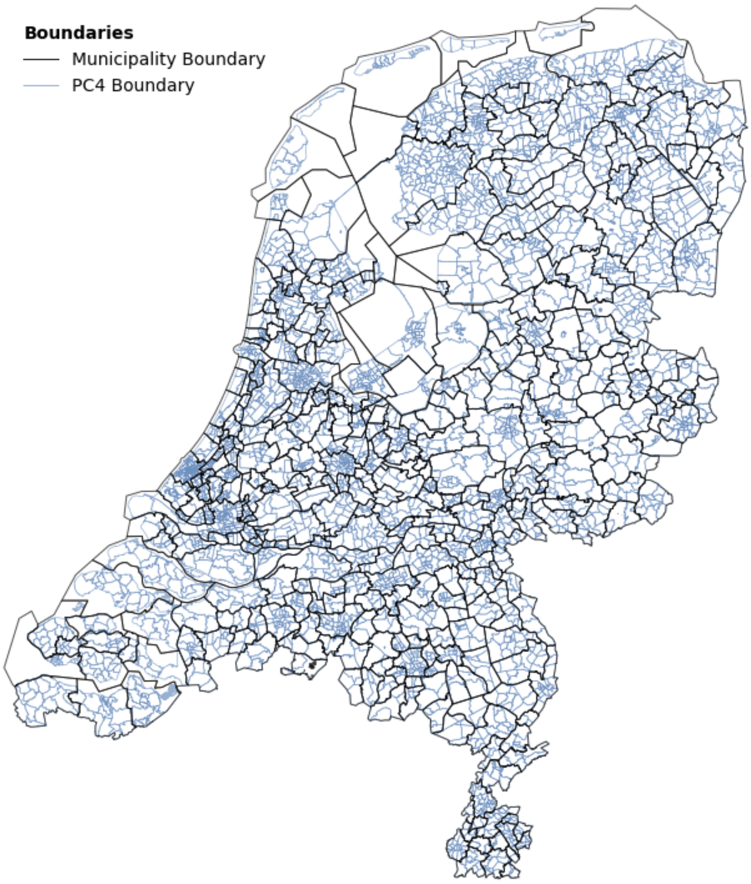

Figure A12: Municipality and PC4 boundries.

B Alternative Model Specification

The enhanced model incorporates Daly's (1982) *sector-mix log-sum approach*, which was developed to include multiple sector-specific size variables (e.g., employment in care, education, industry, etc.) in a theoretically consistent manner. Instead of assuming that all job opportunities contribute equally to the attractiveness of a destination, this approach allows for a weighted combination of sector-specific employment counts. The weights (gamma parameters) are estimated within the utility specification, capturing how strongly each employment sector contributes to the perceived utility of a destination.

The log-sum formulation ensures that the composite size measure remains consistent with random utility theory, particularly when multiple size variables enter the utility nonlinearly. This is important in avoiding issues of multicollinearity or over-representation of destinations with high values across several correlated sectors. By estimating the sector weights jointly, the model captures the relative contribution of each sector to the average individual's destination preference without assuming equal importance a priori. This enhances both the empirical flexibility and theoretical soundness of the model.

In addition to sector-disaggregated employment variables, the model also integrates behavioral attributes such as household composition and work flexibility to provide a comparable variation to the extended model with sectoral share, developed in this study.

Following this methodology, the systematic utility function is specified as:

$$V_{nj}^{\text{enhanced}} = \underbrace{\theta \cdot \log\Big(\sum_{s=1}^{S} E_{s,j} \cdot \exp(\gamma_s)\Big)}_{\substack{\text{sector-mix}\\ \text{log-sum}}} + \underbrace{(\beta_{\text{gender}} D_{n,\text{male}} + \beta_{\text{HH}} H_{nh} + \beta_{\text{age}} A_n + \beta_{\text{flex}} F_n + \beta_{\text{tt}}) \cdot TT_{nj}}_{\substack{\text{person-specific}\\ \text{travel impedance}}} + \sum_{u=2}^{5} \gamma_u \cdot U_{u,j} \tag{B6}$$

where the variables are:

- $E_{s,j}$ is the number of jobs in sector s at zone j, where sectors include: Care, Education, Hospitality/Culture/Sports, Industry/Construction, Office/Services, Shop, and Remaining
- γ_s are sector-specific parameters, with one sector (Shop) normalized to 1 for identification
- θ is the scaling parameter for the overall sectoral employment effect
- A_n is an age category dummy variable (age 30-44 years)
- H_{nh} is a household composition dummy variable (1 if household has children, 0 otherwise)
- F_n is a work flexibility indicator (1 if the individual has flexible work arrangements, 0 otherwise)
- $\beta_{\text{gender}}, \beta_{\text{HH}}, \beta_{\text{age}}, \beta_{\text{flex}}, \beta_{\text{tt}}, \gamma_u, \gamma_s, \theta$ are parameters to be estimated

B.1 Estimation results

Table B11: Daly's sector-mix log-sum model estimation results

Parameter	**Value**	**Rob. Std Err**	**p-value**
Size variables (log-sum)			
θ (scaling parameter)	0.831*	0.0349	0.000
γ Care	0.314	0.475	0.508
γ Education	0.970*	0.403	0.016
γ Hospitality/Culture/Sports	−1.000	1.11	0.365

Parameter	**Value**	**Rob. Std Err**	**p-value**
γ Industry/Construction	−0.896*	0.448	0.046
γ Office/Services	0.391	0.338	0.248
γ Shop	0.677	0.468	0.147
Travel time interactions			
Travel time (base)	−0.0612*	0.00295	0.000
Travel time × Age 30–44	0.00475**	0.00244	0.051
Travel time × Male	−0.0130*	0.00247	<0.001
Work flexibility			
Travel time × Flexibility	0.0163*	0.00268	<0.001
Household composition			
Travel time × With child	−0.00565*	0.00254	0.026
Urbanity level (ref: level 1)			
Level 2 (highly urban)	0.379*	0.107	<0.001
Level 3 (moderately urban)	0.525*	0.109	<0.001
Level 4 (low urban)	0.478*	0.122	<0.001
Level 5 (not urban)	0.382*	0.163	0.019
Model Statistics			
Sample size			1,200
Number of estimated parameters			16
Final log-likelihood			$-5,944.976$
Rho-square			**0.164**
Rho-square-bar			**0.162**
Akaike Information Criterion			11,921.95
Bayesian Information Criterion			12,003.39

*Significant at $p < 0.05$

Estimation is done for a smaller sample of 1200 agents

B.2 Predicted Travel Time Distribution

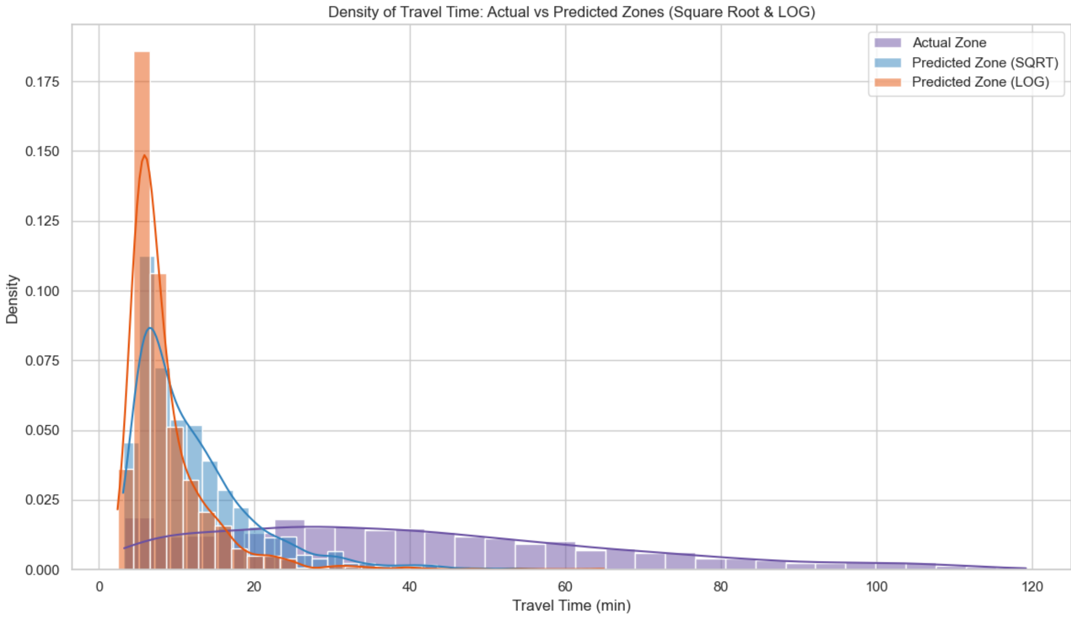

Figure B13: Comparison of distribution of predicted travel time with different transformations.

Figure B13 shows linear, logarithmic, and square root transformations and their effects on predicted destination choice probabilities. The logarithmic and square root transformations assign substantially higher probabilities to short-distance destinations and nearly zero probability to longer commutes, failing to capture the observed long-tail distribution of actual commuting patterns.

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