Making Space for Modal Shift

A quantitative system dynamics approach to understand the effects of citywide road space reallocation on travel behavior

MSc Thesis

Micha Arnoldus

Delft University of Technology

TU Delft

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by

Micha Arnoldus

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	Mr. dr. N. Mouter	TU Delft, 2nd supervisor

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Preface

The MSc thesis that lies before you would not be what it is without the support of some truly important people. First and foremost, I would like to express my deepest gratitude to my two supervisors. Floortje, your approachable supervision style and remarkable ability to boil down complex arguments into plain language have been invaluable. Niek, thank you for your fresh perspective and for your encouragement to refine how I position the thesis and its contributions.

I would also like to thank the participants of the expert interviews for their commitment to my research, despite their busy schedules. I hope my work does justice to the valuable insights you've shared. Another heartfelt thanks goes to Hans, Bert, and Chris for sharing their expertise and providing feedback along the way.

To my family, friends, and housemates, thank you for your patience and understanding during the times I was less available. Maite and Chris, your support and encouragement have been especially crucial in helping me through the toughest moments.

Finally, I'd like to thank Mariana for inspiring and facilitating my systems thinking work over the past year. Who could have imagined that one guest lecture would shape my academic and professional path so profoundly? Both my six-month internship at the OECD and this MSc thesis project have been invaluable and humbling experiences.

This MSc thesis marks the end of my time as a student and concludes my second major systems thinking project. Over time, I've come to appreciate the unique value of a systems approach in guiding sustainability transitions. I look forward to applying the skills and insights I've gained to contribute to these transitions throughout my professional career.

Micha Arnoldus
Delft, November 26

Abstract

Urban mobility systems in European cities face climate, health, and spatial challenges that call for policies to reduce private car use while increasing access by public transport and active modes. Road space reallocation shows promise, but there is limited understanding of how citywide implementation affects travel behavior over time. This research addresses this gap by conceptualizing the effects of citywide road space reallocation on travel behavior and developing a quantitative System Dynamics (SD) model. The method is combined with Scenario Discovery to evaluate the role of uncertainties on the effectiveness of the policy, and expert interviews are conducted to support the validation of the model. Applying the model to a single case study with ongoing road space reallocation indicates that the policy can trigger significant modal shift to cycling for mid-distance trips (1.5–6 km), while modal shift from the car to public transport for long-distance trips (7–10 km) is slower and more uncertain. The level of change depends on uncertainties, including the future availability of bike parking and the uptake of e-bikes. The research contributes a data-light SD model that quantifies existing conceptual models and provides strategic insights for designing robust road space reallocation policies. Next modeling steps should prioritize the inclusion of bike-and-ride, and future empirical research should examine bike adoption over time in cities with improving cycling networks. Recommendations for policy makers include accelerating bike adoption through targeted initiatives, improving monitoring and target-setting, and collaborating across municipalities to address car dependence in suburban areas.

Executive Summary

Reducing dependence on private cars –whether conventional or electric –is essential for addressing climate, health, and transport poverty challenges (Henderson, 2020, Natalie Mueller, 2017, Mattioli, 2021), as well as improving space-efficiency (ITF, 2022), particularly in high-density cities where public space is in high demand for improving health and climate resilience (Orsetti et al., 2022). High-income cities, in particular, must accelerate efforts to reduce private car use to mitigate climate change (University of Leeds, 2019). Various policy instruments can help achieve this, including (parking) regulations, pricing, land use planning, and infrastructural policies. One such policy, road space reallocation, involves reducing public space reserved for private vehicles to create space for walking, cycling, public transport, and green space. An example of implementation at the neighborhood level is Superblocks in Barcelona (Figure 1), which restricts motor vehicle access to inner streets while making space for pedestrians and green space. While systems thinking highlights the potential of road space reallocation to reduce car dependency and promote modal shift (OECD, 2022, Pokharel et al., 2023), the extent to which it can change travel behavior and the circumstances that increase its effectiveness remain under-explored.

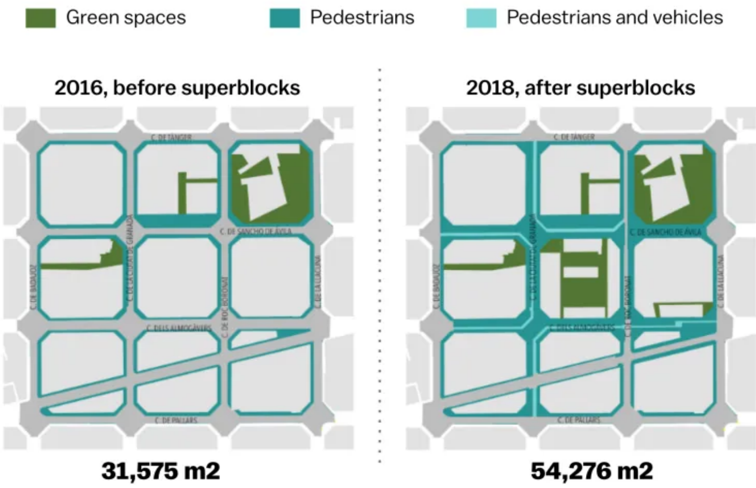

Figure 1: An example of road space reallocation and how it affects public space distribution. The map reflects an implementation of Superblocks in the neighborhood Poblenou in Barcelona, Spain. The indicated surface area before and after implementation refers to the area of public space for citizen use (green spaces, pedestrians, and space shared by pedestrians and vehicles). Extracted from BCNUEJ (2024)

Citywide implimentation of road space reallocation is gaining momentum in European cities. With their high densities, well-developed public transport systems, and supportive EU regulatory frameworks, European cities are particularly well-positioned to reduce dependence on private vehicles through road space reallocation policy (EC, 2021, Halpern and Parnika, 2022). Pontevedra, Spain, pioneered citywide implementation in the 1990s, and the policy is now emerging in larger cities such as Oslo and Paris.

This research addresses a gap by examining the effects of citywide road space reallocation on travel behavior. Existing case studies and empirical research have explored the effects of road space reallocation at the street and neighborhood levels (Hardinghaus et al., 2021, Kuss and Nicholas, 2022, Piras et al., 2022, Cash-Gibson et al., 2024). However, to the best of my knowledge, an analysis of how citywide road space reallocation affects travel behavior over time is missing. The research examines immediate and medium-term effects on travel behavior, based on a three-decade timescale aligned with the Paris Agreement goals. Longer-term feedback between travel behavior, land use, and residential relocation fall outside the scope of this research. With the purpose to inform robust policy design, this research combines quantitative System Dynamics (SD) with Scenario Discovery to assess the role of uncertainty on the policy outcomes. The model is applied to a single case study – Paris – and, due to a data gap, the current public space distribution in the city must be estimated. The research addresses the following main research question (MQ) and sub-questions (SQ):

MQ: To what extent can road space reallocation change travel behavior in European cities?

SQ1 What are the interactions between public space distribution and travel behavior according to literature?

SQ2 What are the dynamics of travel behavior when public space distribution changes over time?

SQ3 What is the current distribution of public space in Paris between pedestrians, cyclists, and motorized vehicles?

SQ4 How do uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy influence to what extent road space reallocation policy in Paris can change travel behavior?

The research makes several contributions. One of its scientific contributions is quantifying existing conceptual models by proposing a data-light SD model that can be further developed into a decision-support tool. One of its societal contributions is providing strategic insights for designing robust road space reallocation policies. The model results indicate that within the context of the case study, it is plausible that the share of distance traveled[1] will surpass the share of distance traveled by car by more than 50% over the course of 30 years. The level of change depends on uncertainties, including the future availability of bike parking and the uptake of e-bikes. Figure 2 summarizes the results.

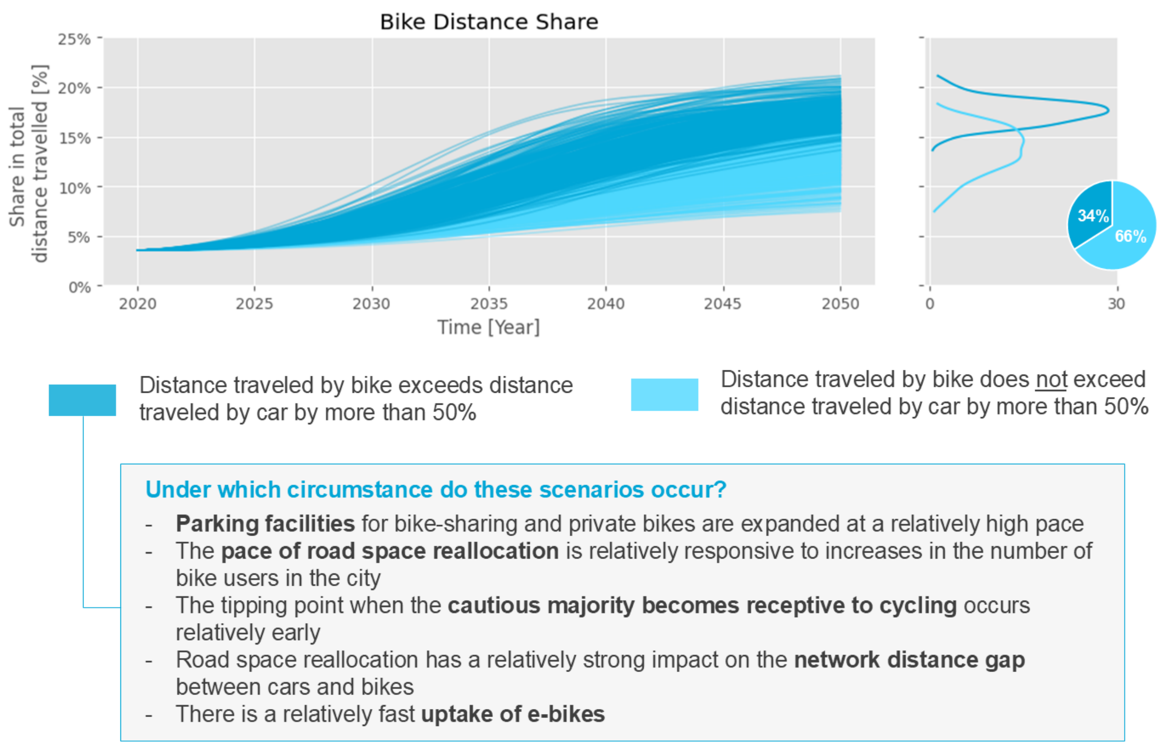

Figure 2: The line chart in the top left section of the figure displays the share of bike travel in total distance traveled over time in an ensemble of 1000 scenarios. The scenario ensemble is clustered based on whether or not distance traveled by bike exceeds distance traveled by car by more than 50% at final time. The density plot in the top right section of the figure displays the distribution of the final time outcomes per cluster of scenarios, and the pie chart displays the relative size of the two clusters in the total sample. The bottom section of the figure describes the circumstances that explain variation between the two clusters, based on the results from applying the Patient-Rule Induction Method for Scenario Discovery.

[1] In this research, distance traveled refers to distance traveled on trips within the city and between the city and the first ring. Trips between the city and places beyond the first ring fall outside the scope of the quantitative model.

Given the context of the case study and the design of its ongoing policy, the findings are most generalizable to European cities with emerging cycling cultures. While the model results show a fast increase in bike use, private car use declines slowly and to a lesser extent. This outcome may be conservative, as bike-and-ride travel is excluded from the quantitative model and could further reduce private car use. The model results, combined with insights from expert interviews conducted during the research inform recommendations for policy makers and future research.

Recommendations for policy makers

- **Accelerating bike adoption**: Urban governments should prioritize policies that address leverage points for bike adoption. Examples include supporting citizen initiatives like Catalonia's Bicibus to foster local cycling cultures, implementing communication strategies to shift perceptions toward sustainable transport modes, and expanding secure bike parking and bike-sharing facilities.
- **Improving monitoring and target-setting**: Policymakers should consider setting targets for bike network coverage as a percentage of the road network, reporting public space distribution for transparency and debate, and reporting modal split by trip distance bands to monitor modal shift for long-distance trips.
- **Collaboration across municipalities**: Cities should engage in regional planning with surrounding municipalities to address private car use for long-distance trips. For example, they can engage in shared infrastructure planning for bike-and-ride facilities and map suburban populations facing low accessibility by sustainable modes.

Recommendations for future research

- **Addressing knowledge gaps**: Longitudinal studies should explore bike adoption dynamics in cities implementing cycling-focused policies (e.g. Paris) and examine suburban car reduction potential by investigating household attitudes and responses to shifts in transport mode attractiveness.
- **Integrating public space and bike adoption dynamics in models**: Following the approach in this research, future transport models should integrate public space distribution to assess the impacts of spatial trade-offs on pedestrian and cyclist safety. Similarly, they should apply Diffusion of Innovation models to capture the non-linear dynamics of bike adoption.
- **Next modeling steps**: The proposed SD model can be improved by incorporating bike-and-ride travel, specifying road types, adding longer trip distance bands, integrating buses and trams, and exploring feedback between e-bike uptake and secure parking availability.

Contents

Glossary

Road space reallocation	The reduction of public space reserved for the movement and storage of private vehicles to create space for walking, cycling, public transport, and green space
Public space	Land area within city boundaries that is publicly accessible
Bike-and-ride	The use of bikes for the first and/or last kilometer of public transport trips
Active modes	Non-motorized modes of transport such as walking and cycling.
Self-containment	The capacity of an area to meet travel demand internally, measured as the share of trips within the boundaries of a zone divided by total trips originating from the zone
SD	System Dynamics, a modeling approach to understand and simulate the non-linear behavior of complex systems over time
PRIM	Patient-Rule Induction Method, an algorithm that derives simple, interpretable rules from simulation experiment outcomes to explain policy-relevant results.
Endogenous variable	A variable whose value is determined by the dynamics and feedback within a model
Exogenous variable	A variable whose value is determined outside of the model and may be varied across experiments to explore uncertainty

1 Introduction

Reducing dependence on private cars – whether conventional or electric – is crucial for addressing challenges related to climate, health, and transport poverty (Henderson, 2020, Natalie Mueller, 2017, Mattioli, 2021). Transport systems that rely less on private car use are also more space-efficient (ITF, 2022). Space-efficiency provides particular benefits to high-density cities, where public space is in high demand for purposes such as improving health and building climate resilience (Orsetti et al., 2022). The urgency of mitigating dangerous climate change calls for especially cities in high-income countries to accelerate efforts for reducing private car use (University of Leeds, 2019).

For urban governments to reduce private car use, several policy instruments are available, such as (parking) regulations, pricing, land use planning, infrastructure policies, marketing, information, and communication (Bert van Wee and Pudāne, 2023). One infrastructural policy is road space reallocation, defined in this research as *the reduction of public space reserved for the movement and storage of private vehicles to create space for walking, cycling, public transport, and green space*. An example is the implementation of Superblocks at the neighborhood level in Barcelona (Figure 1.1). The policy reduced access for motor vehicles from inner streets while making space for pedestrians and green space. Similarly, road space reallocation was implemented in Oslo to make space for bike lanes (Modijefsky, 2021).

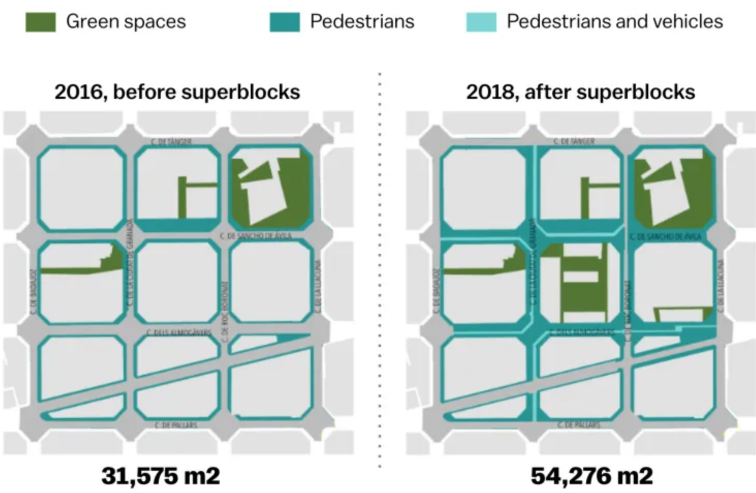

Figure 1.1: An example of road space reallocation and how it can affect public space distribution. The map reflects an implementation of Superblocks in the neighborhood Poblenou in Barcelona, Spain. The indicated surface area before and after implementation refers to the area of public space for green space, pedestrians, and space shared by pedestrians and vehicles. Extracted from BCNUEJ (2024)

Europe hosts several high-density cities with well-developed public transport systems, and the combination of high densities and public transport increases the potential to reduce private car use (Saeidizand et al., 2022). Moreover, the European Union provides European cities with a regulatory framework and resources that align with and support the pursuit of road space reallocation (EC, 2021, Halpern and Parnika, 2022). In recent years, European cities have implemented road space reallocation policies at the street level (e.g. in city centers) and at the neighborhood level (e.g. the example above). However, *citywide* strategies are only now beginning to emerge[1] (e.g. in Oslo and Paris) (Hardinghaus et al., 2021, López et al., 2020, Modijefsky, 2021).

Citywide road space reallocation influences travel behavior, greenhouse gas emissions, health outcomes, traffic safety, and land-use patterns. This research focuses specifically on travel behavior, because changes in travel behavior largely drive the impacts on health and climate outcomes (Girod et al., 2013, van Wee and Ettema, 2016). It examines effects on travel behavior over a three-decade timescale, aligning with the Paris Agreement's climate targets (UNFCCC, 2015). While long-term feedback effects, such as those arising from interactions between travel behavior and land use patterns (including residential self-selection), are important, they fall outside the scope of this research. Instead, the focus is on understanding shorter-term dynamics such as impacts on vehicle adoption and mode choice.

While systems thinking work by OECD (2022) and by Pokharel et al. (2023) highlights the potential of road space reallocation to reduce private car use, the extent to which citywide implementation affects travel behavior over time remains under-explored. Existing case studies, empirical studies, and modeling studies visit examples of road space reallocation (Hardinghaus et al., 2021, Kuss and Nicholas, 2022), investigate the effects of street- or neighborhood-level road space reallocation over time (Piras et al., 2022, Cash-Gibson et al., 2024), compare geographical areas based on urban form characteristics (Khaddar et al., 2023, Saeidizand et al., 2022), or estimate the potential health benefits of a significantly different distribution of public space [2] (Mueller et al., 2020, Li and Wilson, 2023). However, to the best of my knowledge, an analysis of how citywide road space reallocation affects travel behavior over time is missing.

The research takes a quantitative System Dynamics (SD) approach to address the complexity and feedback inherent in transport systems (Abbas, 1994) and because SD can serve to provide strategic insights even with limited empirical data (Forrester, 1987, Sterman, 2000). Existing SD literature has contributed conceptual SD models that evaluate road space reallocation policy (OECD, 2022, Pokharel et al., 2023) and call for a quantitative model being applied to a specific city (Pokharel et al., 2023). This research adopts a single case study approach, selecting Paris due to its local policy debates, its participation in the EU Mission for 100 Climate-Neutral and Smart Cities (EC, 2021), and its ongoing implementation of citywide road space reallocation policy (Paris.fr, 2023, 2024). The ongoing policies serve as a baseline input for the model. Two rounds of expert interviews are conducted to validate the model structure and results, as well as to refine recommendations.

The purpose of this research is to support the design of robust, citywide road space reallocation policies. To design policies that are robust to varying circumstances, it is crucial to account for the uncertainties that may affect policy outcomes. In the studied case, uncertainties in public space distribution, mode choice, destination choice, vehicle adoption, and future policy can be expected to affect policy outcomes. To address these uncertainties, this research combines quantitative SD modeling with Scenario Discovery to assess how uncertainties impact results. The Patient Rule Induction Method (PRIM) (Kwakkel and Jaxa-Rozen, 2016) is used to identify key uncertainties explaining variation across scenarios. These insights support the design of robust policies by highlighting influential uncertainties that call for complementary policies and monitoring.

[1] With the exception of Pontevedra, Spain that applied citywide road space reallocation in the 1990s (Jiao et al., 2019)

[2] Based on the Superblocks model: an urban planning model that reorganizes city blocks into larger car-restricted areas

Research Question

The research addresses two main knowledge gaps: a lack of analysis how citywide road space reallocation affects travel behavior over time, and a lack of quantification of existing conceptual SD models. To address these gaps, the research addresses main research question (MQ) and sub-questions (SQ) below.

MQ: To what extent can road space reallocation change travel behavior in European cities?

Road space reallocation leads to changes in public space distribution. To evaluate the extent to which it can change travel behavior, the research needs to conceptualize the interactions between public space distribution and travel behavior, addressing the first sub-question:

SQ1: What are the interactions between public space distribution and travel behavior according to literature?

To evaluate changes in travel behavior over time, the research needs to hypothesize the system structure and behavior over time under road space reallocation policy, addressing the second sub-question:

SQ2: What are the dynamics of travel behavior when public space distribution changes over time?

To quantify the behavior over time, the research needs to apply the model to a case study. A data gap in the chosen case study – Paris – requires estimating the current distribution of public space, addressing the third sub-question:

SQ3: What is the current distribution of public space in Paris between pedestrians, cyclists, and motorized vehicles?

Uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy influence the effect of road space reallocation policy on travel behavior. To understand the extent to which road space reallocation can change travel behavior over time, these uncertainties need to be accounted for. This addresses the fourth and final sub-question:

SQ4: How do uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy influence to what extent road space reallocation policy in Paris can change travel behavior?

Answering the research questions makes several contributions, such as quantifying existing conceptual SD models and providing strategic insights for designing robust road space reallocation policies. Given the context of the case study and the design of its ongoing policy, the findings are primarily generalizable to European cities with emerging cycling cultures.

Chapter 2 presents the methods used, the experimental setup, and the available data sources. Chapter 3 presents the geography, infrastructure, and ongoing policy in the selected case study. Chapter 4 synthesizes existing conceptual SD models, conceptualizes interactions between public space distribution and travel behavior, and presents a dynamic hypothesis for the effects of citywide road space reallocation. Chapter 5 presents an overview of the quantitative SD model, its underlying assumptions, and the validation of the model. Chapter 6 presents and interprets the results from the geospatial analysis and experiments. Chapter 7 discusses modeling choices, generalizability, applicability of SD, and societal and scientific implications. Chapter 8 concludes on the research question and provides recommendations for policymakers and for future research.

2
Methods and data

The main method of this research is SD combined with Scenario Discovery, and follows the modeling cycle as described in W.L. Auping et al. (2024). The modeling cycle consists of six steps: Problem Articulation, Conceptualization, Formulation, Evaluation, Policy Testing, and Results. In this research, Scenario Discovery is the approach taken for Policy Testing. The modeling cycle is iterative, and steps within the modeling cycle do not necessarily succeed each other chronologically throughout the research process. Four activities provide inputs to the modeling cycle: a theoretical review, a data analysis, a policy review, and two rounds of expert interviews. The following section provides an overview of the methods applied per sub-question. The rest of the chapter explains the use of SD combined with Scenario Discovery, and presents the taken approach for verification and validation, transport modeling, and the expert interviews. It also presents the experimental setup, the available data sources, and how the data are analyzed.

2.1. Overview

SQ1: What are the interactions between the distribution of public space and travel behavior according to literature?

The taken approach for addressing the first sub-question reviews theory to build a dynamic hypothesis. A dynamic hypothesis is a theory for the causes of a problem and how decision variables influence the problem behavior (Sterman, 2000). In this research, the reference mode for the problem behavior is ”high levels of private car use”, while the reference mode for the solution behavior is ”modal shift to public transport and active modes”. The process for building a dynamic hypothesis follows three steps:

1. **Synthesizing conceptual models of the problem behavior.** This step draws on existing conceptual work. It also applies system archetypes (Senge, 2006) to generalize the problem behavior and reflects on how road space reallocation policy intervenes with the archetypical behavior.
2. **Conceptualizing interactions between public space distribution and travel behavior.** This step provides a theoretical basis for the third step. It also provides a basis for formulating the quantitative model developed to address SQ2.
3. **Hypothesizing the solution behavior under road space reallocation policy.** This step has two components: a structural hypothesis and a hypothesized reference mode. The structural hypothesis is a Causal Loop Diagram (CLD) that presents the expected chains of cause-and-effect resulting from the policy. The hypothesized reference mode plots the expected behavior over time.

The variables chosen to reflect the main reference mode are the share of total distance traveled by car, by bike, and by public transport on trips within the city and between the city and the first ring.

SQ2: What are the dynamics of travel behavior when the distribution of public space changes over time?

The taken approach for addressing the second sub-question is formulating a quantitative SD model. The model structure reflects the interactions between public space distribution and travel behavior conceptualized while addressing SQ1. The model purpose is to inform robust policy strategies by:

- Reflecting the pace at which road space reallocation changes citywide public space distribution
- Specifying the dynamics that link public space distribution and travel behavior, most dominant on a 30-year timescale
- Quantifying the influence of uncertainties on the effects of road space reallocation policy on distance traveled by car, by bike, and by public transport on trips within the city and between the city and the first ring.

The reason for choosing 2050 as the time horizon is that climate mitigation targets are set for 2050. The reason for focusing on trips within the city and between the city and the first ring is that these trips currently generate the majority of car traffic in the context of the case study. Additional outcomes of interest include variation in subjective travel time by car, by bike, and by public transport, as well as fraction of city population with bike access. Expert interviews are carried out to support the validation of the model.

SQ3: What is the current distribution of public space in Paris between pedestrians, cyclists, and motorized vehicles?

The approach taken to answer the third sub-question, is carrying out a geospatial data analysis to estimate public space distribution in the chosen case study, Paris. The outcomes of the analysis serve as an input to a stock and flow system in the quantitative SD model that represents public space. Estimating the current distribution of public space allows evaluating the effect of road space reallocation policy, which changes public space distribution over time.

SQ4: How do uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy influence to what extent road space reallocation policy in Paris can change travel behavior?

The approach taken to answer the fourth sub-question, is reviewing current policy plans in the chosen case study, extrapolating these policy plans into the future, and applying Scenario Discovery to explore the role of uncertainties. Uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy are varied across experiments. The PRIM algorithm analyzes the results to explain which uncertainties are most important for explaining variations in the final outcomes of the reference modes. Expert interviews support the validation of model results.

The results from the quantitative model serve to conclude on the main research question to *MQ: To what extent can road space reallocation change travel behavior in European cities?* The research flow diagram in Figure 2.1 visualizes the main information flows between activities in the research and how the activities relate to the four sub-questions.

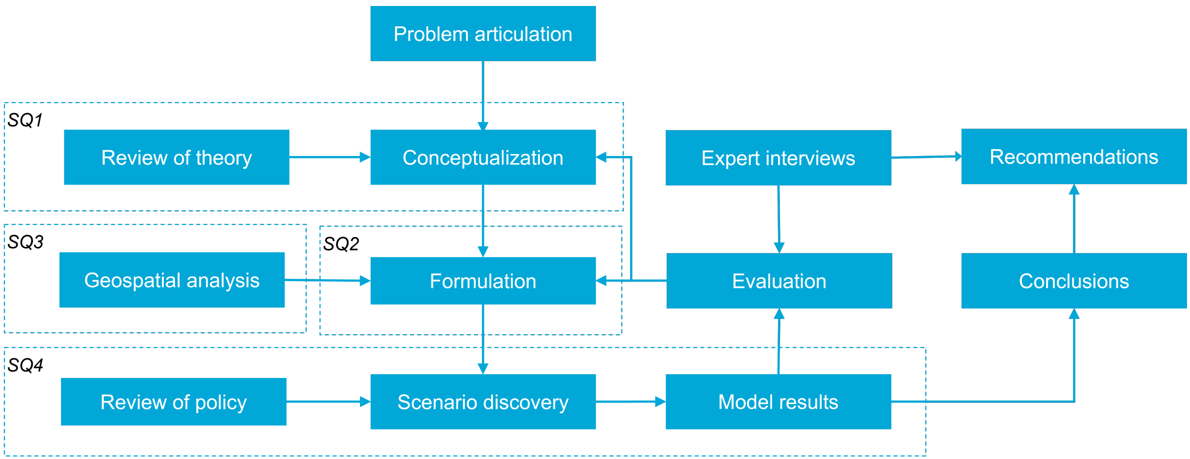

Figure 2.1: Research flow diagram, where arrows reflect the main information flows between activities in the research, and dotted lines demarcate the sub-questions answered during (sets of) activities.

2.2. Quantitative SD and Scenario Discovery

This research uses forward-looking quantitative SD as its main method. SD is a modeling approach to understand and simulate the non-linear behavior of complex systems over time (Forrester, 1961). Quantitative SD modeling uses computer simulations to study how feedback loops, delays, and non-linear interactions shape system behavior over time. Quantitative SD distinguishes itself from other simulation approaches by leveraging knowledge about non-linearity and its crucial contribution to system behavior (Forrester, 1987). Quantitative SD is also highlighted for its ability to communicate strategic insights without demanding detailed empirical data (Sterman, 2000).

SD is applicable to complex social systems, of which cities and transport systems are examples. Early SD work by Forrester (1969) characterized cities as complex systems capable of displaying counterintuitive behavior. Similarly, Abbas (1994) highlighted the complexity and non-linearity inherent in transport systems, advocating for the application of SD to transport problems. Since then, applications of SD to transport have demonstrated its suitability for addressing strategic policy questions,although it poses limitations for detailed modeling of traffic and transport networks (Shepherd, 2014).

The meta-analysis by Shepherd (2014) further notes that SD transport models often face challenges related to spatial disaggregation. Recent applications reflect varying levels of spatial disaggregation: for instance, a model of The Hague by Bax (2023) uses three zones, a model of Vienna by Pfaffenbichler et al. (2010) distinguishes 33 zones, and a model of Copenhagen by Martijn F. Legêne and van Arem (2020) incorporates 860 zones. Given that long-term feedback between land use and transport falls outside the scope of this research, it takes a data-light approach with two spatial components. This choice minimizes spatial disaggregation to improve the model's communicative value and reduce data requirements, allowing replication of the model to different cities with varying levels of data availability.

This research combines System Dynamics modeling with Scenario Discovery for finding policy-relevant scenarios. Scenario Discovery assesses robustness and maps vulnerabilities of simulated policy under uncertainty, for example when there is no knowledge or agreement on the probabilities of plausible scenarios (Lempert et al., 2006, Groves and Lempert, 2007, Bryant and Lempert, 2010). Scenario Discovery analyzes the results from many simulations to find patterns in the data, identifying uncertain parameter ranges that are most likely to lead to policy-relevant outcomes (e.g. highly desirable and/or highly undesirable outcomes). In this research, the PRIM algorithm (Kwakkel and Jaxa-Rozen, 2016) analyzes the experiment outcomes, and policy-relevant outcomes are defined based on the extent to which they meet the hypothesized solution behavior.

2.3. Verification and validation

Within the modeling cycle, the step ”Evaluation” consists of verification and validation (W.L. Auping et al., 2024). Verification checks whether the model is correctly implemented, while validation checks whether the model is *fit for purpose*. Model validation can be understood as a process of building confidence in a model's usefulness (Forrester and Senge, 1980), rather than as a measure of its predictive accuracy. A model that is fit for purpose provides insights into system structure and behavior that are *useful* for decision making (Forrester, 1961). A model's validity is thus assessed relative to the purpose for which the model is designed (Forrester and Senge, 1980).

To evaluate the model, this research selects validation and verification tests proposed by Forrester and Senge (1980), and applies these tests periodically throughout the modeling process. A crucial part of the validation process in this research is face validation with modeling and transport policy experts. The main tests used in this research are structure verification testing, parameter verification, extreme conditions testing, boundary adequacy (structure) testing (including via face validation), dimensional consistency testing, behavioral sensitivity testing (including via face validation), and changed behavior prediction testing.

A selection of tests is documented and included in Appendix D. Face validation with modeling and transport policy experts follows two rounds of semi-structured interviews and is discussed in the next section.

2.4. Expert interviews

The expert interviews are designed for face validation of model structure and model results, but also serve to validate the problem statement and to refine recommendations arising from the model results. The interviews are semi-structured, meaning the participants are asked a predetermined set of questions with room for discussion after each question. The approach for selecting candidates is selecting three experts with professional backgrounds in at least two of the following areas: urban transport policy, transport modeling, and system dynamics. Three participants partake in this research, two of whom were familiar with the local context of the selected case study. More detail on the taken approach, the structure of each round of interviews, and the processed notes from the interviews are included in Appendix A.

2.5. Transport modeling approach

Transport models typically follow four steps: trip generation (G), trip distribution (D), modal split (MS), and traffic assignment (A), in sequences of G/D/MS/A or G/MS/D/A, and with steps D and MS occurring simultaneously in some models (Ortuzar, 2011b). The approach in this research exogenizes trip distribution (D) between zones and trip distance bands[1], leaving only G/MS/A as endogenous steps in the model. For trip generation (G), the number of trips is defined as a function of population size and trip distribution. Trip frequency (i.e. daily trips per person) increases as trip distance decreases, following the law of constant travel time (Hupkes, 1982). Modal split (MS) is modeled using entropy maximization, with subjective travel times representing generalized cost. Traffic assignment (A) is modeled using an aggregate approach, applying Greenshield's relation between traffic density and congested speed, as described in Arnott (2013). The effect of public transport overcrowding on subjective travel time is modeled using an overcrowding multiplier in line with the approach by Pfaffenbichler et al. (2010). The rest of this section presents the chosen trip distance bands, the method for determining (subjective) travel time, the entropy maximization approach, and Greenshield's relation.

The chosen trip distance bands reflect available data on trip distance distribution in the studied case, dimensions of the zones modeled, and distance between the zones modeled. Each trip distance band is represented by an average Euclidian distance and a set of available transport modes (Table 2.1). The rather narrow distributions of the distance decay functions applicable to pedestrian and cycling (D'Apuzzo et al., 2022) are reflected by grouping these modes into single trip distance bands.

Table 2.1: Trip distance bands and mode options per trip distance band

Distance	Range	Average	Options	Applies to
Short distance	0 – 1.5 km	0.5 km	Walking	Urban trips
Mid distance	1.5 – 6 km	5 km	(e-)bike, public transport, car	Urban / Interurban trips
Long distance	6 - 10 km	8 km	Public transport, car	Interurban trips

To model subjective travel time as a function of physical travel time, this research adopts subjective value functions defined based on Walther et al. (1997) and in line with the MARS-model by Pfaffenbichler et al. (2010). Equation 2.1 shows the standard form of the exponential functions. The parameters vary based on the transport mode and the trip component and the exponential form does not apply to the subjective value of in-vehicle travel time by car, which is constant.

$$t_s^1(t) = t * (\alpha + \beta * \varepsilon^{\gamma t}) \tag{2.1}$$

Equation 2.1: $t_s^1(t)$ represents the subjective travel time on trip component 1 for physical time t, where α, β, and γ are parameters that control the shape of the exponential curve.

[1] Exogenizing trip distribution assumes no feedback between endogenous variables and destination choice patterns. Specifically, an exogenous variable determines how generated trips are distributed between relationships in the model (e.g., city<>city, city<>ring, and ring<>ring), and how this distribution evolves over time. This includes the distribution of city<>city trips over distance bands (short, mid, and long distance). Chapter 5 further discusses model boundaries and assumptions.

The taken approach uses entropy maximization to model mode choice, as is common in transport modeling (Ortuzar, 2011a). Entropy maximization can take a simple form when trip distribution is exogenous. In this research, subjective travel time serves as the generalized cost. Equation 2.2 shows the mathematical formulation for mode choice between two transport modes.

$$P_{ij}^{1} = \frac{\varepsilon^{-\beta C_{ij}{}^{1}}}{\varepsilon^{-\beta C_{ij}{}^{1}} + \varepsilon^{-\beta C_{ij}{}^{2}}} \tag{2.2}$$

Equation 2.2: P_{ij}^{1} represents the share of mode 1 on OD-pair ij, C_{ij}^{1} and C_{ij}^{2} the generalized cost of traveling by modes 1 and 2, and β a parameter that controls the dispersion in mode choice.

Greenshield's relation between traffic density and congested speed describes average congestion and is a common approach to modeling congestion at an aggregate level (Arnott, 2013). Equation 2.3 represents the parabolic relation between congested velocity and traffic density as defined by Greenshield.

$$v(t) = v_f(1 - \frac{k(t)}{k_c}) \tag{2.3}$$

Equation 2.3: $v(t)$ represents the congested velocity at time t, v_f the free-flow velocity $k(t)$ the traffic density at time t, and k_c the collision density

2.6. Experimental setup

The software used in this research is Vensim DSS 10.2.1 for the quantitative SD model, with Euler integration, a time horizon of 30 years (2020 - 2050), and a timestep of 0.125. The research uses ema-workbench[2] for Scenario Discovery. The baseline policy input is based on ongoing policy in the studied case, extrapolated into the future, although uncertain aspects in policy ambition are included as uncertainties and varied across experiments. The total number of variables is 318. The number of uncertain parameters is 23, and the number of experiments is 1000, sampled using the Latin Hypercube sampling method. The model and data files can be accessed via GitHub[3]. The uncertain parameters are related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy and are presented in Appendix C.

2.7. Data sources and analysis

This research uses a combination of national census data, travel survey data, and geospatial data. Data analysis was in some cases needed to determine the initial value of stock variables, or to estimate the range of uncertain parameters. Due to a data gap, estimating public space distribution in Paris requires a geospatial data analysis based on four data sources. Due to data quality issues, the estimated proportion between space for motorized traffic and space for pedestrians is of low confidence. Table 2.2 below lists the main data sources used, followed by the steps followed to estimate public space distribution from the available data.

Estimating public space distribution

The definition for public space used in this research is *land area within city boundaries that is publicly accessible*. To fit the aggregate approach taken in this research, the geospatial analysis groups public space functions under three categories: space for motorists, space for cyclists, and space for pedestrians. Space for motorists refers to all road space and parking space for motorized vehicles and includes

[2]The documentation of ema-workbench can be accessed via this link

[3]The GitHub repository can be accessed via this link

[4]A surface map and road axis data of the communal road network shared by Atelier Parisien d'Urbanisme (website) for use within this research

Table 2.2: Main data sources used within this research

Type	Used for	Sources
National census data	Estimating parameters related to population, homes, and car ownership	(INSEE, 2021b,a,c,d)
Regional travel survey	Estimating parameters related to modal split, trip distribution, and physical travel time	(Omnil, 2020)
Geospatial data	Estimating public space distribution	APUR[4], (IDF Mobilite, 2024)

bus lanes[5]. Given the context of the case study (see Chapter 3), space for cyclists refers to dedicated bike lanes only, which are either physically separated or demarcated. Space shared between cyclists and pedestrians is categorized as pedestrian space, and space shared between cyclists and motorized traffic is categorized as space for motorists. Space for pedestrians refers to sidewalks, squares, and greenspace. Other land area that does not qualify as public space is grouped as *Built up area, greenfield, and water*. In the case of Paris, the following data is available for estimating the size and distribution of public space:

- A surface map that distinguishes six surface types
- Road axis data of the communal road network that carries information on the minimum, average, and maximum sidewalk width on either side of a road segment
- A time record of OpenStreetMap data indicating the total length of reported bike lanes that distinguishes five types of bike lanes

The road axis data carrying information on the width of sidewalks is of mixed quality and cannot be summed up to obtain a valid estimate of total sidewalk space (the resulting estimate exceeds total public space). Two possible approaches are (1) extrapolating the average sidewalk width from high-quality sidewalk width estimates[6] to the rest of the network, or (2) using the minimum width value of all sidewalk width estimations regardless of data quality. The latter approach is chosen, because the high-quality estimations appear to correspond with wide sidewalks and would lead to overestimation of sidewalk space. The remainder after subtracting other categories of space use is defined as space for motorized traffic, by lack of available data to directly estimate this variable.

The taken approach to estimate public space distribution follows four steps:

1. Obtain total public space by taking the difference between the areas of all Standard island and Water polygons and the total land area
2. Estimate public space allocated to car parking by multiplying the total number of on-street parking spots by a parking spot footprint of $9.6m^2$, in line with APUR (2019).
3. Estimate public space allocated to cyclists, by multiplying the total length of the dedicated cycling network by $2.2m$, in line with the lane width assumed within the model to convert between hectares and lanes.
4. Estimate public space allocated to pedestrians based on the minimum width value of the available sidewalk width estimations

Given varying data quality and the role of assumptions (e.g. width assumption for bike lanes), confidence judgments are attached to each estimate as follows: the estimate for car parking is of high confidence, the estimate for bike lanes is of moderate confidence, the estimates for pedestrians and motor traffic are of low confidence.

A more detailed description of the data sources used and the results are included in Appendix B.

[5]Not a separate category, because buses fall outside the scope of the model in this research, which considers only underground public transport (Chapter 5)

[6]Labelled as obtained from a "high reliability" calculation method, that calculates of the closest distance between a sidewalk curb and the edge of a Standard island

3
The Case of Paris

This research takes a single case study approach to study the effects of road space reallocation on travel behavior in European cities. The chosen case study is Paris, due to its ongoing citywide road space reallocation policy. This chapter presents the basic geography and public transport infrastructure of the city and its surroundings, describes the dominant travel patterns, and presents the road space reallocation policy plans currently proposed by the city. The local context of the city influence the model design (e.g. exclusion of bus transport) and its initial state (e.g. initial bike infrastructure and the fraction of population with bike access). The proposed policy will influence the model outcomes because it serves as a baseline policy input.

3.1. Geography and public transport infrastructure

The city of Paris is the capital of France is located in the Ile-de-France region and is populated by approximately 2.2 million inhabitants. The city of Paris is embedded in a larger metropolitan area composed of two concentric rings of administrative departments, each with successively lower population density and GDP per capita, and successively larger land area and population. The first ring (la Petite Couronne) is populated by approximately 4.6 million inhabitants, and the second ring (la Grande Couronne) by approximately 5.3 million inhabitants (INSEE, 2020).

The city is connected to the larger metropolitan area by a suburban rail system (RER) and internally connected by a comprehensive metro system that partially extends into the first ring. Ongoing policy pans in Greater Paris (an administrative area that encompasses Paris and the first ring, but excludes the second ring) are increasing the capacity and availability of the metro system. This capacity increase occurs by means of automation, by extending additional lines into the first ring, and by constructing a tangential metro line (Grand Paris Express) that interconnects areas within the first ring. The RER and metro systems are the most dominant public transport modes in the Ile-de-France region (3.4 and 2.7 million trips per day), closely followed by the bus (2.4 trips per day. The tram is a small but emerging public transport mode in Paris (0.4 million trips per day) (Mobilité, 2020).

3.2. Travel patterns

To study the effects of road space reallocation policy on private car use in Paris, at least the first ring needs to be included in the scope of analysis. The daily number of trips by private vehicles between Paris and the first ring is higher than those within Paris[1]. For trips within Paris, private vehicles make up only 5% of daily trips, while they make up 22% of daily trips between Paris and the first ring (Omnil, 2020). Figure D.7 shows that the majority of private vehicle trips to, from, and within Paris take place between Paris and the first ring. The data on Paris aligns with findings by Wadud et al. (2024) that private car use is usually higher on interurban trips compared to urban trips. The study also emphasizes that despite making up a smaller share in the total number of daily trips, domestic travel on long

[1]From all trips within Ile-de-France by motorized private vehicles that start or end in Paris, 48% take place between Paris and the first ring, followed by 32% within Paris, and 19% between Paris and the second ring (Omnil, 2020)

distances accounts for a larger share of distance traveled and carbon emitted when compared to travel on short distances. This highlights the importance of including car traffic from outside the city in the scope of analysis.

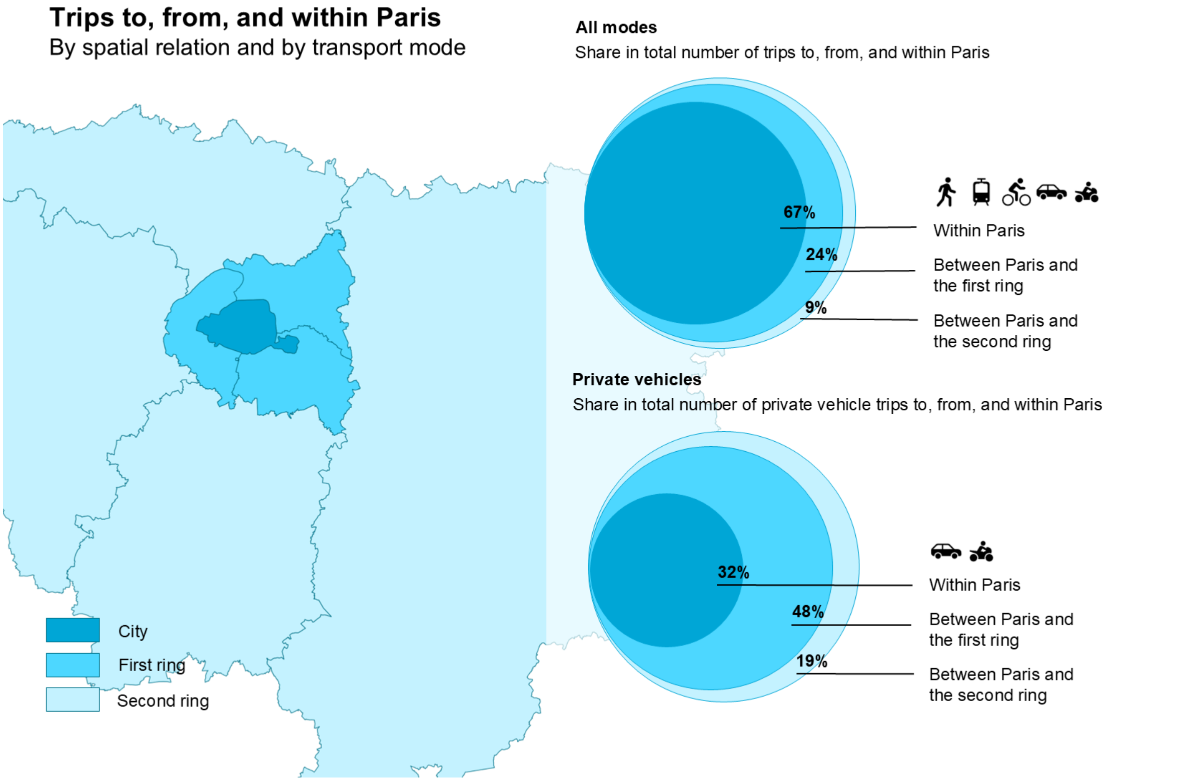

Figure 3.1: The share each spatial relation has in total trips to, from, and within Paris, by all modes and by private vehicles. The majority of private vehicle trips take place between Paris and the first ring. Data adapted from Omnil (2020)

The city of Paris is mono-centric, and features a high concentration of places of interest compared the surrounding municipalities. This concentration of places of interest leads to travel patterns in Greater Paris being oriented towards the city. A common proxy for understanding travel demand is the dispersion of labor force and workplaces, with jobs as a proxy for places of interest[2]. Analysis of data published by INSEE (2023) reveals a higher concentration of jobs in the city of Paris (1.7 jobs per labor force) compared to the first ring (1.0 jobs per labor force). Similarly, data published by INSEE (2023) indicates there are 2.5x as many commuters with homes in the first ring and workplaces in Paris (624 thousand inhabitants) than vice versa (261 thousand inhabitants).

The average trip in the Ile-de-France region takes 24 minutes and covers 4.5 km Euclidian distance. The distribution is skewed towards short trips, with a minority of trips at large distances and travel times. The longest-lasting trips are by public transport, with an average of 45 minutes of travel time on 9 km trips (Mobilité, 2020). For residents of Paris, trips by car are on average 6 minutes faster than trips by public transport, while for residents of the first ring, trips by car are on average 20 minutes faster than trips by public transport (INSEE, 2020).

Car ownership in Greater Paris has peaked[3], while cycling and other micro-mobility are a minor but emerging transport mode[4]. Figure 3.2 presents the current state of car and bike adoption in the city and

[2]The spatial dispersion of jobs, skills, services, and needs drives travel demand. Workplaces can also proxy places of interest other than jobs (e.g. retail, hospitals, and universities)

[3]In Paris and the first ring respectively, the motorization rate peaked at 0.47 and 0.87 cars per household in 1999, and fell to 0.39 (-17%) and 0.81 (-7%) between 1999 and 2017 (APUR, 2021).

[4]In 2020, cycling and micromobility made up 4.5% of the modal split in Ile-de-France, having increased by 78% between 2001 and 2010, and by 33% between 2010 and 2020 (INSEE, 2020).

the first ring. In 2020, the number of private bikes per household (owned or rented through Veligo) was approximately 0.25 in Paris and 0.70 in the first ring (based on Mobilité (2020), de France Mobilites (2024). The data report by Mobilité (2020) remarks that the lack of private space for parking bikes explains private bike ownership being lower in Paris, although there could be more causes. The offer of station-based bike-sharing services is higher in Paris than in the first ring and the number of bike-sharing users per household can be estimated at 0.26 and 0.05 in Paris and the first ring respectively de Paris.

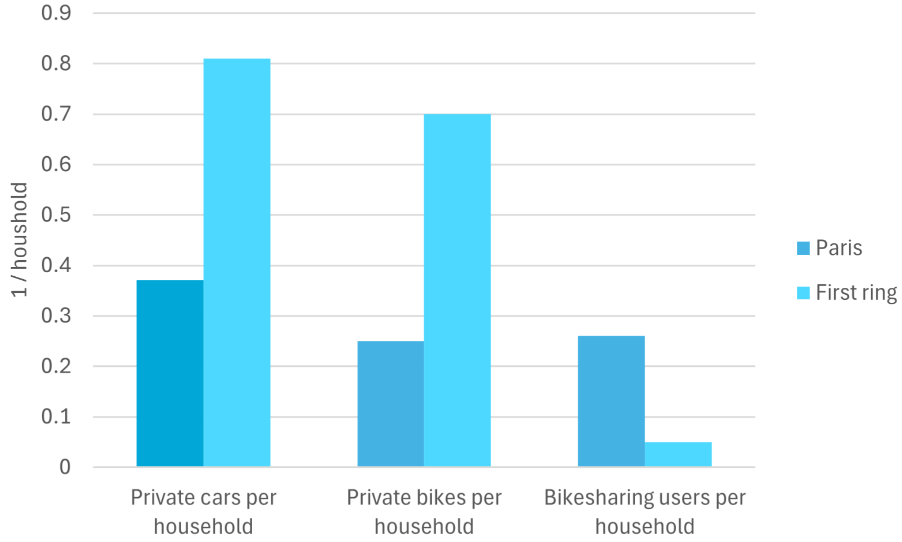

Figure 3.2: Number of private vehicles, private bikes and bikesharing users per household in Paris and the first ring (Petite Couronne). Based on data from Mobilité (2020), de France Mobilites (2024), de Paris

3.3. Proposed policy

A comparison of cities published by Cities (2022) indicates that Paris has a relatively low opportunity for cycling, while congestion levels are relatively high. Figure 3.3 displays how Paris scores compared to the top- and bottom-ranking cities included in the study. To better accommodate walking and cycling and to reduce car traffic, the city of Paris is carrying out a set of policy plans. This section discusses two of those policy plans, in which road space is reallocated to cyclists and pedestrians.

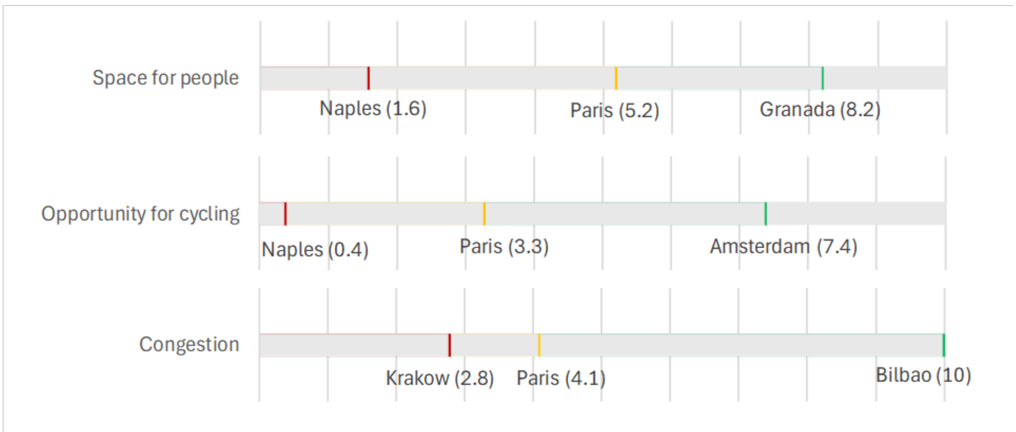

Figure 3.3: Performance scores on a scale between 0 and 10, for Paris and for the bottom and top ranking cities on each category. Scores adopted from Cities (2022). Space for people and opportunity for cycling are scored based on the coverage of walking and cycling paths.

In 2022, Paris introduced the *Plan Piéton*, a policy initiative aimed at increasing the pedestrian-friendliness of streets across the city (Paris.fr, 2023). The most significant intervention under this plan is the pedestrianization of 100 school streets. Additional measures include improving pedestrian infrastructure on 50 streets and fully pedestrianizing 12 km of side streets adjacent to primary roads.

In 2023, Paris launched the second phase of its cycling policy, the *Plan Vélo*, which focuses on promoting cycling as a primary mode of transportation (Paris.fr, 2024). The plan includes adding 130 km of new bike lanes and formalizing 52 km of previously temporary bike lanes. The total length of the Parisian road network is 1,567 km (H ran, 2008). At the time the second phase of the *Plan Vélo* was implemented, OpenStreetMap recorded approximately 1,000 km of bike lanes in Paris (IDF Mobilite, 2024), with 448 km classified as separated from motorized traffic. Of these, 66 km were demarcated, and 382 km featured physical separation. The remaining 635 km consisted of shared lanes, where cyclists share space with buses, cars, or pedestrians.

Shared lanes in Paris typically do not currently meet proposed cycling safety standards, which recommend that cyclists should only share space with slower-moving traffic (Furth et al., 2016). While these lanes still improve connectivity, they are not considered part of the current safe cycling network of Paris in this research. Based on this consideration, the safe cycling network in Paris was approximately 30% complete at the time of policy implementation, measured as its relative coverage of the road network. The policy aims to add 182 km of bike lanes by 2026, representing an average annual increase in coverage of 2.9% of the road network. If this pace of construction is sustained, and assuming new lanes and intersections meet proposed safety standards, a fully developed, safe cycling network could be completed by 2045.

4 Theory & Dynamic hypothesis

This research applies quantitative SD to understand the effects of road space reallocation policy on travel behavior. Before formulating a quantitative SD model, a dynamic hypothesis of the problem behavior (high levels of car use) and the solution behavior (modal shift to public transport and active modes) needs to be conceptualized. This chapter builds the dynamic hypothesis in three steps. First, it conceptualizes the problem behavior by synthesizing existing conceptual SD models by OECD (2021, 2022) and Pokharel et al. (2023), applying system archetypes, and hypothesizing how road space reallocation intervenes with the archetypical behavior. Next, the chapter reviews literature to map interactions between public space distribution and travel behavior. Finally, it proposes a dynamic hypothesis for the effects of road space reallocation policy on travel behavior. The dynamic hypothesis provides a basis for formulating the quantitative model, which is presented in Chapter 5. It also informs the clustering of scenario outcomes presented in Chapter 6, based on whether the scenarios are expected or unexpected.

4.1. Problem behavior

System dynamics work by OECD (2021, 2022) and by Pokharel et al. (2023) has proposed conceptual SD models to explain increasing private car use. The proposed conceptual SD models link the availability of public space with the attractiveness of public transport, walking, and cycling relative to driving and owning private cars. The conceptual SD model by OECD (2021) builds on earlier work by Sterman (2000) and highlights three dynamics of car dependency:

1. Induced car demand
2. Urban sprawl
3. Erosion of public transport

Similarly, the conceptual SD model by Pokharel et al. (2023) distinguishes ”cycles of road expansion and congestion” (i.e. induced car demand), ”urban sprawl”, and a ”public transport death spiral” (i.e. erosion of public transport). The model by Pokharel et al. (2023) includes growing personal income, the supply of parking, and urban sprawl oriented planning as exogenous variables that accelerate induced car demand and urban sprawl. Figure 4.1 synthesizes existing conceptual SD models in a Causal Loop Diagram (CLD). For conciseness, the diagram makes three main simplifications: it groups car use and car ownership into one variable, it groups variables related to urban sprawl into one variable[1], and it omits a variable for urban sprawl oriented land use planning.

The rest of this section visits the three dynamics, identifies two system archetypes, and reflects on how road space reallocation intervenes with the archetypical behavior. System archetypes represent common underlying structures of problem behaviors that recur across different contexts and systems (Senge, 2006).

[1]Detailed causal theory of urban sprawl can be consulted in the master thesis by Bax (2023)

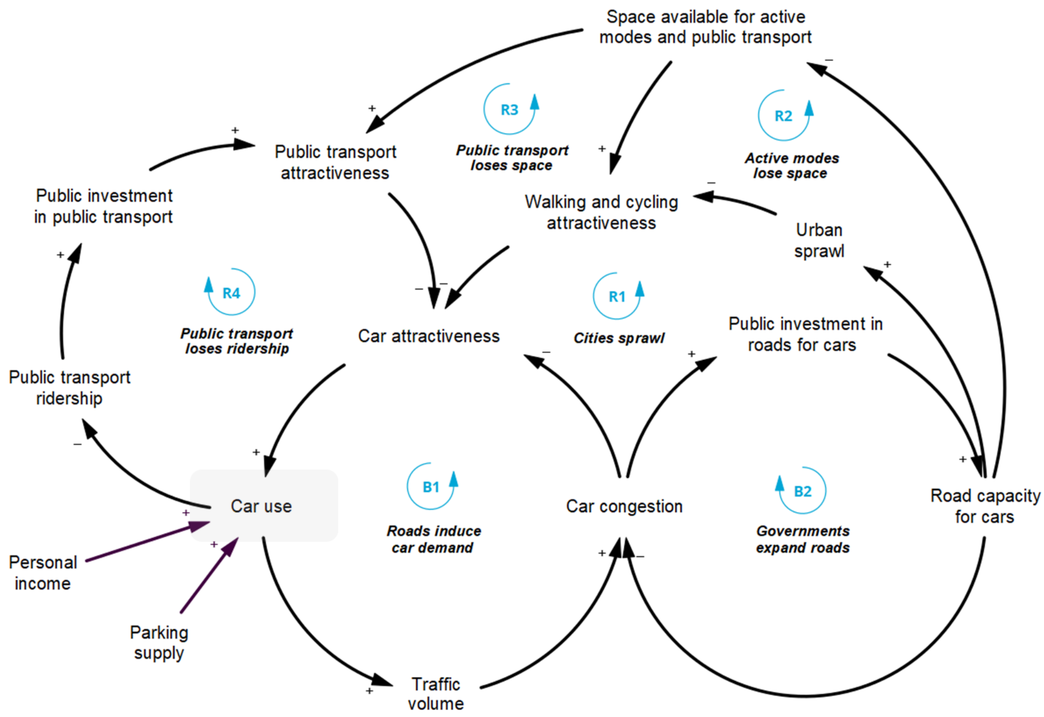

Figure 4.1: Causal Loop Diagram that synthesizes proposed conceptual SD models to explain increasing private car use. Positive relationships are marked with a "+" sign, indicating that an increase in one variable leads to an increase in another, while negative relationships are marked with a "−" sign, indicating that an increase in one variable leads to a decrease in another. Labels of reinforcing feedback loops are prefixed by "R", and labels of balancing feedback loops are prefixed by "B". Delay between variables is marked by a "||" sign. The reference mode (private car use) is marked in grey. Synthesized from Sterman (2000), OECD (2022), Pokharel et al. (2023)

Induced car demand

The first dynamic, *induced car demand*, is a self-reinforcing feedback loop of increasing private car use that occurs when governments respond to congestion by adding road capacity for cars. Figure 4.1 represents the dynamic via two balancing feedback loops: roads induce car demand (B1), and governments expand roads (B2). Together, the two connected balancing feedback loops form a self-reinforcing feedback loop.

Urban sprawl

The second dynamic, *urban sprawl*, refers to low-density land-use patterns that emerge from and reinforce private car use. Private car use increases the average distance people can travel to destinations, which triggers low-density land-use patterns where the proximity of destinations declines[2]. Urban sprawl leads to declining accessibility by active modes, since the number of destinations within walking and cycling distance declines. Urban sprawl is conceptualized as a self-reinforcing feedback loop because it increases car attractiveness relative to public transport, walking, and cycling, triggering more urban sprawl (R1 in Figure 4.1).

Erosion of public transport

The third dynamic, *erosion of public transport*, refers to a widening attractiveness gap between public transport and cars that arises from a reduction in public space and public investment allocated to sustainable modes. Active modes and public transport lose space to cars (R2 and R3 in Figure 4.1), and public transport loses ridership, which triggers a downward spiral of investment in public transport (R4 in Figure 4.1).

[2]Not only low-density, but also the functional segregation of urban areas lead to lower proximity of destinations.

System archetypes

The system archetypes proposed by Senge (2006) represent common underlying structures of problem behaviors that recur across different contexts and systems. Two system archetypes can be observed in the problem behavior above. The dynamic of induced car demand, combined with urban sprawl, resembles the system archetype referred to as ”shifting the burden”. This archetype occurs when a problem symptom (congestion) is addressed via an external intervention (expanding road capacity) that undermines the internal solution to the problem (reducing car demand). In the problem behavior analyzed here, the possibility to reduce car demand is undermined, both by reducing car congestion, and by reducing atractiveness of walking, cycling, and public transport.

The dynamic of erosion of public transport resembles the system archetype referred to as ”success to the successful”. This archetype occurs when the provision of resources (investment, space, and infrastructure) to one group (private car users) increases the chances of that group succeeding (growing accessibility by private cars leading to growing private car use), such that resources are devoted to further increase their success (more investment in roads for cars). Meanwhile, resources (investment, space, and infrastructure) of the other group (e.g. public transport users) diminish, leading to declining success (e.g. declining accessibility by public transport leading to declining ridership) and even less resources for that group.

This research focuses on the role of road space reallocation in addressing the problem behavior, which raises the question how the policy impacts the two archetypes identified above. Two observations can be made. First, in a system where governments implement road space reallocation, the link between congestion and public investment in roads for cars breaks or becomes weaker, thus breaking or weakening the ”shifting the burden” archetype. Although this change does not immediately change the state of the system, it can allow for policy efforts that pursue the internal solution (reducing car demand) to be more successful. Second, road space reallocation provides resources to sustainable modes (space and infrastructure), which increases the chances of public transport services to succeed. The spatial and infrastructural dimension of the ”success to the successful” archetype breaks or becomes weaker.

The analysis by OECD (2022) identifies road space reallocation as a ”transformative policy”, because it changes the system structure and thereby reinforces the effectiveness of other policies. The following sections hypothesize the effects of road space reallocation on travel behavior in more detail.

4.2. Public space distribution and travel behavior

Travel behavior can be conceptualized based on utility theory, where choices between modes, destinations, and whether to travel at all (i.e. trip frequency) result from individuals weighing costs against benefits (Annema, 2023). The exact conceptualization of costs, benefits, and their impact on travel behavior, however, varies by discipline and has evolved over time (Dijst et al., 2023).

Traditional economic utility theory emphasizes rational dimensions such as travel cost and travel time, whereas behavioral sciences emphasize subjective dimensions. Subjective dimensions include the impact of environmental qualities on how travel is experienced (e.g. perceived safety and comfort), or behavioral-psychological phenomena that precede travel choices (e.g. perceived feasibility of a choice). The theory of planned behavior (Ajzen, 1991) highlights attitudes, social norms, and perceived behavioral control as drivers of behavior (Figure 4.2). From a behavioral-psychological perspective, triggering changes in travel cost, travel time, and environmental qualities can make a city more or less conducive to a particular type of travel behavior. However, more is needed to explain how travel behavior might respond to these changes. It matters which travel choices are faster and cheaper, but it also matters whether these choices are perceived as feasible[3] and whether they resonate with subjective norms and attitudes.

[3] Notably, people tend to bias towards current behavior, by overestimating the negative aspects of alternative behavioral options (such as the time required to commute by public transport) while underestimating the positive aspects (Dijst et al., 2023, Golob et al., 1979).

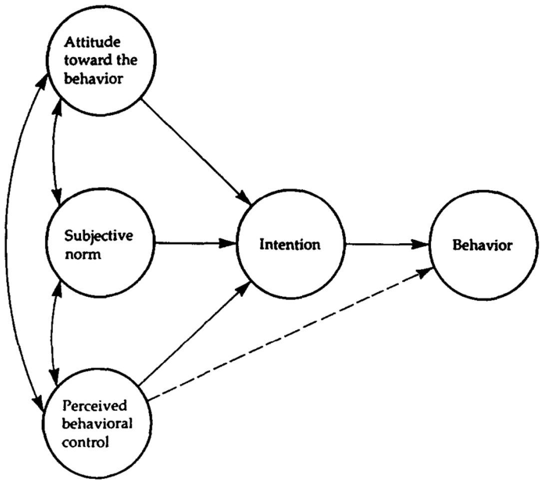

Figure 4.2: Diagram representing the Theory of Planned Behavior. Extracted from Ajzen (1991)

Infrastructural policies such as road space reallocation intervene most at the level of travel time, perceived safety and comfort, and economic cost. As an example, removing road capacity and regulating parking increases travel times by car and parking costs, and reallocating this space to separated bike lanes increases perceived safety and comfort for cyclists. In line with Annema (2023), this type of factors can be conceptualized as resistance factors that constrain choices. The relative size of resistance factors by different modes matter for destination and mode choice. Road space reallocation causes a shift in travel time and perceived safety and comfort, such that resistance to travel by car increases in exchange for reducing the resistance to travel by other modes of transport.

The rest of this section conceptualizes the interactions between public space distribution and travel behavior, by focusing on six variables that influence travel behavior:

1. Walking attractiveness
2. Cycling attractiveness
3. Bike adoption
4. Metro and rail attractiveness[4]
5. Private car attractiveness
6. Private car adoption

In transport literature, particularly in transport gravity modeling, the term "attractiveness" is often used to describe the potential of a place to attract people (Khadaroo and Seetanah, 2008). However, this research focuses more on comparing transport modes rather than destinations. Here, "attractiveness" refers to a transport mode's potential to become the preferred option for a given trip. This section also uses the concept of subjective travel time, which acts as a resistance factor combining physical travel time with perceived safety and comfort. This factor is equivalent to common resistance measures such as "generalized travel cost" or "generalized travel time" (Annema, 2023), but without the financial cost component. A mode's attractiveness is the inverse of subjective travel time by that mode, assuming constant trip destinations[5].

The conceptualization in this chapter serves as an input to a system dynamics model. Due to the aggregate nature of system dynamics modeling, public space characteristics are represented with city-level averages, such as the average number of car lanes per road. The subsections below conceptualize how public space distribution interacts with each of the six variables. Figure 4.3 summarizes the findings.

[4] A modeling choice excludes bus attractiveness from the scope of analysis, given that most public transport in the selected case study is underground.

[5] For example, if subjective travel time to a destination by car increases, car attractiveness decreases, and if subjective travel time by bike to a destination decreases, bike attractiveness increases

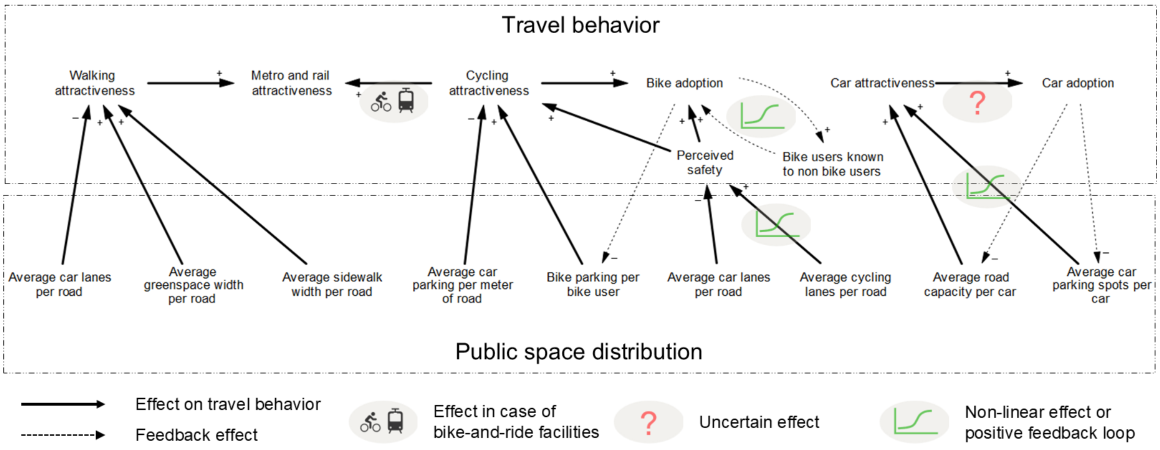

Figure 4.3: Diagram that summarizes how this chapter conceptualizes the interactions between variables related to public space distribution and variables related to travel behavior. Solid arrows indicate effects on travel behavior, and dotted arrows indicate feedback effects. Grey circles mark additional characteristics as specified in the legend. Due to the aggregate approach of this research, the variables related to public space distribution represent city-level averages.

Walking attractiveness

The car-dominance of urban environments (i.e. the car-oriented design of space and the presence of car traffic) explains a large share of the resistance factors that keep citizens from walking more (Methorst, 2021, Schoon, 2019). Some factors are directly linked to public space distribution (e.g. the width of sidewalks or the presence of greenspace), whereas other factors are either closely linked to public space distribution (e.g. motorized traffic, which linked to the presence of road infrastructure), primarily pertain to design choices (e.g. illumination at night time), or arise from and reinforce pedestrian friendliness (crowdedness). On average, women are affected more than men, especially by factors that influence perceived safety, such as illumination and crowdedness, which increase social control (Clifton and Livi, 2005). A study by Guzman et al. (2022) identifies measurable characteristics to assess walkability in cities. Street characteristics and their influence on walking attractiveness include: sidewalk width (+), speed and flow of motorized traffic (-), street cross-time (-), pedestrian flow (+), and presence of trees (+). The characteristics align with a study by Ausserer et al. (2013), in which pedestrians most frequently cited cars and traffic lights as impediments. The main desires expressed by the interviewees were reduced car traffic and increased green space.On an aggregate level, the characteristics can be represented by average sidewalk width per road (+), average greenspace width per road (+) and average number of car lanes per road (-).

Cycling attractiveness

Public space distribution significantly influences cycling attractiveness, particularly through the quality of cycling infrastructure, the presence of parallel car infrastructure, and the availability of bike parking facilities. The "Level of Traffic Stress" (LTS) is commonly used to assess the perceived safety and comfort of cycling networks, and is determined by speed limits, street width, bike lane width, number of through lanes, and intersection design (Furth et al., 2016, Cabral and Kim, 2020, Bas et al., 2023, Cervero et al., 2019). A safe and comfortable cycling route requires segregated bike lanes or shared spaces with slower-moving traffic, ensuring no gaps or missing links (Furth et al., 2016, Cabral and Kim, 2020, Bas et al., 2023). Cyclists also prefer independent paths or roads without car parking, and as cycling use increases, secure and large-scale bike parking becomes increasingly important (Eva Heinen and Maat, 2010, Embassy, 2024, Martens, 2007).

At the aggregate level, cycling attractiveness can be modeled using variables such as average cycling lanes per road (+), average car lanes per road (-), average car parking per meter of road (-), and bike parking per user (+). A key factor in cycling safety and comfort is network continuity (e.g. the absence of missing links). This implies that during early stages of network development, the effect of average cycling lanes per road on cycling attractiveness is non-linear, with growing importance of additional links in the network.

Bike adoption

How public space distribution affects bike adoption depends on the state of infrastructure and the current level of bike adoption in a given urban area. A comparative case study by Aldred and Jungnickel (2014) distinguishes established cycling cultures and emerging cycling cultures. The chosen case study reflects an emerging cycling culture, given the relatively low number of bike users compared to public transport and private car users. The emergence of cycling over time can be understood using the Diffusion of Innovation model, which segments the population into innovators, early adopters, early majority, late majority, and laggards (Rogers, 1995). A segmentation study in Edmonton, Canada by Cabral and Kim (2020) can serve to estimate the size of these segments. The study identifies the Comfortable Cyclists (16-25%), a Cautious Majority (62-65%), and the Uncomfortable or Uninterested (13-19%).

Previous research applying the Diffusion of Innovation model to cycling (Perez-Macias et al., 2024, Nehme et al., 2016, Schoner et al., 2016) emphasizes the role of infrastructure in adoption rates. According to Nehme et al. (2016), two key factors influence cycling uptake: the number of bike users known to an individual and the perceived safety of routes to regular destinations. This model implies that a positive feedback loop forms during bike adoption, as the growing number of cyclists known to non-cyclists accelerates the spread of cycling across the population.

The Cautious Majority makes up a 2 - 3 times larger fraction of the population than Comfortable Cyclists, and has higher safety expectations. This implies that there may be a growing effect of additional safe bike lanes on the fraction of the population receptive to cycling. However, based on current literature, the tipping point in cycling network development at which the Cautious Majority starts becoming receptive to cycling remains difficult to determine.

Metro & rail attractiveness

Public space distribution has two types of effects on metro and rail attractiveness. One type of effect influences the in-vehicle component of metro & rail trips, and the other type of effect influences the out-vehicle component. Given that metro & rail operate either underground, or aboveground without intersections with other traffic, the main effects arising from public space distribution are indirect. They arise from synergies between active modes and metro and rail.

When a public transport system is overcrowded, the attractiveness of the *in-vehicle* trip component is influenced by public space distribution via cycling attractiveness. The level of overcrowding in metro and rail systems declines when a modal shift to cycling occurs for mid-distance trips, and further declines when bike-and-ride becomes common practice for long-distance trips. Bike-and-ride is *the use of bikes for the first and/or last kilometer of public transport trips*. Established bike-and-ride systems are designed so that private bikes can be used to access the departure station, and shared bikes can be used to cover the last kilometer from the arrival station to the trip destination (Martens, 2007). In metro systems, cycling for short-distance trips and bike-and-ride for long-distance trips can liberate capacity in the metro system because it absorbs peak hour demand[6] (ITF, 2017). In rail systems, bike-and-ride optimizes capacity by allowing customization of trips (i.e. changing departure and destination stations based on reliability and crowding) (ITF, 2017)

Metro and rail trips start and end with walking or cycling trips to and from stations, which means that the *out-vehicle* trip component is influenced by public space distribution via walking and cycling attractiveness. The walkability of urban environments determines, for example, how far people are willing to walk to access a public transport station (UITP, 2024). In cases when bike parking and bike sharing are available at stations ("bike-and-ride facilities" in Figure 4.3), cycling infrastructure makes long-distance public transport accessible to more citizens and provides a faster connection to stations compared to feeder public transport services such as buses and trams (ITF, 2017).

[6] It replaces both trips where the metro is the main transport mode and trips where the metro serves as the feedering mode to access long-distance public transport such as rail systems and bus rapid transport (ITF, 2017).

Private car attractiveness

Similar to metro and rail attractiveness, public space distribution affects private car attractiveness by influencing in-vehicle and out-vehicle components of private car trips. Private car attractiveness is influenced by road capacity via congestion, and to parking supply via parking search time and out-vehicle time. Road capacity for cars affects travel time by determining the threshold for congestion to occur, while the supply of nearby parking affect parking search time and out-vehicle time (Parmar et al., 2020, Assemi et al., 2020). Private car attractiveness is most sensitive to parking search time and out-vehicle time, due to perceived discomfort on these trip components (Ponnambalam and Donmez, 2020, Parmar et al., 2020). Additional in-vehicle time generally does not impact how travel time is experienced (Parmar et al., 2020). Moreover, when time spent searching for parking increases in a city, congestion levels increase (Shoup, 2021), which further increases travel time.

On an aggregate level, the above characteristics and their influence on car attractiveness can be represented by average road capacity per car (-) and average car parking spots per car (-). The sensitivity of subjective travel time to parking search time and out-vehicle time, and the feedback effect on congestion both imply that the effect of average car parking spots per car on car attractiveness is non-linear.

Private car adoption

The effects of declining car attractiveness on car adoption are difficult to conceptualize, but reductions in private car adoption are plausible in cities where access to sustainable modes is adequate. In the short- to mid-term, these reductions are most likely to occur among young adults as they decide whether or not to adopt their first car. While car-oriented urban environments are known to drive car adoption (Mattioli, 2021), limited research explores the effects of transitioning to less car-oriented environments on car adoption. Research has explored national car adoption trends and policy acceptance. For instance, research in France and Canada highlights a declining propensity for car adoption among young adults, though this trend may reflect delayed rather than avoided car ownership due to later workforce entry (Ortar et al., 2018, Grimal, 2020, Bayart et al., 2020). Higher-educated groups[7] are identified as more likely to support policies reducing car use, even when they own cars (Roukouni and Cats, 2024, Groth et al., 2021), suggesting that these groups, along with young adults, may be the first to step away from car ownership when relative car attractiveness declines.

The theory of planned behavior implies that the need and the preference to drive interact. Car dependency nurtures a car culture by increasing private car use, with positive attitudes towards the car. Meanwhile, car culture may sustain negative attitudes and low perceived feasibility towards sustainable modes, even when accessibility by sustainable modes increases. Either way, accessibility shortages by sustainable transport modes should not be conflated with car-centric attitudes and vice versa.

4.3. Solution behavior

The dynamic hypothesis presented in this section applies the above theory to hypothesize the principal effects of road space reallocation on travel behavior. The hypothesis focuses on changes in mode choice and changes in destination choice. Changes in mode choice and destination choice also affect trip frequency. For example, when travel time per trip falls, trip frequency increases (Hupkes, 1982). This effect is accounted for in the quantitative model (see Chapter 5), but - for reasons of conciseness - it is not explicitly visualized and described in the hypothesis below. The hypothesized effect of road space reallocation on mode choice is associated to the choice between cycling and public transport for mid-distance trips (1.5- 6 km), and to the choice between public transport and car use for long-distance trips (6- 10 km). The hypothesized change in destination choice is associated to the share of destinations chosen within walking and cycling distance. The rest of this section further explains the structural hypothesis and presents the hypothesized reference mode.

Reallocating road space to cyclists increases the attractiveness of cycling by increasing the safety

[7] Car-dependency is likely to act as a confounding variable between education level and attitudes toward cars. Literature on car dependency argues that many low-educated groups rely on cars because because alternative transport modes are more often insufficient or unavailable for these groups (Jeekel, 2018).

and connectivity of the cycling network and by increasing bike parking availability. The relative attractiveness of cycling for mid-distance trips increases, which acts on two balancing feedback loops: *Emergence of cycling* (B1 in Figure 4.4) and *Traveling nearby: by public transport or by bike?* (B2 in Figure 4.4). A shift from public transport use to cycling for mid-distance trips reduces overcrowding, which increases the attractiveness of public transport: a balancing effect on the relative attractiveness of cycling for mid-distance trips. Moreover, attractiveness of cycling increases the attractiveness of bike-and-ride trips, which increases the relative attractiveness of public transport for long-distance trips[8].

Reallocating space away from motorists reduces the attractiveness of driving and owning a car, by reducing car parking supply and increasing car congestion. The attractiveness of public transport for long-distance trips relative to driving increases, which triggers two balancing feedback loops: *Travelling far: by public transport or by car?* (B4 in Figure 4.4) and *Public transport capacity shift* (B3 in Figure 4.4). Declining car ownership and car use by car owners reduces congestion and parking search and out-vehicle time, while increased public transport use for long-distance trips increases overcrowding: a balancing effect on the relative attractiveness of public transport for long-distance trips. Reallocating space to pedestrians increases the attractiveness of walking, which increases the attractiveness of public transport and the share of destinations chosen within walking distance.

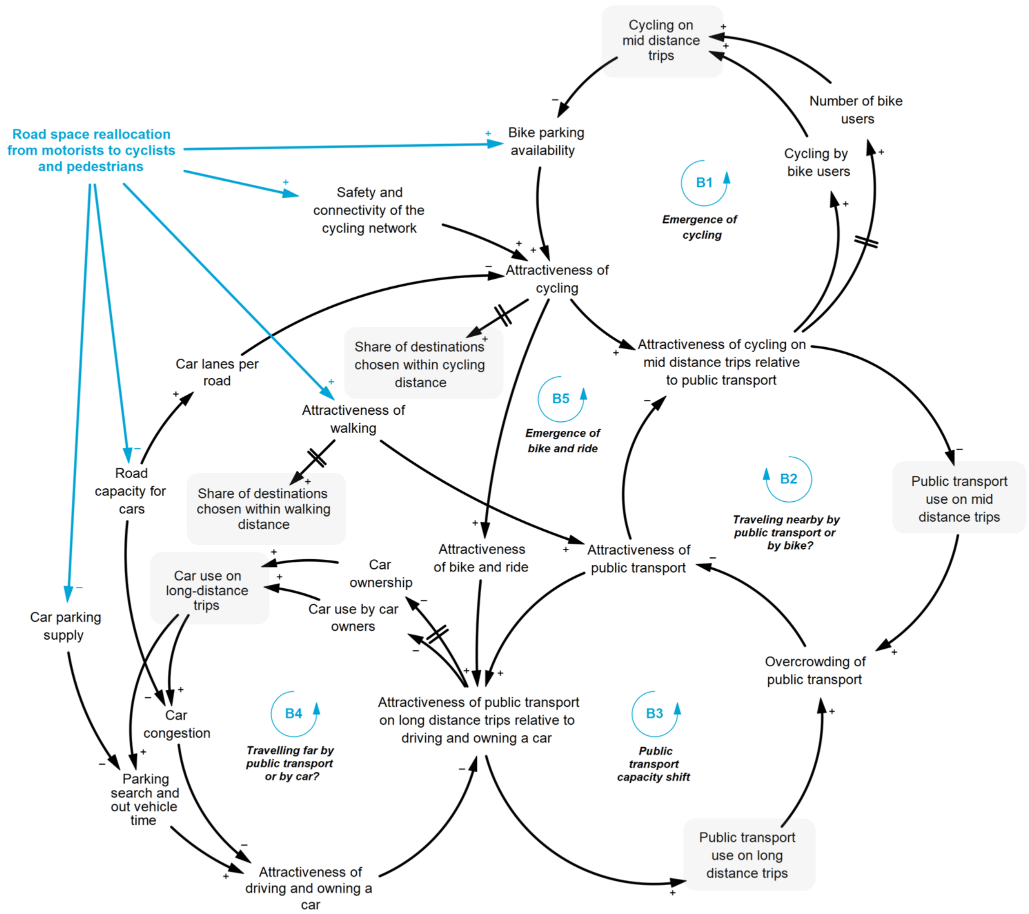

Figure 4.4: Causal Loop Diagram of the hypothesized system structure given road space reallocation. The diagram represents the effects of road space reallocation on travel behavior that are expected to be most dominant on a timescale of three decades. Positive relationships are marked with a "+" sign, indicating that an increase in one variable leads to an increase in another, while negative relationships are marked with a "−" sign, indicating that an increase in one variable leads to a decrease in another. Labels of reinforcing feedback loops are prefixed by "R", and labels of balancing feedback loops are prefixed by "B". Delay between variables is marked by a "||" sign. There is no single variable reflecting the reference mode, but variables that express travel behavior are marked in grey.

[8] Due to the spatial scope of the quantitative model chosen for this research, bike-and-ride is not included in the quantitative model.

The chosen unit for the main reference mode the share of total distance traveled for trips within Paris and between Paris and the first ring and focuses on cycling, public transport, and the car. Walking is excluded from the main reference mode, as changes for the other modes are expected to be more dominant. The hypothesized reference mode reflects a gradual modal shift away from public transport to cycling that arises from modal shift for mid-distance trips. It also reflects a modal shift away from the private car to public transport for long-distance trips that succeeds the modal shift for mid-distance trips. The rate of modal shift increases when the safe cycling network approaches complete coverage of the road network (Figure 4.5).

The hypothesized reference mode follows from the hypothesized system structure displayed in Figure 4.4. The system structure suggests that road space reallocation to cyclists will gradually increase cycling while also increasing the attractiveness of public transport via reduced overcrowding. Meanwhile, road space reallocation away from the car combined with increased attractiveness of public transport will trigger modal shift from the private car to public transport. The link between the safety and connectivity of the cycling network and cycling attractiveness is non-linear. Therefore, cycling will increase at a faster rate once the network approaches completion (indicated by the ”75% completion of safe cycling network” mark in Figure 4.5). The accelerated modal shift from public transport (paused growth) to cycling (increased growth) should – after some delay related to vehicle adoption and mode choice – be followed by accelerated modal shift from private car use (increased decline) to public transport (increased growth). After some years, the number of bike users ranges half the population receptive to cycling, and change rates will slow down. Bike use diffuses to the remaining population receptive to cycling, but at a lower rate.

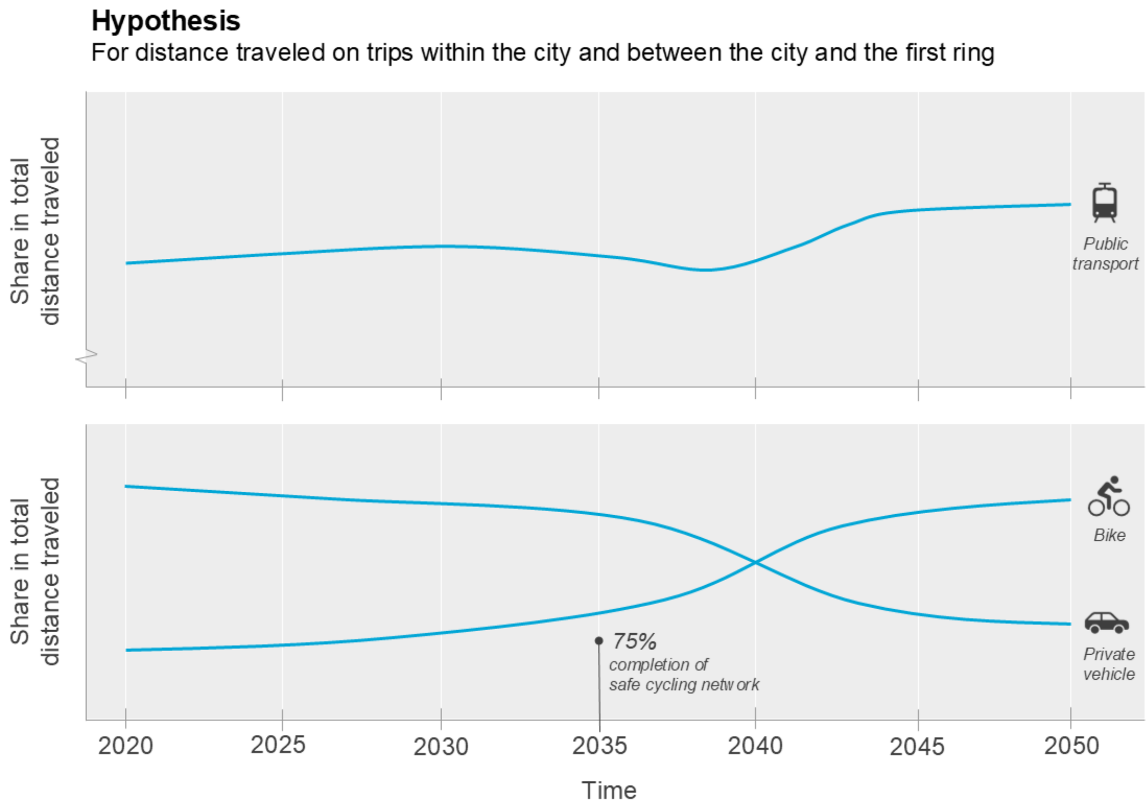

Figure 4.5: Hypothesized reference mode of distance traveled by public transport, bike, and private vehicle in the scenario of road space reallocation. The y-axis does not include a scale because the figure aims to show relative growth and decline over time. The initial values in 2020 reflect the available data on trips within Paris and between Paris and the first ring, when assuming that average distance traveled by car, by bike, and by public transport is 5 km for trips within the city, and that average distance traveled by car and by public transport is 8 km for trips between the city and first ring. At the time of drafting this report, no travel survey data was available that reports distance traveled per mode. However, the available data includes number of trips per mode and per spatial relation (Omnil, 2020), allowing for this approximation.

4.4. Concluding remarks

This chapter created the theoretical basis for developing a quantitative system dynamics model that explores the effects of citywide road space reallocation on travel behavior over time. Through synthesizing existing conceptual SD models, analyzing system archetypes, and reviewing literature on public space distribution and its influence on travel choices, a dynamic hypothesis was formulated. The dynamic hypothesis informs the structure of the model presented in Chapter 5, and the clustering of scenario outcomes in Chapter 6 of model results based on whether the scenarios are expected or unexpected. Notably, effects related to bike-and-ride conceptualized above are excluded from the quantitative model due to the chosen spatial scope of the model.

5 System dynamics model

This chapter presents the quantitative SD model developed in this research to evaluate the effects of road space reallocation on travel behavior over time. The model is based on the theory discussed in Chapter 4. This chapter first presents the model boundaries and a high-level overview of the model structure. Next, each of the five subsystems is presented based on the inputs, main stocks, outputs, and uncertainties. The last section of the chapter presents the validation of the model, arguing why the model is deemed fit for purpose.

5.1. Model boundaries

The chosen model boundaries are based on the model purpose (see Chapter 2), the key variables identified in the dynamic hypothesis, and the local context of the chosen case study. Figure 5.1 visualizes the deliberate inclusion and exclusion of variables.

The chosen model boundaries limit the extent to which the model reflects geography, features of public space, destination choice, and transport modes. Key model boundaries related to geography are the exclusion of zones beyond the first ring, the lack of disaggregation to smaller zones, and the exclusion of public space outside the city. Key boundaries related to features of public space are the exclusion of a separate category for greenspace and other place functions, which is grouped into pedestrian space, and for bus space, which is grouped into space for motorists. The key boundary related to destination choice is that the level of change in destination choice is exogenous. Key boundaries related to transport modes are the exclusion of public transport by bus and tram, and the exclusion of bike-and-ride travel. Chapter 8 highlights expansions of model boundaries that should be prioritized in future research.

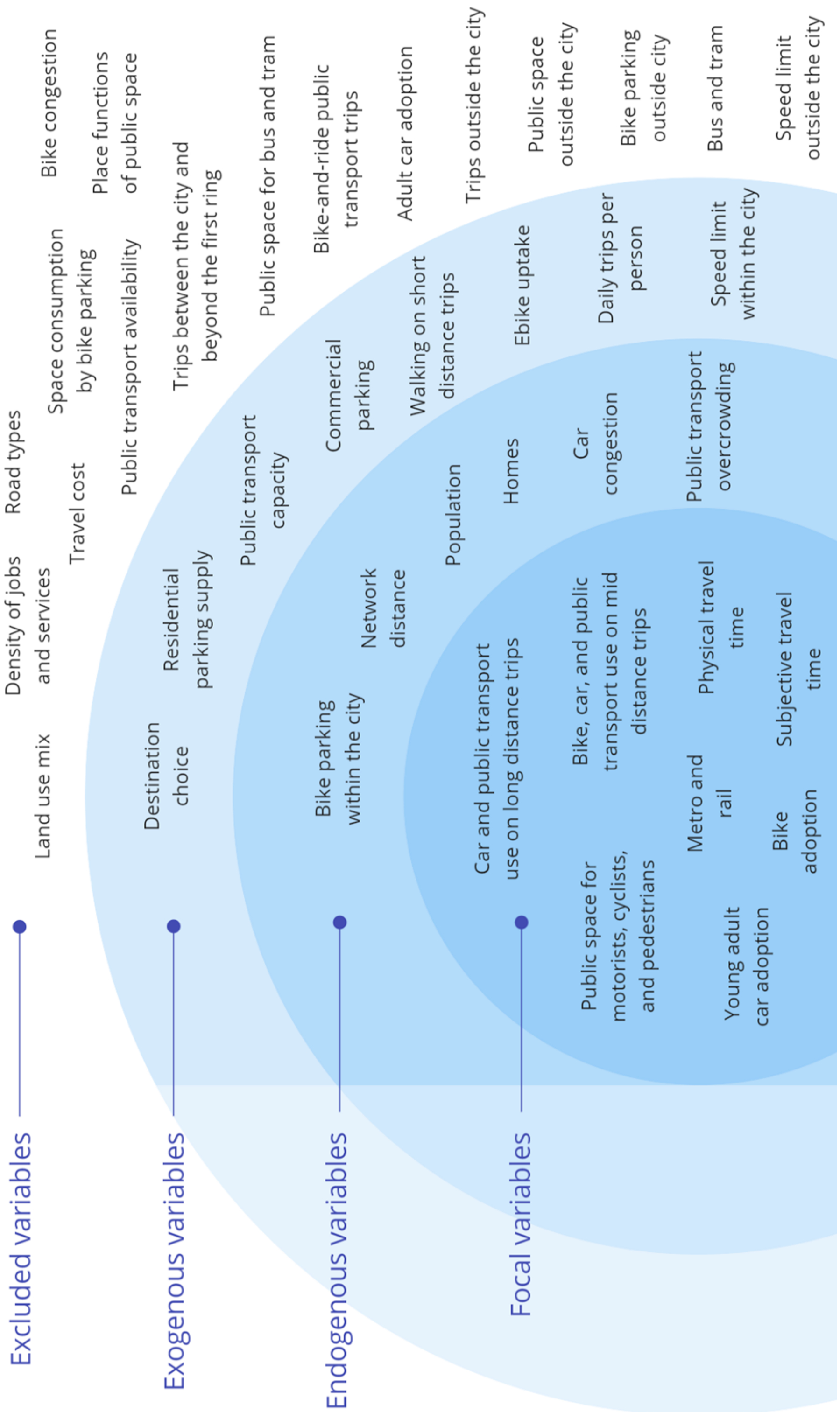

Figure 5.1: Bulls-eye diagram visualizing the boundaries chosen for the model by mapping to which extent the model includes relevant variables.

5.2. Subsystems and assumptions

This section presents the five subsystems in the model and lists assumptions underpinning each subsystem. Assumptions inherent to the chosen transport modeling approaches (see Chapter 2) are not discussed in this section. The subsystems are *Public space*, *Car adoption*, *Bike adoption*, *Mode choice*, and *Destination choice*. Figure 5.2 shows a high-level overview of the five subsystems and the causal links that connect them.

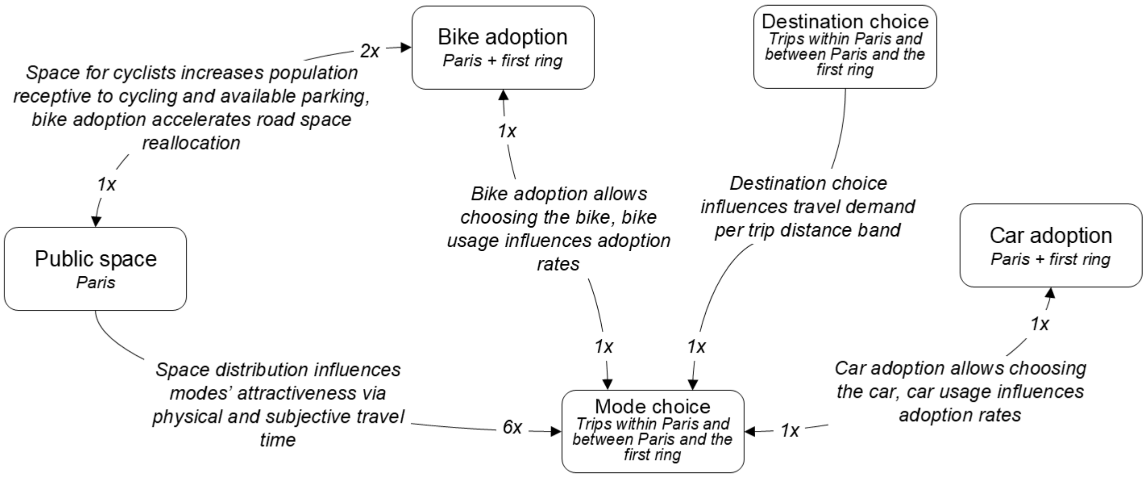

Figure 5.2: High-level overview of subsystems and causal links, including the direction(s) of links, the number of links and a short description of each link.

5.2.1. Public space

The model represents public space as a single sub-scripted stock-and-flow system (i.e. a stock variable disaggregated into one set of categories) that is renewed over time (Figure B.2). The categories represent functions of space and distinguish space for motor traffic, space for car parking, space for cyclists, and space for pedestrians. Renewal occurs in three steps:

1. Public space in the current distribution periodically undergoes maintenance.
2. During maintenance, the public space is reallocated among motorists, cyclists, and pedestrians according to the desired distribution
3. The renewed space returns to the *Public Space* stock, changing the average distribution of public space.

The subsystem is influenced by five uncertainties related to future policy: the *desired pedestrian space share*, and the *desired share of car space used for car parking*, the sensitivity of the *renewal rate of public space* to the fraction of the urban population with bike access, the number of *parking spots per home constructed*, and *bike parking per added space for cyclists*. The renewal rate determines at which rate public space enters maintenance. The desired pedestrian space share and the share of car space used for car parking influence the proportions to which space is redistributed, and the number of parking spots per home constructed influence influences to what extent residential parking supply changes. The net rate at which bike parking is constructed is defined as a linear function of the rate at which space for cyclists is added, and depends on bike parking per added space for cyclists.

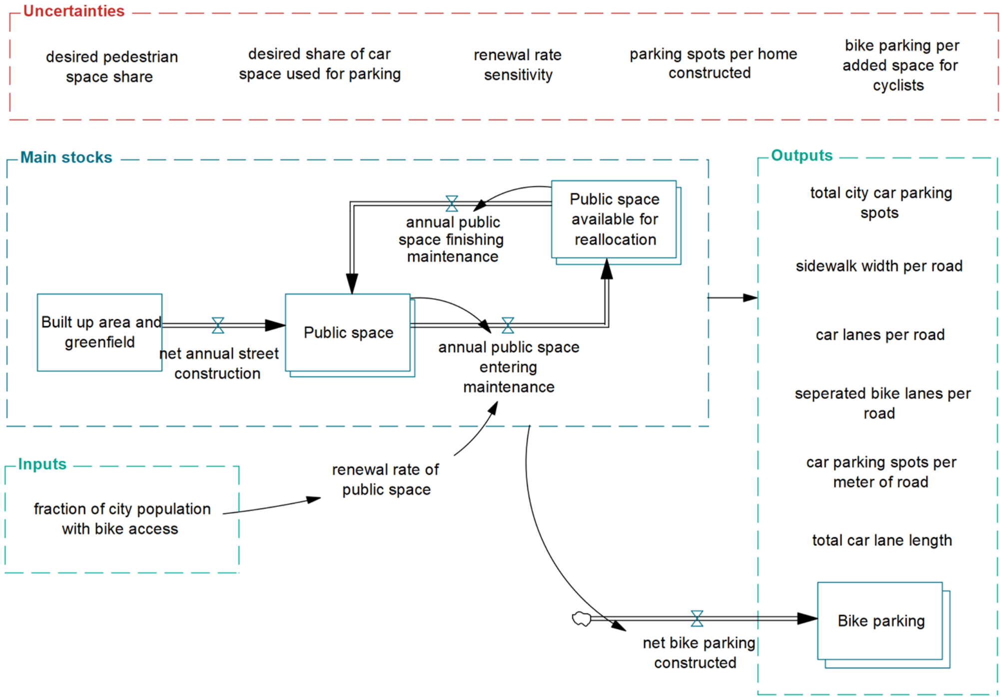

Figure 5.3: Simplified representation of the public space subsystem, highlighting the inputs, main stocks, outputs, and uncertainties that influence the subsystem. Rectangles indicate stocks, arrows with faucets (⧖-symbols) indicate flows between stocks. Double rectangles indicate that a stock is sub-scripted, meaning the variable is disaggregated into categories. Sinks (cloud-symbols) indicate model boundaries. Normal arrows are causal links.

The amount of public space in each of the categories of space inform variables that feed into other subsystems of the model: average sidewalk width per road, average car lanes per road, average separated bike lanes per road, average parking spots per meter of road, number of public parking spots, total car lane length, bike network completion, and bike parking.

Main assumptions:

- The average distribution of public space entering maintenance matches the overall average (i.e. streets enter maintenance at random, with no prioritization that would shift the average distribution of public space in maintenance relative to the overall average).
- The desired public space distribution is equal for all road types.
- The construction of bike parking is coupled with public space renewal and occurs at a rate proportional to the addition of space for cyclists.

5.2.2. Car adoption

The model represents car adoption as a double sub-scripted population stock-and-flow system (Figure 5.4), disaggregated into two sets of categories. One set of categories represents zones and distinguishes city and ring, the other set of categories represents car adoption status and distinguishes young adult, adult without car, and adult with car. Young adults age to become either an adult without car or an adult with car. The percentage point shift in car adoption by young adults aging (relative to car adoption by current adults) is influenced by the level of car usage by current adults with cars. Higher car usage leads to a shift towards higher levels of car adoption and vice versa. The subsystem is influenced by two uncertainties related to vehicle adoption: *reference shift in car adoption* and *car adoption sensitivity to car usage*. The uncertainties determine the size of the shift in car adoption among young adults and its responsiveness to changes in car usage by car users.

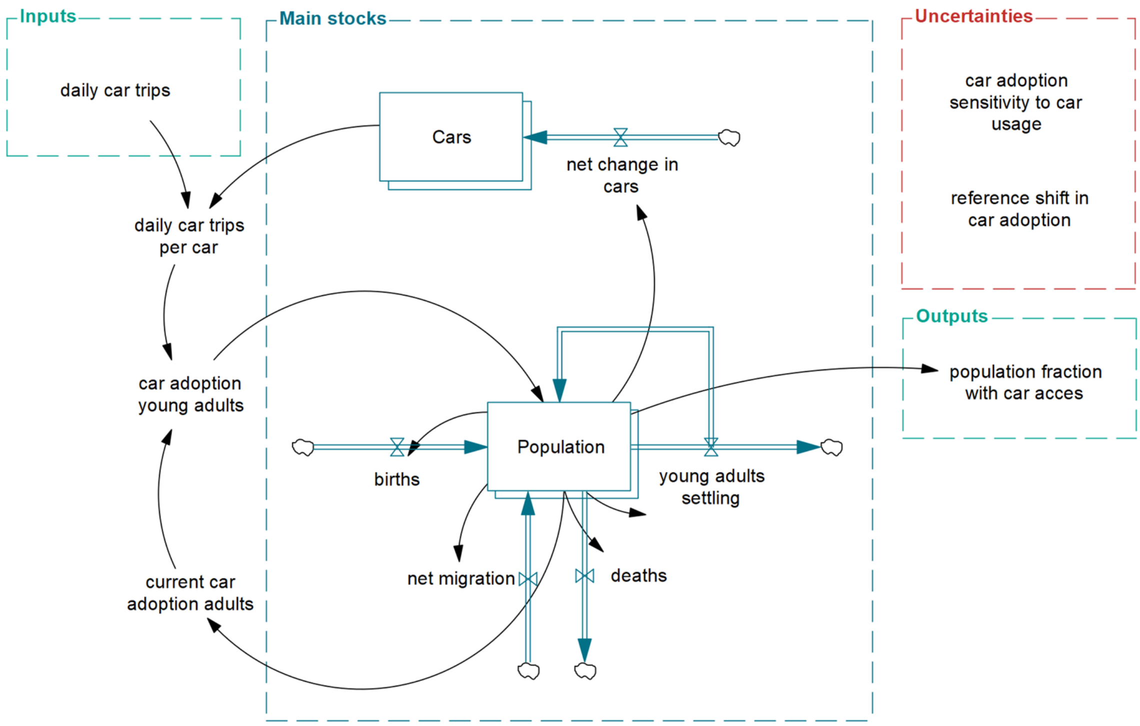

Figure 5.4: Simplified representation of car adoption subsystem highlighting the inputs, main stocks, outputs, and uncertainties that influence the subsystem. Rectangles indicate stocks, arrows with faucets (⧖-symbols) indicate flows between stocks. Double rectangles indicate that a stock is sub-scripted, meaning the variable is disaggregated into categories. Sinks (cloud-symbols) indicate model boundaries. Normal arrows are causal links.

The subsystem is influenced by one endogenous variable - daily car trips - and by one effect variable representing the effect of car usage on the shift in car adoption. Changes in the subsystem influence the total number of cars in the city and in the ring.

Main assumptions:

- Changes in young adult car adoption are the principal driver of changes in car adoption.
- The level of car ownership among adult population is constant.
- The level of car usage by current adults with cars proxies the attractiveness of adopting a car for young adults.
- Residential self-selection does not occur (e.g. a reduction in car ownership due to car-owning households out-migrating and households without cars immigrating)

5.2.3. Bike adoption

The model represents bike adoption using a Diffusion of Innovation model (Figure 5.5). The main stock, bike users, is disaggregated into two sets of categories: zones (city and ring), and ownership type (bike-sharing and private bike[1]). Bike users meet non-bike users receptive to cycling at a certain rate (the contact rate), and depending on a set of factors, the non-bike users either adopt cycling or not (contact fruitfulness). A fraction of bike users discontinues after the period of use, or - in the case of bike-sharing users - they upgrade to private bikes. Bike network completion influences the fraction of population receptive to cycling in a non-linear manner. The level of bike usage (bike trips per bike user) and the availability of bike parking (bike parking per bike user) influence contact fruitfulness. Five uncertainties influence the subsystem: the tipping point at which the cautious majority of the population becomes receptive to cycling, the sensitivity of contact fruitfulness to available bike parking, the sensitivity of contact fruitfulness to bike usage by bike users, the bike-sharing to private bike upgrade fraction, and the contact rate.

[1] Private bike also includes bike subscription services such as Veligo or Swapfiets.

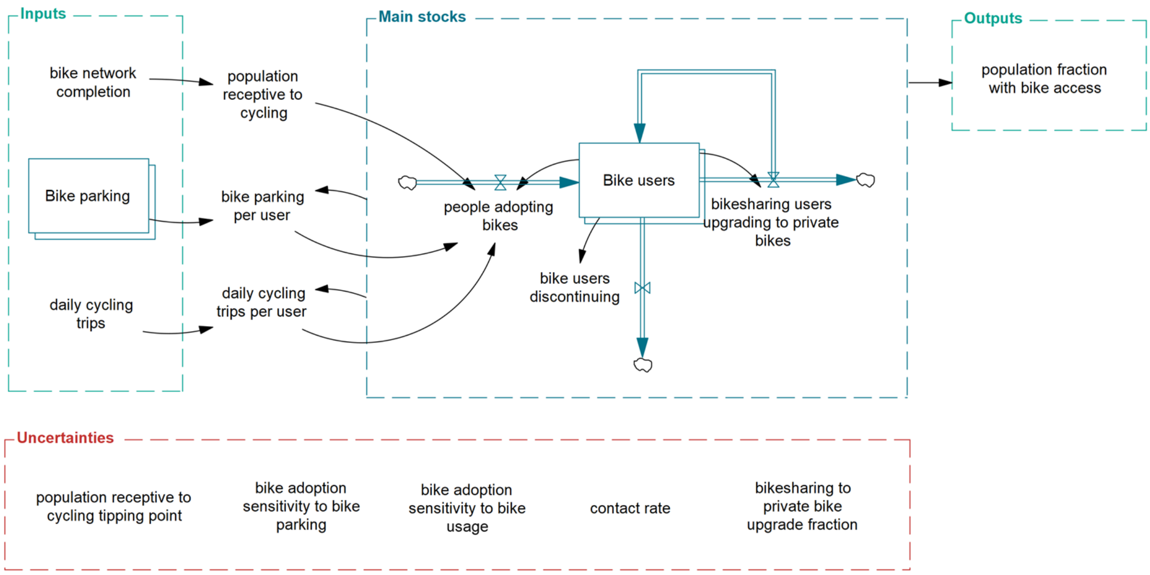

Figure 5.5: Simplified representation of bike adoption subsystem highlighting the inputs, main stocks, outputs, and uncertainties that influence the subsystem. Rectangles indicate stocks, arrows with faucets (⧖-symbols) indicate flows between stocks. Double rectangles indicate that a stock is sub-scripted, meaning the variable is disaggregated into categories. Sinks (cloud-symbols) indicate model boundaries. Normal arrows are causal links.

Variables from other subsystems that influence bike adoption include bike network completion, bike parking, and daily cycling trips. Changes in the subsystem influence the fraction of population with bike access.

Main assumptions:

- Bike adoption emerges primarily based on word-of-mouth advertising between bike users and population receptive to cycling.
- The fraction of the population receptive to cycling depends primarily on bike network completion.
- The fruitfulness of contacts depends primarily on parking availability and the level of bike usage by bike users
- Population change does not directly affect the number of bike users in the city
- Joining a bike-sharing service is a faster decision compared to adopting a private bike

5.2.4. Mode choice

The model represents mode choice based on subjective travel time, which is a function of physical travel time and factors that influence the perceived safety and comfort of traveling by a given mode. The main stock, smoothed subjective travel time, is disaggregated into three modes of transport (cycling, public transport, and car) and into two trip distance bands (mid-distance trips and long-distance trips) (Figure 5.6). Smoothed subjective travel time represents subjective travel time after an information delay (perception time). For each trip distance band, and for fractions of population with access to different sets of modes, gaps in smoothed subjective travel time per mode determine the modal split (using the approach presented in Chapter 2). Depending on the mode of transport, the relation between physical travel time and subjective travel time is defined in a different way.

Endogenous variables influencing how subjective travel time by car changes include daily car trips, total car lane length, cars, and number of parking spots. Daily car trips and total car lane length determine average congestion, which influences physical travel time on car trips. Number of parking spots per car influences subjective parking search and egress time. Endogenous variables influencing subjective travel time by public transport include daily public transport trips and average sidewalk width per road. Daily public transport trips affects the overcrowding level, and sidewalk width per road affects subjective public transport access and egress time.

Endogenous variables influencing how subjective travel time by bike changes include bike lanes per road, car lanes per road, and parking spots per meter of road. Bike lanes per road influences physical travel time on cycling trips by determining the network to euclidean distance ratio (the more the ratio exceeds 1.0, the longer the detour). The combination of average separated bike lanes per road, average car lanes per road, and parking spots per meter of road determine the subjective cost of cycling time.

Other endogenous variables directly influencing mode choice are the fraction of population with bike access and the fraction of population with car access.

Main assumptions:

- Changes in mode choice are exclusively driven by gaps in subjective travel time. Travel cost plays a negligible role.
- City population with car access chooses between public transport and car use on mid-distance trips.
- City population with bike access chooses between public transport and bike use on mid-distance trips
- City population with only public transport corresponds to the smallest of city population without car access and urban population without bike access[2] and always chooses public transport on mid-distance trips.

[2]Compromising assumption due to the aggregate nature of SD modeling

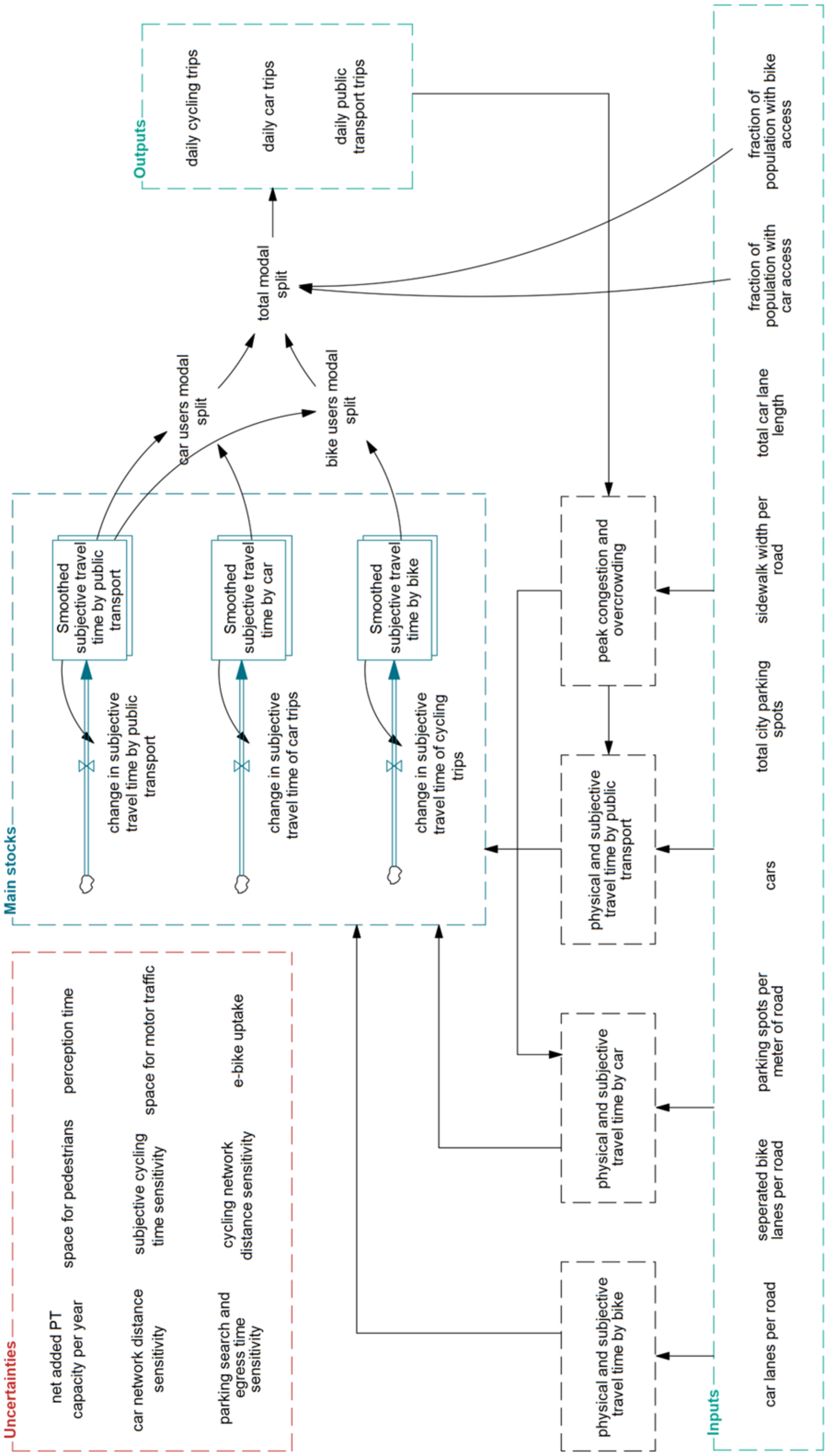

Figure 5.6: Simplified representation of mode choice subsystem highlighting the inputs, main stocks, outputs, and uncertainties that influence the subsystem. Rectangles indicate stocks, arrows with faucets (⧖-symbols) indicate flows between stocks. Double rectangles indicate that a stock is sub-scripted, meaning the variable is disaggregated into categories. Sinks (cloud-symbols) indicate model boundaries. Normal arrows are causal links. Grey dotted boxes represent a collection of variables.

5.2.5. Destination choice

The model represents destination choice based on how travel demand, expressed in daily trips per ring population and daily trips per city population, shifts between spatial relations and trip distance bands. The main stocks represent daily trips per person for a specific spatial relation (e.g. daily trips per ring population to city represents citizens in the ring traveling from the ring to the city). The stock for daily trips per city population within the city is sub-scripted into trip distance bands.

Changes in destination choice are represented as flows between spatial relations or between trip distance bands within a spatial relation. Flows between spatial relations represent changes in self-containment (i.e. the capacity of a zone to meet travel demand internally). A flow between trip distance bands is *net increase in proximity of destinations*, which represents changes in proximity of destinations within the city. Daily trips per person shift between trip distance bands based on a destination shift rate. 5.7 visualizes the subsystem.

Given the law of constant travel time, shifts in trip distance cause shifts in trip frequency, such that on average, people spend a constant amount of time per day traveling.

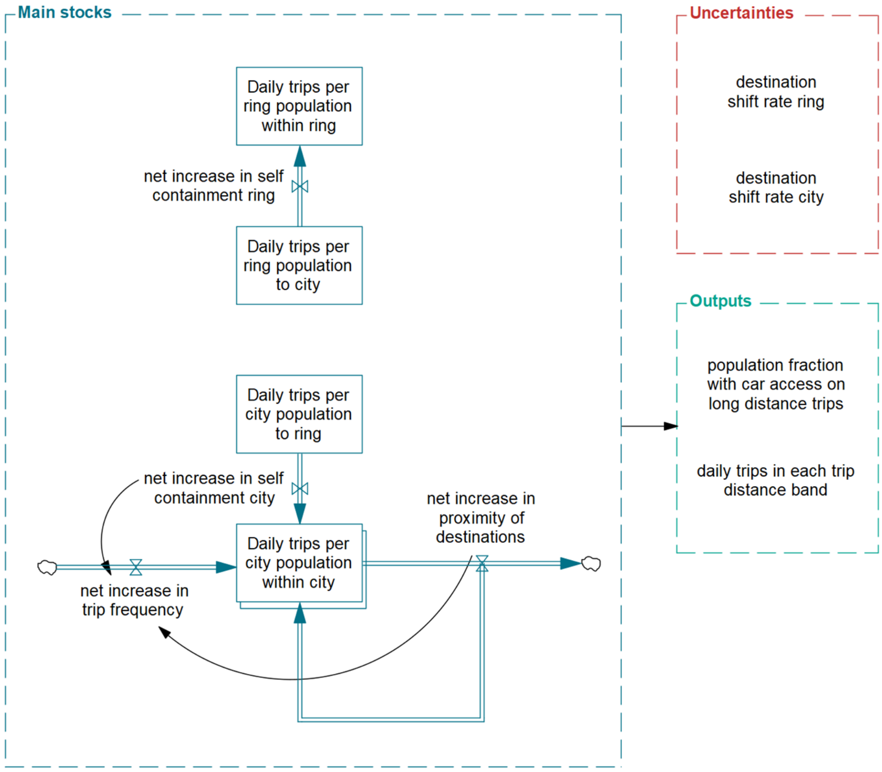

Figure 5.7: Simplified representation of destination choice subsystem highlighting the main stocks, outputs, and uncertainties that influence the subsystem. Rectangles indicate stocks, arrows with faucets (⧖-symbols) indicate flows between stocks. Double rectangles indicate that a stock is sub-scripted, meaning the variable is disaggregated into categories. Sinks (cloud-symbols) indicate model boundaries. Normal arrows are causal links.

Destination choice is not influence by inputs, but only by uncertainties: *destination shift rate city* and *destination shift rate ring*.

Main assumptions:

- Self-containment increases over time in both the city and the first ring
- The share of daily trips at short distances increases over time within the city

5.3. Validation

The validation and verification process established confidence that the model is fit for purpose and correctly implemented. Certain improvements are reserved for future research, but this does not diminish the current model's usefulness to inform robust policy strategies. This section argues why the model is deemed fit for purpose, and supports this assertion by presenting the outcomes of specific validation tests carried out during model development. Boundary adequacy (structure) testing checks that the model structure endogenizes the parts of the system most critical for meeting the model purpose. Behavioral sensitivity testing and changed behavior prediction testing validate the model's response to changes in parameters and policy design. Face validation with modeling and transport policy experts further increases confidence in the model structure and behavior. The model is deemed fit for its intended purpose of informing robust policy strategies, and some improvements are highlighted as next modeling steps.

The specified model purpose is to inform robust policy strategies by:

- Reflecting the pace at which road space reallocation changes citywide public space distribution
- Specifying the dynamics that link public space distribution and travel behavior, most dominant on a 30-year timescale
- Quantifying the influence of uncertainties on the effects of road space reallocation policy on distance traveled by car, by bike, and by public transport on trips within the city and between the city and the first ring.

Parts of the system structure that are key for meeting the model purpose are modeled endogenously, with a deliberate selection of boundaries. For example, to reflect the pace at which road space reallocation changes citywide public space distribution, a stock-and-flow structure of public space is included. To specify the dynamics that link public space distribution and travel behavior, six causal relations connect the public space subsystem with the mode choice subsystem. The model structure also endogenizes bike adoption and car adoption. Different structures for car adoption were explored in this research (i.e. structures involving residential self-selection and periodic car replacement) but proved difficult to conceptualize without expanding model boundaries to include migration dynamics. Although alternative structures would change the rate of change, they would not change the type of change in the subsystem (i.e. changes in the flows to and from a slowly-changing stock). Therefore, instead of varying model structure, a broad range is chosen for parameter uncertainty in the chosen structure for the car adoption subsystem.

Parts of the system structure that are not crucial in light of the model purpose are modeled exogenously. For example, feedback effects related to land use and destination choice are not expected to be dominant on a 30 year timescale – the timescale specified in the model purpose. Therefore, spatial disaggregation is minimized and the destination choice subsystem is designed such that it is only influenced by exogenous variables. While not modeling feedback, exogenous change rate variables reflect the expected direction of change (i.e. an increasing proximity of destinations), and are varied across experiments to incorporate uncertainties related to future policy (e.g. land-use policies).

Face validation of the model structure increased confidence in the chosen model structure, either by validating decisions made in the early stages of model development or by guiding subsequent improvements. (see Appendix A). An example of an improvement informed by the interviews is including an uncertain parameter that makes the share of parking in the desired share of public space for motorists variable. Another example is adding positive feedback between the number of bike users and the renewal rate of public space. While the interviews build confidence that the current model structure is fit for purpose, they also identified potential future improvements. A key model expansion suggested during the interviews is specifying road types, and is proposed for future research (see Chapter 8). Regardless of the suggested improvements, the current structure already successfully generates strategic insights for designing robust policy strategies.

Model behavior was mainly validated using face validation and behavioral sensitivity testing. Participants of the expert interviews found the relationships between model outputs and uncertain parameters to be consistent with their understanding of transport systems and the studied case. For example, the model's sensitivity to the rate at which bike use spreads (see Chapter 6) was considered realistic, as initial increases in bike use rely more on increasing access to bikes and receptiveness to cycling rather than on how cycling compares to public transport. The processed notes from the interviews are documented in Appendix A. Behavioral sensitivity testing also validated that variables in the model respond as expected to changing conditions. In one test, subjective travel time of one mode of transport is doubled, and the effect on the reference mode is as expected (the share in total distance traveled falls, after a delay that matches the specified delay time). In another test, part of the road network is removed, and the effect on the distance traveled by car and congestion is as expected (the share in distance traveled falls, and congested speed during peak hour falls).

This research assumes that the proposed policy will not replace pedestrian space with additional bike lanes, but expert interviews suggested exploring model behavior if it does. A changed behavior prediction test was carried out to check whether the model generates the expected behavior when half of the bike lanes are constructed on former pedestrian space, rather than former car space. The results show expected effects in the outcomes of interest for this research (the share of distance traveled by public transport falls due to declining walking attractiveness, while the share of distance traveled by car grows). A selection of validation tests are documented in Appendix D.

Some outliers in the model results may reflect implausible behavior, given lack of data and literature for informing more precise ranges for uncertain parameters (see Appendix C). This also means that during the experiments, uncertain parameters may combine to form implausible scenarios. However, the model purpose is to inform robust policy strategies, and it does not need to provide accurate predictions and probabilities. With this in mind, the model is deemed valid and fit for purpose.

6
Results

This chapter presents the results of the geospatial analysis and the results from the experiments. It also compares the results from the experiments to the hypothesized reference mode. The results presented in this chapter inform the discussion, conclusions, and recommendations of the research.

6.1. Geospatial analysis

The geospatial analysis provides high confidence estimates for total public space and the share of on-street parking in public space over the period 2019 - 2022 and a moderate confidence estimate for the share of space for cyclists in public space. The estimate for the share of space for motor traffic and the share of pedestrian space is of low confidence (as explained in Chapter 2). Total public space in the chosen case study, Paris, is approximately 2677 ha. Figure B.2 visualizes total public space.

Figure 6.1: Visualization of the results from estimating total public space in the chosen case study.

The public space consumption of car parking is estimated at 197 ha (7%) and the space consumption of bike lanes at 99 ha (4%). The exact share of pedestrian space and space for motor traffic in the remaining 2381 ha is uncertain, but estimated at 1515 ha (57%) and 866 ha (32%) respectively (Figure 8.1)

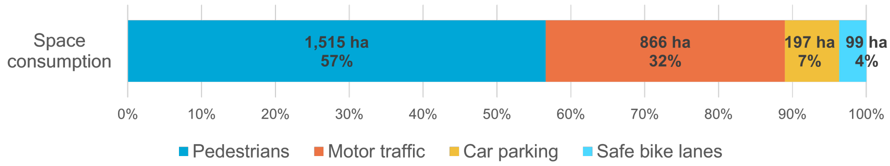

Figure 6.2: Estimated public space distribution between pedestrians, motor traffic, car parking, and cyclists, within the chosen case study. The estimate for car parking is adapted from APUR (2019) and of high confidence. The estimate for bike lanes is of moderate confidence. It counts demarcated bike lanes and separated bike lanes recorded in OpenStreetMap (IDF Mobilite, 2024) and assumes a lane-width of $2.2m$. The estimated proportion between space for pedestrians and space for motor traffic is based on lower quality data and of low confidence (Appendix B)

6.2. Experiments

This section presents the results of the experiments for the main reference mode and a description of the results from PRIM. It also presents the behavior over time for outcomes of interest that are supportive in explaining the behavior of the reference modes. Appendix D documents the results for a larger set of outcomes of interest, as well as the direct results from PRIM that inform the textual description of results from PRIM presented in this section.

Figure 6.3 shows the results over time for distance traveled by bike and textually summarizes the main outcomes from applying PRIM.

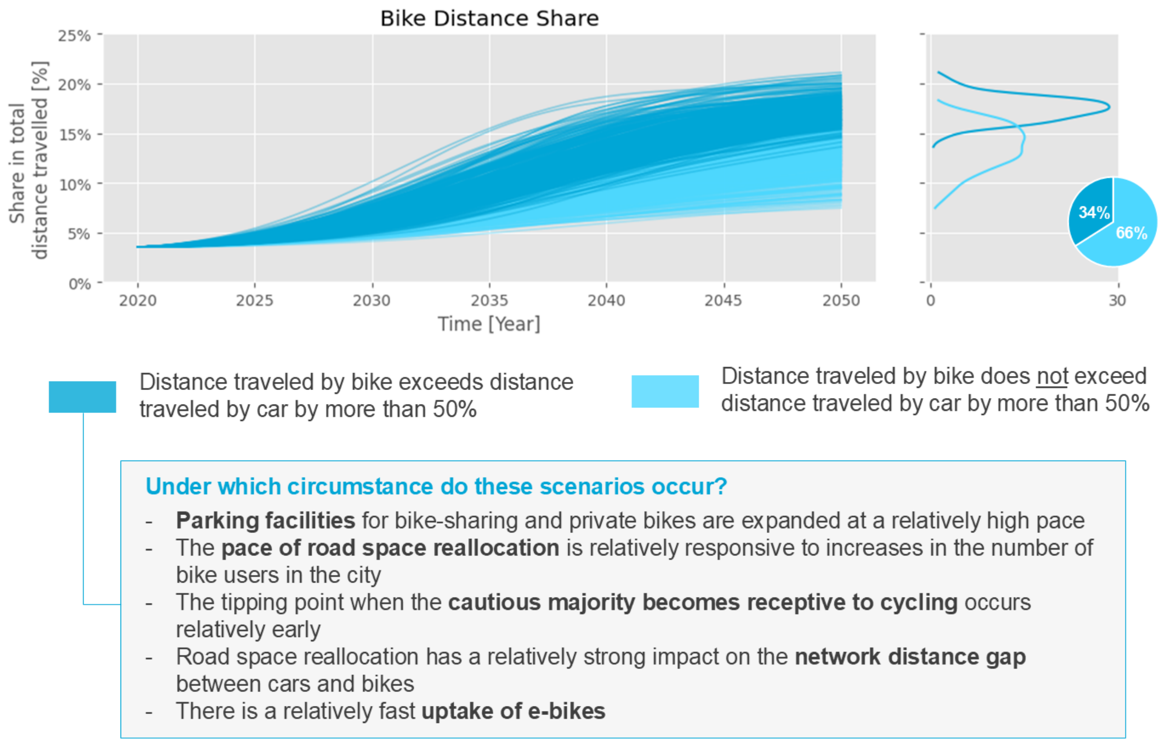

Figure 6.3: The line chart in the top left section of the figure displays the share of bike travel in total distance traveled over time in an ensemble of 1000 scenarios. The scenario ensemble is clustered based on whether or not distance traveled by bike exceeds distance traveled by car by more than 50% at final time. The density plot in the top right section of the figure displays the distribution of the final time outcomes per cluster of scenarios, and the pie chart displays the relative size of the two clusters in the total sample. The bottom section of the figure describes the circumstances that explain variation between the two clusters, based on the results from applying PRIM.

The experiment results for the main reference mode show numerical variations of 110% - 495% (bike), 19% - 58% (car), and 0% - 20% (public transport) at final time relative to initial time. Figure 6.4 shows the outcomes over time for distance traveled by public transport and by car.

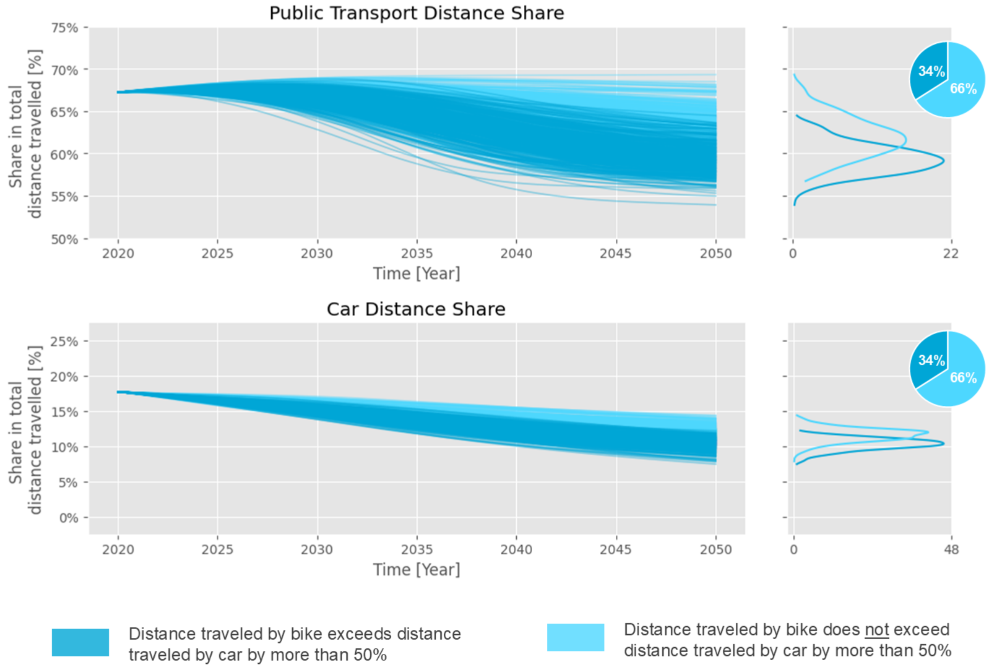

Figure 6.4: The line chart in the top left section of the figure displays the share of total distance traveled by public transport and by car over time in an ensemble of 1000 scenarios. The scenario ensemble is clustered based on whether or not distance traveled by bike exceeds distance traveled by car by more than 50% at final time. The density plot in the top right section of the figure displays the distribution of the final time outcomes per cluster of scenarios, and the pie chart displays the relative size of the two clusters in the total sample.

The experiment results for fraction of city population with bike access show variations of 28% - 235% at final time relative to initial time. Figure 6.5 shows the outcomes over time for fraction of city population with bike access.

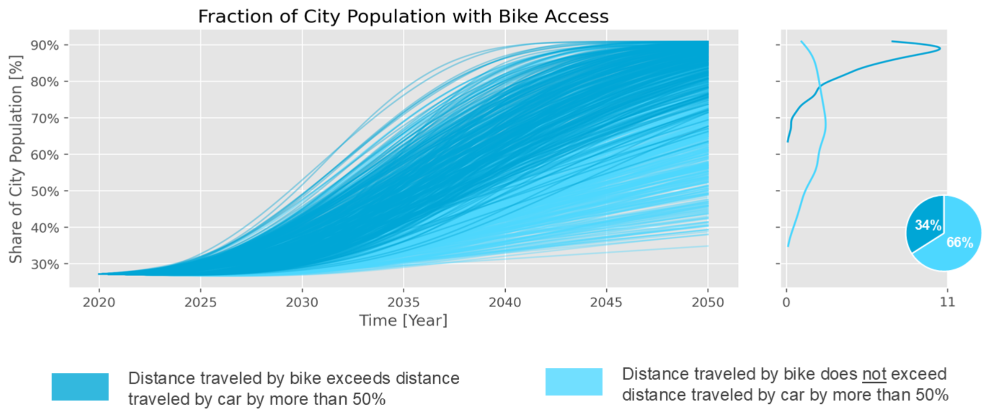

Figure 6.5: The line chart in the left hand section of the figure displays the fraction of the city population with bike access over time in an ensemble of 1000 scenarios. The scenario ensemble is clustered based on whether or not distance traveled by bike exceeds distance traveled by car by more than 50% at final time. The density plot in the top right section of the figure displays the distribution of the final time outcomes per cluster of scenarios, and the pie chart displays the relative size of the two clusters in the total sample.

The experiment results for subjective travel time show variations of 21% - 60% (bike), 0% - 32%

(car), and 0% - 31% (public transport) at final time relative to initial time. Figure 6.6 shows the results over time for the variation in subjective travel time by bike.

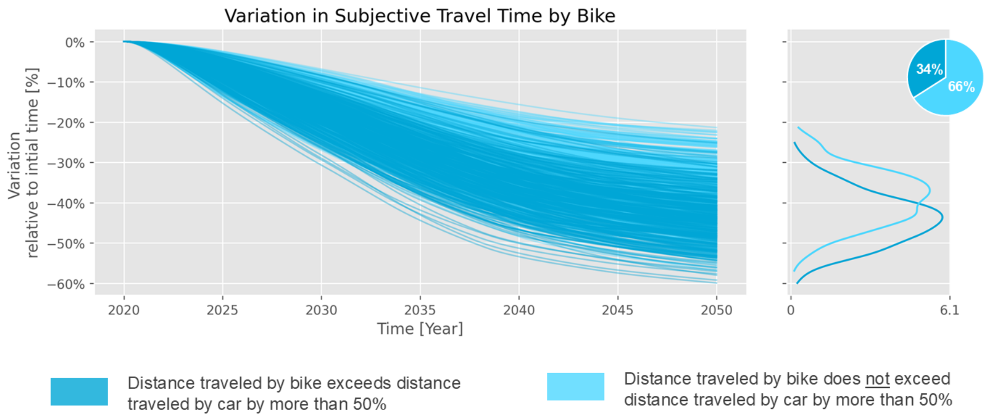

Figure 6.6: The line chart in the left hand section of the figure displays the variation in subjective travel time by bike over time, relative to initial time, in an ensemble of 1000 scenarios. The scenario ensemble is clustered based on whether or not distance traveled by bike exceeds distance traveled by car by more than 50% at final time. The density plot in the top right section of the figure displays the distribution of the final time outcomes per cluster of scenarios, and the pie chart displays the relative size of the two clusters in the total sample.

Figure 6.6 shows the results over time for the variation in subjective travel time by car and by public transport.

Figure 6.7: The line charts in the left hand section of the figure display the variation in subjective travel time by public transport and by car over time, relative to initial time, in an ensemble of 1000 scenarios. The scenario ensemble is clustered based on whether or not distance traveled by bike exceeds distance traveled by car by more than 50% at final time. The density plot in the top right section of the figure displays the distribution of the final time outcomes per cluster of scenarios, and the pie chart displays the relative size of the two clusters in the total sample.

6.3. Experiment results compared to the hypothesis

The scenario outcomes for distance traveled by bike and distance traveled by car resemble the hypothesized reference mode presented in Chapter 4, while the outcomes for distance traveled by public transport show a different behavior. Loop dominance provides a useful framework to understand why the results meet or deviate from expectations. Loop dominance refers to certain feedback loops being more influential than others based on the state of the system (Richardson, 1995). This section elaborates on the experiment results, how PRIM results explain variations in outcomes, and how loop dominance clarifies expected and unexpected behaviors.

The behavioral mode for the share of total distance traveled by bike is accelerated growth followed by stabilization, with bike use surpassing car use in most scenarios (86%) by 2050. Key dynamics include the fast, non-linear growth of bike adoption compared to the slower, linear decline in car adoption. Road space reallocation drives immediate modal shift from public transport to cycling for mid-distance trips (1.5 – 6 km), while modal shift from car to public transport for long-distance trips (7 – 10 km) is more gradual and uncertain. This accelerated growth in bike use occurs across all scenarios, but the level of change depends on uncertainties such as bike parking availability and the uptake of e-bikes, which respectively influence contact fruitfulness and travel time gaps between modes. By contrast, the behavioral mode for car use shows a slow decline and is tied to feedback mechanisms that limit variation in subjective travel time by car, even as road space reallocation progresses. Notably, in 90% of scenarios, subjective travel time improves for all modes, including cars, under road space reallocation policy. While a faster decline in car use was expected, the direction of change in the behavioral modes for both cycling and car use match the hypothesis.

The behavioral mode for public transport shows a decline followed by stabilization, deviating from the hypothesized growth behavior. Loop dominance provides three explanations for this behavior. First, the emergence of cycling becomes the dominant feedback loop, due to a fast growing fraction of the population with bike access and fast declining subjective travel time for bikes. This dominance leads to significant modal shift away from public transport on mid-distance trips, where public transport initially holds the largest share and is thus most affected. Second, the hypothesis that public transport would gain ridership from cars for long-distance trips[1] was less realized. This is due to the dominance of a balancing feedback loop[2], which caused car congestion and parking search times to decrease more quickly than expected as car use declined. Third, declining demand for total trips between the city and the first ring disproportionately impacted public transport, given its initial dominance on long-distance trips (75% modal share). These three behaviors combined led to public transport's share in total distance traveled declining, rather than growing.

6.4. Concluding remarks

The results of the geospatial analysis show that over the period 2019 - 2022, the majority of public space in the chosen case study was allocated to pedestrians (±57%), followed by motor traffic and car parking (±39%). Among the categories considered, bike lanes take up the smallest share in total public space (±4%). The results of the experiments show that the modeled reference mode displays only one mode of behavior under road space reallocation policy, but the level of change is sensitive to uncertain parameters. The most important uncertain parameters are related to the pace of bike adoption and include the allocation of bike parking. Other important uncertain parameters are related to the uptake of e-bikes and the network distance gap between cars and bikes. The scenario outcomes match the hypothesized modal shift on mid-distance trips, but - due to loop dominance - modal shift for long-distance trips is less than expected. These results inform the discussion, conclusions, and recommendations of the research.

[1] Referred to as *Public transport capacity shift* in Chapter 4

[2] Referred to as *Traveling far: by public transport or by car?* in Chapter 4

7 Discussion

This chapter discusses the results from Chapter 6 in light of choices made during the research and presents the scientific and societal implications. First, the chapter discusses modeling choices, generalizability, and applicability of SD. Next, it discusses the implications of the findings from a societal and scientific perspective. Based on the discussion below, chapter 8 concludes on the research question and presents recommendations for policy makers and for future research.

7.1. Discussion of modeling choices

The findings in this research provide valuable insights into the effects of citywide road space reallocation on travel behavior over time. However, the interpretation of these findings should account for limitations stemming from modeling choices . This section discusses important modeling choices, their implications, and highlights next modeling steps to better reflect bike-and-ride systems, pedestrian and cyclist safety, impacts of e-bike uptake, and the environmental impact of long-distance trips.

While the model comprehensively reflects the dynamic of bike adoption and modal shift for mid-distance trips, next modeling steps could improve how it reflects car adoption and modal shift for long-distance trips. By excluding bike parking and public space distribution outside the ring – and thereby road space reallocation policy outside the city – the chosen model scope did not allow for modeling bike-and-ride travel. However, bike-and-ride systems can trigger modal shift from the car to public transport on long distances – a behavior that has been observed in the Netherlands (Martens, 2007). Since most current car traffic in the chosen case study originates from the first ring and involves long-distance trips, this modeling choice limits the possibility of modal shift from cars to public transport represented in the model. Future modeling steps should therefore prioritize modeling bike-and-ride systems, for example by modeling public space distribution in the first ring and bike parking facilities at public transport stations in the first ring.

Additionally, broadening the geographical scope of the model would provide a more comprehensive perspective on environmental impacts. By including trips beyond 10 km, the model could account for the most emission-intensive trips, which are particularly relevant to environmental outcomes. For example, trips in the 13–26 km range typically account for the largest share of transport emissions (Wadud et al., 2024). Next modeling steps should therefore expand the model to include these longer trips and align its findings more closely with environmental objectives.

While the model identifies leverage points for complementary policies, it does not directly simulate their implementation. Alongside road space reallocation, measures such as pricing policies, access restrictions, and speed limit adjustments could reinforce the effects of road space reallocation. For example, the current model identifies the significance of the network distance gap between cars and bikes. This finding suggests that car access restrictions combined with more direct routes by bike could be particularly effective. Future research could focus on the impacts of complementary policies such as access restrictions to better understand combined effects.

The current model's citywide average representation of public space limits the level of detail in modeled policy targets and safety dynamics for pedestrians and cyclists. The current model represents public space distribution using a citywide average with discrete categories of road space, and without incorporating speed and design factors. A suggestion arising from the expert interviews (Appendix A) is specifying road types to allow setting separate public space distribution targets for different road types. It should also be kept in mind that beyond the reallocation of space, designing streets for lower speeds can diminish the impact of cars on pedestrian and cyclist safety and allow the creation of shared spaces for multiple modes (Nello-Deakin, 2019).

Another important safety consideration is the potential increase in collision risks on bike lanes associated with higher speeds from e-bike uptake. Future modeling steps could include links between e-bike adoption, perceived safety, and travel behavior. Additionally, expert interviews (Appendix A) indicate that the importance of secure bike parking increases with e-bike uptake. Since the findings in this research already highlight the importance of bike parking, exploring this feedback should be prioritized in future modeling steps.

7.2. Case-specific limitations and generalizability

The generalizability of the model and its results to other European cities is influenced by case-specific factors, including transport infrastructure, urban form, bike adoption, and tourism. The chosen model boundaries assume underground rail and metro as the dominant public transport modes, simplifying public space categories and omitting impacts on buses and trams, such as the benefits of exclusive bus lanes for regularity, speed, and comfort (González et al., 2019). This assumption limits applicability to cities where bus and tram systems are more prominent. Additionally, the mono-centric urban form, with concentrated jobs and services in the city center, informed the model's zoning approach based on concentric rings, which may be less suitable for polycentric cities. Other contextual factors include low bike ownership (0.25 bikes per household) and peaked car ownership. Therefore, bike adoption emerged as a dominant feedback loop, while this dominance might differ in cities with widespread cycling. The model's exclusion of tourism-related travel demand, designed to improve generalizability to less touristic cities, may affect its validity in cities with seasonal surges in public transport use.

7.3. Applicability of SD

Although SD brings many advantages, its application in this research posed methodological limitations related to street design factors, modeling networks, and distributions across space and population. For example, street design factors like illumination and benches impact walking attractiveness (Methorst, 2021), and intersection design impacts cycling attractiveness (Cervero et al., 2019). Moreover, because SD models cannot capture networks (Shepherd, 2014), modeling congestion required assuming internally isotropic zones (i.e. an even distribution of economic activity and travel demand within zones). Lastly, due to the aggregate nature of System Dynamics (SD), models cannot account for overlapping populations with access to multiple transport modes. Instead, populations are typically segmented into distinct groups based on their primary mode of access, which limits the ability to capture individuals who use or have access to multiple modes simultaneously. Agent-Based Modeling (ABM) could address limitations related to modeling networks and distributions across space and population. Hybrid modeling approaches that combine ABM and SD may allow the two methods to address each other's limitations for modeling transport problems (Howick et al., 2024). Nonetheless, this research confirms the ability of SD to capture non-linearity, feedback, and delay. The research findings also demonstrate its potential to provide strategic insights for transport problems without relying on extensive empirical data.

7.4. Societal implications

This research makes three key contributions to robust policy design and public debates related of road space reallocation. First, it provides strategic insights for designing robust policies that account for cultural and infrastructural dynamics. Second, it contributes to more informed debates on the potential value of citywide road space reallocation in European cities. Third, it quantifies citywide public space distribution in the studied case, highlighting public space distribution is skewed towards car use and providing a basis for evaluating spatial efficiency. These contributions are elaborated below, integrating findings from the quantitative model, geospatial analysis, and expert interviews.

The model results highlight the strategic importance of promoting cultural change alongside infrastructural change and extending the scope of infrastructural change to bike parking. The model highlights the sensitivity of modal shift to bike adoption dynamics, emphasizing the need for complementary policies that build cycling cultures. This aligns with Tschoerner-Budde (2020), who emphasizes the importance of ”a shift from a discussion on transport systems and towards mobility cultures”. The results also indicated the extension of bike parking facilities as a key uncertainty limiting bike adoption in many scenarios. In a ”decide and provide” approach to transport planning, planners build for envisioned travel behavior rather than historically observed travel behavior (ITF, 2021). This research highlights the importance of extending such ”decide and provide” approach from cycling networks towards bike-sharing and private bike parking facilities, to increase bike adoption rates. The process leading to the placement of bike parking facilities at public transport stations in the Netherlands demonstrates that effective coordination across authorities is crucial to ensure that the provision of bike parking is recognized as part of their responsibilities (Martens, 2007).

By exploring the expected effects of road space reallocation on travel behavior and subjective travel times, this research contributes to more informed discussions about the value of the policy in European cities. One critical finding is the potential for declining car use to improve safety and comfort across all modes, including private cars, under road space reallocation[1]. However, as Gössling (2020) points out, road space reallocation often encounters political resistance, in part due to the symbolic value of cars and the common framing of the policy as anti-car. According to Gössling (2020), effective communication strategies should highlight the benefits of cycling – such as health improvements, shorter travel times, and improved safety – rather than focusing solely on the disadvantages of car use. The expert interviews also reflected this approach to framing cycling as a practical choice, with participants emphasizing the need to communicate cycling as ”the right mode for the right trip”. Overall, the model results and inputs from the expert interviews demonstrate there is scope for emphasizing the practical advantages of road space reallocation for all road users, including car users.

The geospatial analysis provides a valuable contribution by quantifying citywide public space distribution in European cities, revealing a significant skew toward car use. In the period 2019-2022, motor traffic and car parking take up approximately 40% of space, while bike lanes take up 4%: the smallest share in total public space. This imbalance not only limits space-efficiency but also raises concerns about the prioritization of access by car over access by sustainable modes. While some nuance is required when interpreting these results – given that public space serves multiple functions, as emphasized by Nello-Deakin (2019) – the findings align with broader critiques of urban planning in European cities, such as those by Gössling (2020). Quantification of citywide public space distribution can serve as a basis for public debate and advocacy, enabling stakeholders to challenge existing inefficiencies and push for different priorities in urban design. Beyond the studied case, the research builds on work in cities like Berlin, Amsterdam, and Barcelona that show similar dominance of car space (Transformative Urban Mobility Initiative (TUMI), 2023, Nello-Deakin, 2019, Ajuntament de Barcelona, 2024).

7.5. Scientific implications

This research makes four key contributions to transport modeling, SD, and future empirical studies. First, it quantifies existing conceptual SD models, proposing a data-light SD model that can be further developed into a decision-support tool. Second, it integrates public space distribution and Diffusion of Innovation with transport modeling, addressing spatial trade-offs and their implications for safety and bike adoption. Third, the research highlights key knowledge gaps related to bike adoption and car adoption, which can guide future empirical research. The contributions are elaborated below.

[1]The model findings demonstrate that when citywide road space reallocation is implemented, and car use declines, remaining car users are in most scenarios not negatively impacted in terms of subjective travel time (see Chapter 6), while the safety and comfort for traveling by other modes strongly improves.

This research advances SD modeling by quantifying existing conceptual SD models and introducing a data-light model that can be further developed into a decision-support tool. By applying the model to a case study, it explores the dynamic behavior that arises from the system structure conceptualized by OECD (2022) and Pokharel et al. (2023). It extends an earlier contribution by Bax (2023) by proposing a forward-looking model and focusing on public space distribution. The proposed model demonstrates that a data-light approach is possible when applied to shorter timescales (thirty years in this research), city or regional geographical scales, and questions for which feedback between transport and land use is less important. Aggregate transport models typically use a gravity model (de Almeida Correia and van Wee, 2023, Ortuzar, 2011a): a method also used in SD transport models (Shepherd, 2014), such as the MARS model (Pfaffenbichler et al., 2010). Unlike activity-based models (de Almeida Correia and van Wee, 2023), which disaggregate data to the household level, gravity models require fewer computational resources. However, gravity models demand spatial disaggregation, a limitation that is often emphasized when it comes to SD applied to transport (Shepherd, 2014). A data-light model – such as proposed in this research – is particularly useful when data is scarce and when easy replication to other cases is a priority. It also improves the communicative value of the model. As such, the proposed model could be further developed into a decision-support tool that can be replicated across multiple cities.

This research addresses critical limitations in traditional transport modeling approaches by integrating public space distribution and Diffusion of Innovation dynamics. Transport models typically take network-based approaches (de Almeida Correia and van Wee, 2023), treating infrastructures for different modes in isolation and neglecting the interactions and spatial trade-offs between them. This has been criticized by Bas et al. (2023), who emphasizes that transport models are typically not sensitive to how road infrastructure impacts non-motorized modes such as walking and cycling. This research contributes to addressing this limitation by integrating public space distribution with transport modeling. For example, it includes impacts of car infrastructure on the perceived safety and comfort for trips made by active modes and public transport, highlighting the spatial trade-offs urban policy makers are facing. Moreover, when it comes to cycling, the proposed model integrates a Diffusion of Innovation model into a transport model to represent bike adoption. Although earlier work has applied a Diffusion of Innovation model to cycling qualitatively (Perez-Macias et al., 2024, Nehme et al., 2016, Schoner et al., 2016), this research integrates it into a quantitative transport model. This integration contributes to the ability of transport models to evaluate how travel behavior responds to the development of safe cycling networks.

This research also identifies critical knowledge gaps related to bike and car adoption that can guide future empirical studies. Current literature on bike adoption emphasizes segmentation based on infrastructure sensitivity (Cabral and Kim, 2020) and standards for safe, connected cycling networks (Cervero et al., 2019). However, receptiveness to cycling has not been researched over time as cycling infrastructure improves. A key uncertainty uncovered in this study is the tipping point at which the cautious majority becomes receptive to cycling. Advancing this knowledge gap is essential for designing effective cycling infrastructure and policies and for promoting policy transfer across cities based on empirical evidence. Similarly, research on car adoption has explored national trends (Ortar et al., 2018, Grimal, 2020, Bayart et al., 2020) and policy acceptance (Roukouni and Cats, 2024) However, specific research on the potential for reducing private car adoption in suburban areas is scarce. In the studied case, car traffic in the city mostly originates from commuters living in the first ring, highlighting the importance of advancing this knowledge gap.

8 Conclusions & Recommendations

This research argued that urban mobility systems in European cities face climate, health, and spatial challenges that call for policies to reduce private car use while increasing access by public transport and active modes. The research focused on road space reallocation, which was highlighted in earlier studies as a promising policy. The purpose of this research was to support the design of robust city-wide road space reallocation policy, and addressed two main knowledge gaps: a lack of analysis how citywide road space reallocation affects travel behavior over time and a lack of quantification of existing conceptual SD work that evaluates road space reallocation. This chapter presents the answers to each of the four sub-questions as well as the main question of the research. Next, it presents recommendations for policy makers and for future research. These recommendations build on findings, implications, and limitations discussed in Chapter 7.

SQ1: What are the interactions between public space distribution and travel behavior according to literature?

For traveling to a given destination, public space distribution affects physical travel time, perceived safety, and comfort associated with different available modes. The resistance factors for car use rise with reductions in road capacity and parking availability per car, while the attractiveness of cycling and walking improves with wider sidewalks, separated bike lanes, and green space. Car attractiveness is especially sensitive to parking availability. Public space distribution also determines the attractiveness of the first and last kilometer of public transport trips, particularly when bike-and-ride facilities enable accessing metro and rail stations by bike. A safe and well-connected cycling network can influence the adoption of bikes by increasing the share of the population receptive to cycling and can trigger a positive feedback loop as bike use spreads. Interactions between public space distribution and car adoption are uncertain, but young adults and higher-educated groups may be more likely to step away from car ownership, should other transport modes become more attractive. Lastly, travel resistance factors and access to vehicles also determine destination choice and trip frequency, with more destinations chosen at shorter distances when active travel is more dominant and vice versa.

SQ2: What are the dynamics of travel behavior when the distribution of public space changes over time?

When the distribution of public space changes over time, the relative attractiveness associated to different transport modes change, leading to modal shift among population groups with access to multiple modes. Moreover, the receptiveness of the population to adopting new modes of transport can change over time as the available space and the safety of infrastructure improve. In the context of the chosen case study, road space reallocation to cyclists is expected to increase distance traveled by bike, such that it surpasses distance traveled by car. Road space reallocation can also trigger a modal shift from the car to public transport on long distances, especially if bike-and-ride facilities are in place. Due to delay in behavioral responses to changes in the physical system, modal shift for long-distance trips will come later than shift on mid distances. Modal shift for long-distance trips will also be slower and more uncertain, depending mainly on how car ownership evolves in suburban areas. While changing public space distribution affects the attractiveness and adoption of transport modes, it will also affect destination choice and trip frequencies. In the context of the chosen case study, road space reallocation towards active modes is expected to lead to higher trip frequencies at shorter distances. This change also strongly depends on changes in land use factors, such as the proximity of jobs and services.

SQ3: What is the current distribution of public space in Paris between pedestrians, cyclists, and motorized vehicles?

Over the period 2019 - 2022, the public space consumption of car parking is estimated at 197 ha (7%) and the space consumption of bike lanes at 99 ha (4%). The exact share of pedestrian space and space for motor traffic in the remaining 2381 ha is uncertain, but can be estimated at 1515 ha (57%) and 866 ha (32%) respectively. The current dominance of road space and space for car parking impact the perceived safety and comfort of cycling and walking. The dominance of car space combined with little space for safe bike lanes limits the potential for bike adoption and modal shift to cycling. Road space reallocation policy shifts the hierarchy such that space for safe bike lanes ranges the same order magnitude as space for motorized traffic.

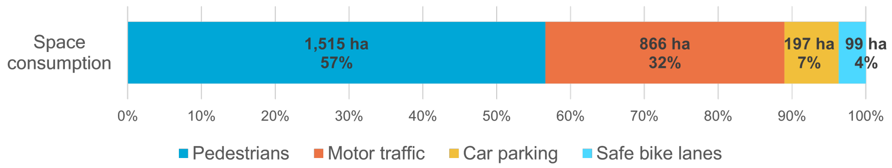

Figure 8.1: Estimated public space distribution between pedestrians, motor traffic, car parking, and cyclists, within the chosen case study. The estimate for car parking is adapted from APUR (2019) and of high confidence. The estimate for cyclists is of moderate confidence. It counts demarcated bike lanes and separated bike lanes recorded in OpenStreetMap (IDF Mobilite, 2024) and assumes a lane-width of $2.2m$. The estimated proportion between space for pedestrians and space for motor traffic is based on lower quality data and of low confidence (Appendix B)

SQ4: How do uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy influence to what extent road space reallocation policy in Paris can change travel behavior?

Uncertainties related to mode choice and vehicle adoption are the most important for changing the distance share of car, bike, and public transport[1]. Based on the modeling choices and the assumed ranges for uncertain parameters in this research, the extent to which road space reallocation can change travel behavior in the chosen case study is especially sensitive to the following key uncertainties.

- **The pace at which bike parking facilities are constructed**: this uncertainty affects the rate at which bike use spread to the cautious majority of the population.
- **Acceleration in road space reallocation policy**: this uncertainty affects the strength of a positive feedback loop, where growing bike adoption accelerates efforts to improve cycling infrastructure.
- **Tipping point in receptiveness to cycling**: expert interviews indicated this tipping point likely occurs when 20–60% of the bike network is completed. However, the exact position and shape of this curve remain unclear and affects the rate at which bike use spread to the cautious majority of the population.
- **Uptake of e-bikes**: this uncertainty affects the level of modal shift from public transport to cycling on mid-distance trips (1.5–6 km)
- **Network distance gap between modes**: it is uncertain to what extent road space reallocation policy will reduce detours for cyclists and increase detours for cars. This uncertainty affects the level of modal shift.

[1] Uncertainties related to current public space distribution and destination choice are less important, although they do appear in the outcomes from applying PRIM. destination choice does impact total distance traveled and the modal share of walking and cycling expressed in trips.

MQ: To what extent can citywide road space reallocation change travel behavior in European cities?

Citywide road space reallocation in European cities can increase bike adoption as well as modal shift, primarily from public transport to cycling, but also from the car to public transport and cycling. Public space takes approximately 50 years to renew, meaning desired changes in public space distribution take decades to manifest themselves. In the context of the case study and based on modeling choices and assumptions in this research (see Chapter 7), the extent to which citywide road space reallocation can increase bike adoption over the course of thirty years is from an initial estimated value of 27% to a maximum of approximately 90% of the population. The extent to which it can increase the distance share of cycling is from an initial estimated value of 4% to a maximum of approximately 18% (for trips within the city and between the city and the first ring). The extent to which it can decrease the distance share of cars is from an initial estimated value of 18% to a minimum of approximately 8%. The extent to which it can decrease the distance share of public transport is from an initial estimated value of 67% to approximately 54%. The level of change depends most on uncertainties related to mode choice and vehicle adoption. While the effect was not quantified in this study, bike-and-ride facilities can increase modal shift for long-distance trips resulting from road space reallocation.

8.1. Recommendations for policy makers

This section summarizes policy recommendations for accelerating bike adoption, improving monitoring and target-setting, and collaboration across municipalities. The recommendations follow from the key uncertainties identified in the model, and insights arising from the expert interviews.

- **Accelerating bike adoption**: The rate at which bike use spreads to the cautious majority of the population was identified as a critical leverage point in this research, and the availability of parking facilities were highlighted as a limiting factor. Based on these findings, examples of policies that urban policy makers can consider include:
  - Supporting cycling-focused citizen initiatives, such as Catalonia's Bicibus (Bicibus, 2024) and France's S'cool bus (Solutions, 2024), to nurture the local cycling culture while reducing private car use.
  - Communication strategies to change perceptions towards sustainable modes and reduce car-centric mindsets (OECD, 2022, Gössling, 2020)
  - Increasing secure bike parking facilities and bike-sharing at workplaces and public transport stations.
- **Improving monitoring and target-setting**: The expert interviews and model validation process highlighted the importance of clear and specific targets. track progress. Setting specific and measurable targets can help monitoring, evaluating, and communicating policy progress. Examples of actions urban policy makers can consider include:
  - Setting targets for bike network coverage as a percentage of the total road network and with quality standards tailored to street types.
  - Periodically reporting public space distribution in line with Ajuntament de Barcelona (2024) to create a basis for public debates and evaluating spatial efficiency.
  - Reporting modal split by trip distance bands to address long-distance trips, which contribute disproportionately to car traffic and emissions (Wadud et al., 2024).
- **Collaboration across municipalities**: The quantitative results highlighted that in the chosen case study, a decline in car adoption in the first ring is important and not directly triggered via road space reallocation in the city. Moreover, the conceptual model suggests the potential for bike-and-ride to foster modal shift from the car to public transport on long distances, although this effect was not quantified. Examples of actions that urban policy makers can consider include:
  - Engaging in shared infrastructure planning for bike-and-ride, via shared policy strategies for modal shift from cars to public transport for regional, long-distance commuting.
  - Identifying population groups and neighborhoods in suburban areas where households are most receptive to changing their travel behavior, as well as those facing barriers. The insights can guide targeted efforts in suburban areas to encourage modal shift and to improve accessibility by sustainable modes.

8.2. Recommendations for future research

This section summarizes recommendations for addressing knowledge gaps, adjusting transport models, and improving the design of the proposed model. These recommendations are based on uncertainties in model conceptualization, insights arising from the expert interviews, and considerations of model replicability across cases (see Chapter 7)

- **Addressing knowledge gaps**: To reduce uncertainties in policy outcomes, future empirical research can address key knowledge gaps by:
  - Conducting longitudinal studies on bike adoption processes, particularly in cities implementing citywide policies that enhance cycling safety and network connectivity (e.g., Paris).
  - Mapping the car reduction potential in suburban areas by examining car-owning households' attitudes and ownership decisions in response to shifts in transport mode attractiveness.
- **Integrating public space and bike adoption dynamics in transport models**: To better evaluate spatial trade-offs in urban areas and their impact on travel behavior, future transport models can be expanded by:
  - Integrating spatial trade-offs and interactions between infrastructures to assess how public space distribution affects the safety and comfort of pedestrians and cyclists. This better allows evaluating how infrastructural changes impact travel behavior.
  - Integrating Diffusion of Innovation models to capture non-linear patterns of bike adoption in areas with emerging cycling cultures.
- **Next modeling steps**: To increase validity and replicability, the model proposed in this research can be improved by:
  - Including bike-and-ride travel to evaluate the potential for modal shifts on long-distance trips.
  - Including an additional, longer trip distance band to improve the model's relevance from an environmental perspective.
  - Specifying road types to better capture spatial trade-offs and test more specific policy targets.
  - Including buses and trams to improve the replicability of the model to cases where above-ground public transport is more prominent.
  - Exploring feedback between e-bike uptake and the availability of secure bike parking to account for the particular demand of e-bike users for secure parking.

Reflection

This final chapter reflects on the research process and my personal development throughout the project. It highlights the challenges, lessons, and growth I experienced over the course of six months.

Research process

One of the most valuable insights related to the research process is the value of expert input. Experts proved to be an invaluable source of knowledge, with even simple remarks often getting me on the right path. In hindsight, starting the face validation process earlier would have allowed me to incorporate more fundamental changes into the model and the broader research. I now see the validation process not only as a tool for refining the model but as an ongoing opportunity for insight and learning throughout the research.

Reflecting on the iterative nature of research, I realize that much more iteration is needed in the later stages of the project. Although I dedicated significant time to refining the initial stages, I underestimated the importance of refining the interpretation of findings and their implications. In hindsight, I could have adjusted my priorities to allow more time for iterations in these final stages. I would also recommend drafting preliminary discussion and conclusion sections early on in the research process, as maintaining these sections throughout could help to continuously track and evaluate research choices and their implications.

The modeling process provided valuable insights into the nature of quantitative SD and revealed curious aspects of transport modeling. I gained a deeper appreciation for the SD principle that "structure explains behavior" and its capacity to perform effectively with limited empirical data. This understanding also made me realize that I could have embraced greater parameter uncertainty to expand the model boundaries, such as incorporating road types or public space distribution beyond the city. Furthermore, one particularly curious aspect of transport modeling is model calibration (e.g. calibrating initial values to match the observed modal split), which sparked questions I could not explore within the project's time constraints. Specifically, exploring uncertainty in the dispersion of mode choice by varying sets of initial parameter values could provide valuable insights into the sensitivity of transport models to uncertainty hidden in the calibration process. While time limitations prevented me from pursuing this, it presents an interesting direction for testing transport model assumptions, that could be explored using tools like the ema-workbench.

Finally, I recognize that – while SD modeling is powerful for identifying leverage points and informing high-level strategies – it does not warrant an actor perspective. Applying complementary methods like Action Research or Mission-Oriented approaches could help co-develop solutions to such governance challenges. For example, as highlighted in the discussion, shared infrastructure planning involves many stakeholders and requires coordination.

Personal development

This project was a journey of personal growth, and I often found myself getting in my own way. I started with a blend of optimism and ambition that proved to be unsustainable, as reflected in my overly ambitious initial research proposal – which my supervisors kindly pointed out was closer to a PhD in scope. I realize now that part of my optimism stemmed from my experience working in teams, since tasks that take a week of individual work can often be accomplished in two days collaboratively. While I missed the energy and support of a team, it was valuable to be entirely in charge of my own project and deadlines. This autonomy taught me to balance ambition with feasibility, and the importance of building in time buffers to manage risk more effectively. It also taught me to reach out pro-actively to people outside my project to learn from their insights and expertise.

Completing a MSc thesis was not just a writing challenge but also a test of logical thinking and diligence. I learned that knowing a lot about a topic can paradoxically make it harder to communicate about it. The process of refining my writing forced me to break down my logic into clear, digestible steps that others could follow. Refining this skill has been immensely useful and builds on my writing experience gained during my internship. While I realize there is still a lot to gain, the effort to make complex ideas accessible was a rewarding and humbling aspect of this journey.

Through it all, I came to appreciate the attention to detail that research demands. While I missed the energy and support of a team, this experience helped me develop a deeper understanding of my individual strengths and areas for growth. It also reinforced how much I value collaboration, and I look forward to applying these lessons and skills in future projects, hopefully as part of a team once again.

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A
Expert interviews

Two rounds of interviews are held, one round of interviews for validating the problem and model structure, followed by a round of interviews for validating model results. The latter round of interviews is also used to collect suggestions for improving the experimental setup and recommendations.

In individual sessions with participants, the researcher presents a set of slides and asks a set of questions. The researcher takes notes of the responses given by the participants and processes the notes directly after the interview. The researcher invites the participants by email to revise the processed notes with the aim of validating that the notes represent what the participants said, or meant to say, during the interview. The sections below present for each round of interviews the interview structure, the expertise of the participants, and the processed notes. An informed consent form was used to confirm permission to use the anonymized inputs in the research.

A.1. Validation of the problem and model structure

Interview structure

1. Explain the context of the research and the purpose of the session
2. Summarize the problem statement
3. Ask how the problem statement reflects the participant's perception of the problem
4. Explain in detail the model boundaries and the model structure
5. Ask how the model structure reflects the participant's perception of the system

Expertise of the participants

- Programs director at a public interest think tank with a background in international transport and land-use policy, knowledge of systems thinking, and familiarity with the case of Paris
- System dynamics modeler with experience applying system dynamics to transport.

Processed notes

Validation of the problem:

- The attribute "high quality PT" may not pertain to an entire urban area. In Paris, public transport in the first ring is of lower quality compared to the city center.
- A density threshold may be more relevant than a size threshold when formulating the main research question
- "Space as a limiting factor" also applies to the problem of climate adaptation and biodiversity. Relying on less space-consuming modes liberates space for climate adaptation and nature restoration as directed by recent EU legislation.
- Other modeling work tends to focus on one single relationship or parts of the system, rather than the structure of the system

- Based on the assumptions and chosen level of aggregation, it could make sense to make the model purpose explicit as to inform strategy on an aggregate and long-term level, and to disclaim the model is not meant to inform design and location choice of individual interventions.
- There is potential for changing urban space, but there is a limit to what extent road space can change mode choice
- In Paris, most of modal shift through road space reallocation is to gain from cycling
- In Paris, cycling is linked to (political) identities, unlike the Netherlands for example

Validation of system structure:

- Many models take average congestion, and it should not be an issue to take this approach in your research
- Linking migration and car ownership is difficult, because drivers of migration are more complex than represented in the model currently. For example, some out-migration from Paris could be linked to the desire for more space and a larger home. Moreover, autochthone citizens settling with or without cars cannot be grouped together with immigrants settling with or without cars, since immigrants could come from many different places and related lifestyles, with different levels of comfort around using public transport or bikes.
- A distinction between primary and secondary roads would be suitable, given the often differentiated approach to pedestrianization and access restrictions. Policies tend to aim at more reallocation on local roads and less reallocation on primary roads.
- Regionalizing subsystems should be more consistent across the model. If other subsystems distinguish between Paris and the first ring, the bike adoption subsystem should do so too.
- The [former version of the] road space subsystem does not reflect the real system. Assuming a fraction of roads are renewed annually, and setting a new standard distribution for renewed roads better reflects the nature of road maintenance activities
- Owning a private bike might weigh more strongly in deciding to choose the bike compared to having a bike-sharing subscription.

Other input:

- The experiments should be designed to demonstrate the difference between reallocating space for pedestrians to cyclists and reallocating space for motorists to cyclists. Comparing different policy types might show the counterproductive effect of cycling lanes on former sidewalks on pedestrian safety and modal shift towards more sustainable modes.
- The choice of distances for the trip distance bands needs to be justified

A.2. Validation of model results

Interview structure

1. Explain the context of the research and the purpose of the session
2. Summarize the model purpose, state the main research question and the selected case study
3. Summarize the model structure
4. Present the dynamic hypothesis
5. Present and describe the model results and how different sets of scenarios compare to the dynamic hypothesis
6. For each selection of outcomes analyzed using PRIM:
   (a) Present and explain the results from PRIM
   (b) Ask whether the relation between the outcomes and the explaining variables matches the expectations of the participant
7. Ask whether the participant has suggestions for changing the experimental setup
8. Present preliminary policy recommendations
9. Ask whether the preliminary recommendations match the participant's recommendations based on the model
10. Ask whether the participant would suggest additional policy recommendations

Expertise of the participants:

- Programs director at a public interest think tank with a background in international transport and land-use policy, knowledge of systems thinking, and familiarity with the case of Paris.
- Transport researcher at an international level with a research background in accessibility, land use interactions, and modeling urban transport.

Processed notes

Validation of model results:

- How results relate to uncertain parameters seems valid.
- It makes sense that the outcome is more sensitive to the speed at which bike use spreads, than to the relative attractiveness of cycling compared to public transport. The first step in bike adoption is access to bikes. People cycle, not because public transport is bad, but because they are open to becoming a potential bike user due to certain factors.
- It makes sense that scenarios where long distance travel demand is higher, the share of cycling is lower, given the distance decay function for cyclists.
- It makes sense that subjective travel time by car would shift when parking supply shrinks. Public space and parking supply can be seen as components of a system of provision supporting the private car.
- The lower end of outcomes for daily distance traveled by bike seems improbable. Cyclists tend to be resilient when it comes to availability of dedicated parking space. In Paris, parking is not as institutionalized now, but if it is not prohibited, limited parking should not limit cycling that much. Therefore, sensitivity to available bike parking might currently be at the lower end of the uncertainty range in Paris. The scenario of high sensitivity might occur when Paris adopts more stringent policy towards bike parking outside designated parking space, or when more bikes get stolen when doing so.
- In high density areas, the contact rate is most likely high. The scenario of low contact rates might occur during a pandemic.
- The results for high subjective travel time by car if parking requirements are strict make sense, because parking regulations increase cruising time, and cruising times increase congestion.

Suggestions for experimental setup:

- You could make road space reallocation policy endogenous, and start asking the question: where is the tipping point? It could be interesting to look for a threshold in policy support, which could inform a target on minimum network completion, after which bike use is likely to accelerate and modal split is likely to change substantially away from car dominance. This threshold might be different depending on density, mix-uses and PT availability, which is also a relevant thing to explore.
- You could design an experiment based on the question: what happens if space is allocated from pedestrians to cyclists compared to space being a allocated from motorists to cyclists.
- The [former] definition and emphasis on residential parking may not match the reality of the policy maker. From a policy perspective, and especially in a case like Paris, there is only little renewal of built environment. Instead, you might be able to add a lever of how much of the space removed from motorists is parking space and see how that affects the outcomes.
- The definition of bike network completion, where you count only separated bike lanes, may not be valid. A fully segregated bike network is not always optimal, so the completion point and related acceleration in bike use may be invalid or require rephrasing: emphasize connectivity rather than level of segregation.
- The definition of the policy variable for desired public space distribution may not match the reality of the policy maker. It could be more helpful to disaggregate to different road types, where the spatial trade-off is different, and take a set of possible standards for each road type. Then vary these standards and explore the implications on the model results.

Suggestions for recommendations:

- Cities should flip the units: express completion not in terms of total km built but in % of a complete network of bike infrastructure.
- Although there is a certain resilience among cyclists, legitimizing space for bike parking could help. For example, cargo bikes are limited in Paris, which may be due to lack of parking.
- Cities should also look beyond how much cycling facilities have been built, but rather ask: does it make a network?
- It makes sense to recommend expanding bike parking, but it's not just about the quantity of parking, but about the security of parking. In bike parking we can differentiate short-term and long-term parking, and the security of parking The perception of safety is important: knowing you can leave your bike somewhere unattended.
- The security of bike parking may gain importance as bikes get more expensive.
- Communication efforts could work most earlier in the process of bike adoption, where you could focus on the idea of "the right vehicle for the right trip".
- There is a whole range of other factors at play that may differ per geographic area, such as workplace facilities and cultural factors such as gender culture, i.e. the gender expectations for how women show up may conflict with the practice of cycling in some cultures.

Other input:

- The point of acceleration which you are currently placing between 60%- 80% might be more towards the middle. It seems more likely that on the course between 20- 60% completion could be where the critical mass starts to become a potential bike user.

B

Geospatial analysis

Description of data sources used

In the case of Paris, the following data is available for estimating the size and distribution of public space:

- Land use data (Figure B.1) that distinguishes the following surface types:
  - **Planted island** (a small area in public space, often within roadways or urban environments, that is dedicated to vegetation).
  - **Embankment** (a raised area of land, often used in urban design to manage terrain or water flow).
  - **Traffic island** (a physical space, often in roads or junctions, used to manage vehicle movement or provide pedestrian safety).
  - **Platform** (riverfront promenades)
  - **Water** (water bodies such as fountains, ponds, canals, and rivers)
  - **Standard island** (miscellaneous category that refers to both built up area and forested area)
- Road axis data of the communal road network[1] that carries information on the minimum, average, and maximum sidewalk width on either side of a road segment.
- Time record of OpenStreetMap data (IDF Mobilite, 2024) indicating the total length of reported bike lanes of the following types:
  - **Seperated bike lanes** (dedicated lanes for cyclists, typically separated from motor vehicle traffic)
  - **Greenways** (multi-use paths that are often used by cyclists and pedestrians, typically in natural or park settings).
  - **Bike lanes** (painted lanes on the road designated for bicycles, often without physical separation from other vehicles)
  - **Contraflow bike lanes** (bike lanes that allow cyclists to travel in the opposite direction of motor vehicle traffic on one-way streets)
  - **Shared bus and bike lanes** (lanes that are shared between buses and cyclists, allowing both to travel in the same space).
- A document that reports the total number of parking spots in public space (APUR, 2019)

[1] Shared by Atelier Parisien d' Urbanisme (website) and available at the repository of this thesis (repository)

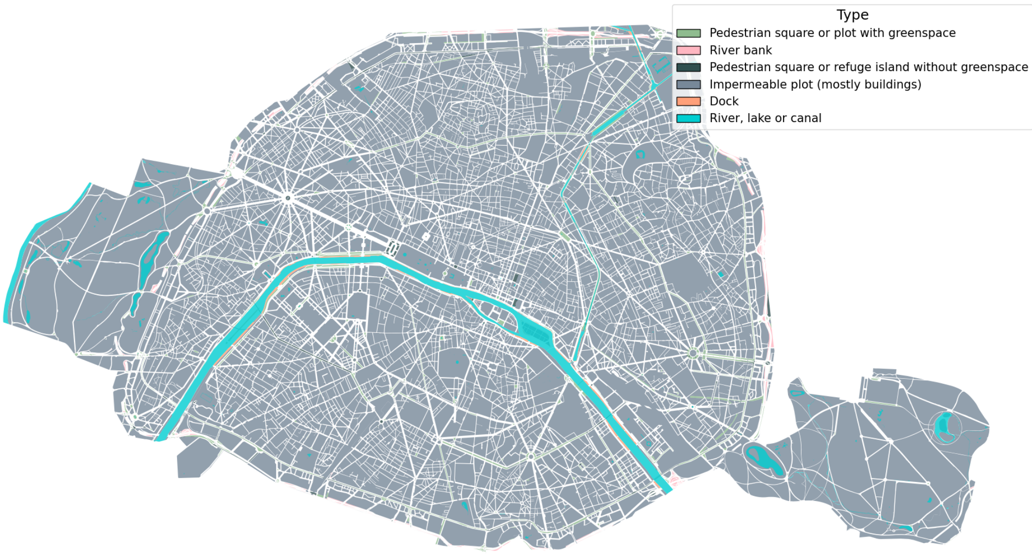


Figure B.1: Map showing different types of land use within Paris. Data shared by Atelier Parisien d'Urbanisme (website) for use within this thesis

B.1. Results

Figure B.2: Map showing results from estimating total public space.

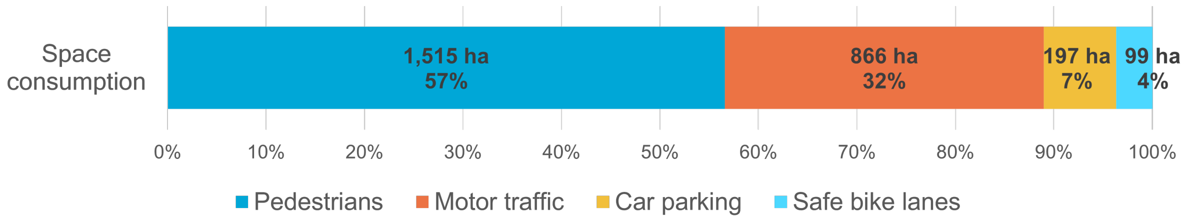


Figure B.3: Estimated public space distribution between pedestrians, motor traffic, car parking, and cyclists, within the chosen case study. The estimate for car parking is adapted from APUR (2019) and of high confidence. The estimate for cyclists is of moderate confidence. It counts demarcated bike lanes and separated bike lanes recorded in OpenStreetMap (IDF Mobilite, 2024) and assumes a lane-width of $2.2m$. The estimated proportion between space for pedestrians and for motor traffic is based on lower quality data and of low confidence (Appendix B)

C

Uncertainties

This appendix explains the uncertain parameters selected to explore uncertainties and the chosen ranges for these parameters.

C.1. Uncertain parameters

Uncertainties related to current public space distribution, mode choice, destination choice, vehicle adoption, and future policy motivate the inclusion of 22 uncertain parameters in the model. Table C.1 lists all uncertain parameters and explains the chosen ranges. The sub-sections below explain the selection of uncertain parameters.

Uncertainty related to future policy

Uncertainties related to future policy will affect the pace, design, and ambition level of road space reallocation, the increase in public transport capacity, the increase in bike parking, the proximity of destinations in the city, and the level of change in self-containment of the first ring (i.e. the capacity of the first ring to meet travel demand internally). The pace of the road space reallocation policy may accelerate as bike adoption increases. Current policy plans do not clarify the long-term ambition for pedestrianization and the proportion to which car parking will be removed compared to space for motor traffic. Proximity of destinations is expected to increase from mixed land-use plans in the city. Self-containment in the ring around Paris is expected to increase due to the construction of a tangential metro line (the Paris Grand Express) and urban development along this metro line. The impact of these uncertainties are explored by varying the following variables:

- RENEWAL RATE SENSITIVITY
- DESIRED PEDESTRIAN SPACE SHARE
- DESIRED SHARE OF Car SPACE USED FOR PARKING
- PARKING SPOTS PER HOME CONSTRUCTED
- CHANGE IN BIKE PARKING PER ADDED SPACE FOR CYCLISTS
- NET ADDED PT CAPACITY PER YEAR
- DESTINATION SHIFT RATE RING
- DESTINATION SHIFT RATE CITY

The latter two variables - DESTINATION SHIFT RATE RING and DESTINATION SHIFT RATE CITY - simultaneously represent uncertainty in destination choice.

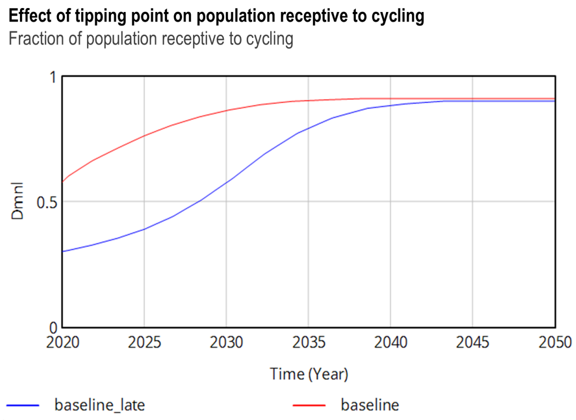


Figure C.1: How the tipping point uncertainty influences population receptive to cycling in the model

Uncertainty in vehicle adoption

Uncertainties related to vehicle adoption will affect the level of change in car ownership and the speed at which bike use spreads across the population. The impact of these uncertainties are explored by varying the following variables:

- REFERENCE SHIFT IN CAR ADOPTION
- CAR ADOPTION SENSITIVITY TO USAGE
- TIPPING POINT SWITCH
- BIKE ADOPTION SENSITIVITY TO PARKING
- BIKE ADOPTION SENSITIVITY TO USAGE
- CONTACT RATE
- BIKESHARING TO PRIVATE BIKE UPGRADE FRACTION
- EBIKE UPTAKE SWITCH

Figure C.1 displays how the variable TIPPING POINT SWITCH influences population receptive to cycling over time.

Uncertainty in mode choice

Although the model endogenizes mode choice, the sensitivity of mode choice to changes in subjective travel time, the perception time between changes in subjective travel time and changes in mode choice, and the level of change in (subjective) travel time triggered by changes in public space are uncertain. The impact of these uncertainties are explored by varying the following variables:

- SUBJECTIVE CYCLING TIME SENSITIVITY
- CYCLING NETWORK DISTANCE SENSITIVITY
- PT ACCESS EGRESS SENSITIVITY
- PARKING SEARCH AND EGRESS SENSITIVITY

Uncertainty in destination choice

The model exogenizes destination choice, which creates uncertainty related to the feedback between public space, mode choice, and destination choice. Uncertainty in the effect of road space reallocation policy on trip distribution between zones and between trip distance bands are reflected by varying the following variables:

- DESTINATION SHIFT RATE RING
- DESTINATION SHIFT RATE CITY

The variables simultaneously represents uncertainty in future policy.

Data uncertainty

The data analysis produced a relatively accurate estimate of total public space, space consumed by car parking, and space consumed by bike lanes. However, how the remaining space is allocated between motorized traffic and pedestrians could not be accurately determined. This inaccuracy creates uncertainty in the relative effect of road space reallocation policy on total road capacity, and uncertainty in the potential effects of changing road capacity and changing pedestrian space on travel behavior. The impact of these uncertainties are explored by varying lookup multipliers to the following two effect variables:

- SENSITIVITY TO SIDEWALK DATA UNCERTAINTY
- SENSITIVITY TO CAR LANE DATA UNCERTAINTY

The inaccuracy is not represented by directly varying INITIAL PUBLIC SPACE DISTRIBUTION because this would cause initialization issues.

Table C.1: Explanation of the chosen ranges for the 22 uncertain variables. Incr: 0 means that the range is continues, Incr: 1 means that the range is discrete and takes only integere values.

<table>
<tr><th>Category</th><th>Subsystem</th><th>Type</th><th>Variable</th><th>Min</th><th>Max</th><th>Incr</th><th>Unit</th></tr>
<tr><td>Future policy</td><td>Public space</td><td>effect sensitivity</td><td>RENEWAL RATE SENSITIVITY</td><td>0.5</td><td>2</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">The base assumption is for the renewal rate to increase by one third of its current value by the time cycling uptake reaches 50% of the population (see Appendix E). Since this effect size is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.</td></tr>
<tr><td>Future policy</td><td>Public space</td><td>constant</td><td>DESIRED PEDESTRIAN SPACE SHARE</td><td>0.584</td><td>0.638</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">Pedestrian space share would increase by 1.8%-points (to 58.4% based on estimate for current share) on average if the full road network was reallocated in proportion to current reallocation plans. Since the final ambition for pedestrianization is uncertain and may increase, this share is varied between a 1.8% and 7.2%-point increase (four times current ambition).</td></tr>
<tr><td>Future policy</td><td>Public space</td><td>constant</td><td>DESIRED SHARE OF CAR SPACE USED FOR PARKING</td><td>0</td><td>0.29</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">Currently, 19% of space for motorists is parking space. This is uncertain: road space reallocation could consume parking space to a larger or smaller extent. The desired share is varied between zero on-street parking and 10%-points more than today.</td></tr>
<tr><td>Future policy</td><td>Public space</td><td>constant</td><td>PARKING SPOTS PER HOME CONSTRUCTED</td><td>0</td><td>0.3</td><td>0</td><td>spots/ homes</td></tr>
<tr><td colspan="8">Currently, there are 0.33 residential parking spots per home in the city. This is expected to decline in future residential housing, but to which extent is uncertain. The chosen range is between 0 and 0.3 parking spots per home.</td></tr>
<tr><td>Future policy</td><td>Public space</td><td>constant</td><td>CHANGE IN BIKE PARKING PER ADDED SPACE FOR CYCLISTS</td><td>0</td><td>2</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">The model estimates the initial number of bike parking spots per ha of space for cyclists at 434 spots/ha for private bikes, and 234 spots/ha for bike-sharing. It is uncertain to what extent bike parking will expand as the cycling network is extended. For added bike space, the chosen range is between 0 and 2 times current bike parking per space for cyclist.</td></tr>
<tr><td>Vehicle adoption</td><td>Car adoption</td><td>constant</td><td>REFERENCE SHIFT IN CAR ADOPTION</td><td>0.05</td><td>0.25</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">It is uncertain to which extent young adults are currently avoiding car ownership rather than postponing car ownership. A wide range in percentage point shift in car adoption (5 - 25%) is adopted, relative to current adult car adoption.</td></tr>
<tr><td>Vehicle adoption</td><td>Car adoption</td><td>effect sensitivity</td><td>CAR ADOPTION SENSITIVITY</td><td>0.5</td><td>2</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">The base assumption is for the current shift in young adult car adoption to vary by a maximum of 30% if car usage varies by 50% (see Appendix E). Since this elasticity is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.</td></tr>
<tr><td>Vehicle adoption</td><td>Bike adoption</td><td>switch</td><td>TIPPING POINT SWITCH</td><td>0</td><td>1</td><td>1</td><td>Dmnl</td></tr>
<tr><td colspan="8">Two curves are included in the model that describes how soon the cautious majority becomes receptive to cycling: an early and a late tipping point. The early tipping point assumes the case study is currently at the tipping point, the late tipping point is assumed at an extra 20%-point completion of the cycling network. This assumption is informed by the expert interviews.</td></tr>
<tr><td>Vehicle adoption</td><td>Bike adoption</td><td>effect sensitivity</td><td>BIKE ADOPTION SENSITIVITY TO PARKING</td><td>0.5</td><td>2</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">The base assumption is for bike usage and bike parking availability together to multiply the reference contact fruitfulness (0.02) by up to 4 times (see Appendix E). Since this effect size is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.</td></tr>
<tr><td>Vehicle adoption</td><td>Bike adoption</td><td>effect sensitivity</td><td>BIKE ADOPTION SENSITIVITY TO USAGE</td><td>0.5</td><td>2</td><td>0</td><td>Dmnl</td></tr>
<tr><td colspan="8">The base assumption is for bike usage and bike parking availability together to multiply the reference contact fruitfulness (0.02) by up to 4 times (see Appendix E). Since this effect size is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.</td></tr>
</table>

Category	Subsystem	Type	Variable	Min	Max	Incr	Unit
Vehicle adoption	Bike adoption	constant	CONTACT RATE	1	3	0	Dmnl
The contact rate (parameter controlling how fast information spreads across a population) is uncertain. A wide range is chosen of 1 - 3.							
Vehicle adoption	Bike adoption	constant	BIKESHARING TO PRIVATE BIKE UPGRADE FRACTION	0.05	0.25	0	Dmnl
The share of bikesharing users upgrading to private bike use after two years is uncertain. A wide range is assumed of 5 - 25%.							
Vehicle adoption	Bike adoption	switch	EBIKE UPTAKE SWITCH	0	1	1	Dmnl
The pace and final state of e-bike uptake is uncertain. The model varies between two discrete scenarios, both starting from the current level of adoption, but continuing at different speeds and until different final states (see Appendix E).							
Mode choice	Mode choice	effect sensitivity	CAR NETWORK DISTANCE SENSITIVITY	0.5	2	0	Dmnl
The base assumption is for the car network distance to Euclidean distance ratio to increase to 1.8 when only half of the network is car-accessible, and decrease to 1.1 if average car lanes per road becomes 4 (see Appendix E). Since this effect size is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.							
Mode choice	Mode choice	effect sensitivity	CYCLING NETWORK DISTANCE SENSITIVITY	0.5	2	0	Dmnl
The base assumption is for distance to Euclidean distance ratio to double when zero roads have bike lanes, and to fall to 1.1 when all roads have bike lanes (see Appendix E). Since this effect size is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.							
Mode choice	Mode choice	effect sensitivity	SUBJECTIVE CYCLING TIME SENSITIVITY	0.5	2	0	Dmnl
The base assumption is for subjective cost of cycling to vary by a maximum of 0.8 Minutes per Minute (in the most extreme scenario, where three additive effects stack up. This value is not reached in any of the experiments). Since this effect size is uncertain, it is varied by X^y if X is the subjective value factor, and y varies between 0.5 and 1.5.							
Mode choice	Mode choice	effect sensitivity	PARKING SEARCH AND EGRESS SENSITIVITY	0.5	2	0	Dmnl
The base assumption is for parking search and egress time to vary between 5 and 14 minutes depending on city parking per city car (see Appendix E). Since this effect size is uncertain, it is varied by X^y if X is the normalized effect from the base assumption, and y varies between 0.5 and 2.							

D

Experiment results

This appendix documents outcomes over time for outcomes of interest other than those presented in the main text. It also documents the results from applying PRIM, a selection of behavior sensitivity tests, and an alternative behavior prediction test.

Outcomes over time

Figure D.1 shows the results for walking distance share. Figure D.2 shows the results for variation in pedestrian space.

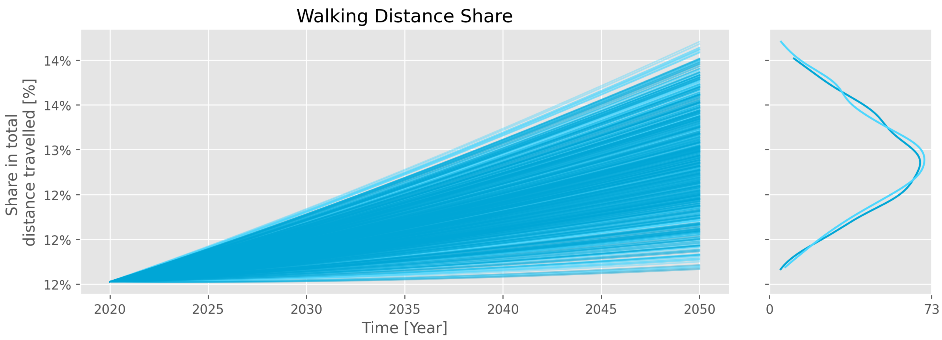


Figure D.1: The line charts in the left hand section of the figure display walking distance share over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

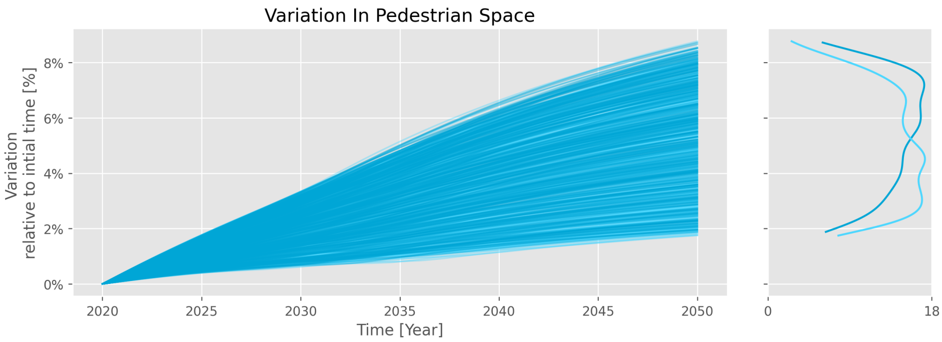


Figure D.2: The line charts in the left hand section of the figure display variation in pedestrian space over time, relative to initial time, and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.3 shows the results for bike network completion.

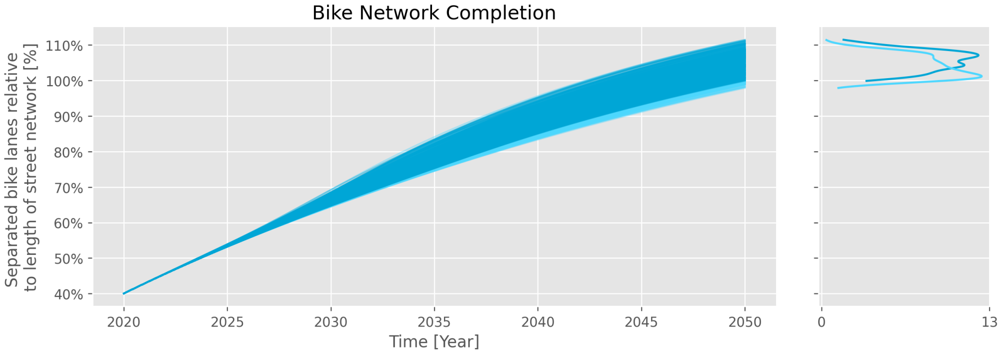


Figure D.3: The line charts in the left hand section of the figure display bike network completion over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.4 shows the results for variation in subjective travel time by bike.

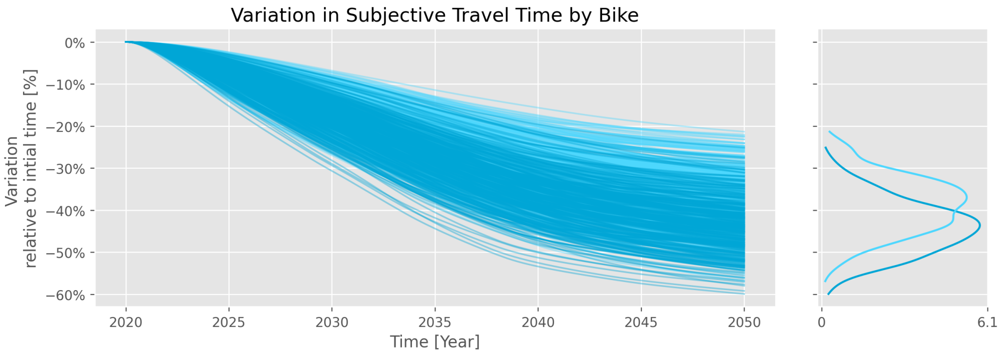


Figure D.4: The line charts in the left hand section of the figure display variation in subjective travel time by bike over time, relative to initial time, and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.5 shows the results for variation in subjective travel time by PT.

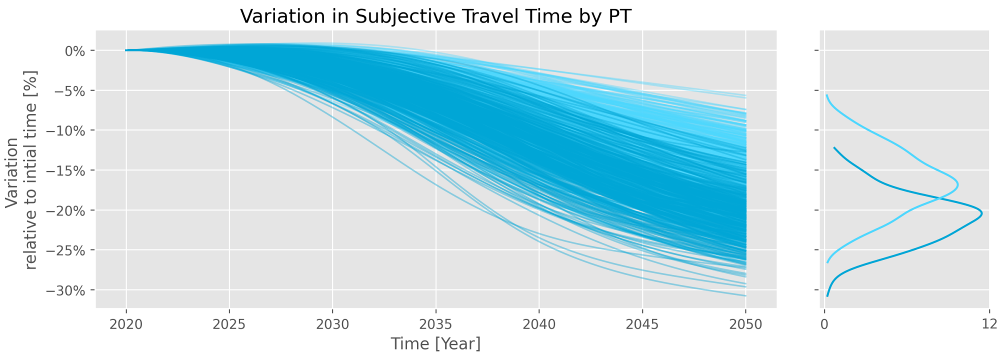


Figure D.5: The line charts in the left hand section of the figure display variation in subjective travel time by PT over time, relative to initial time, and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.6 shows the results for variation in subjective travel time by car.

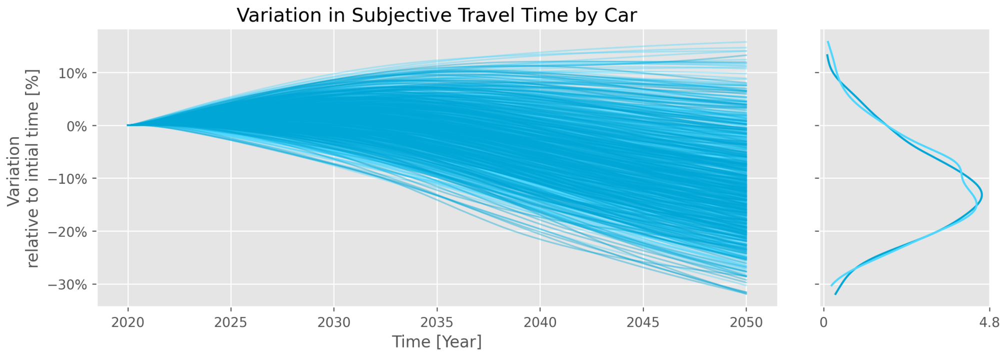


Figure D.6: The line charts in the left hand section of the figure display variation in subjective travel time by car over time, relative to initial time, and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.7 shows the results for car trips share.

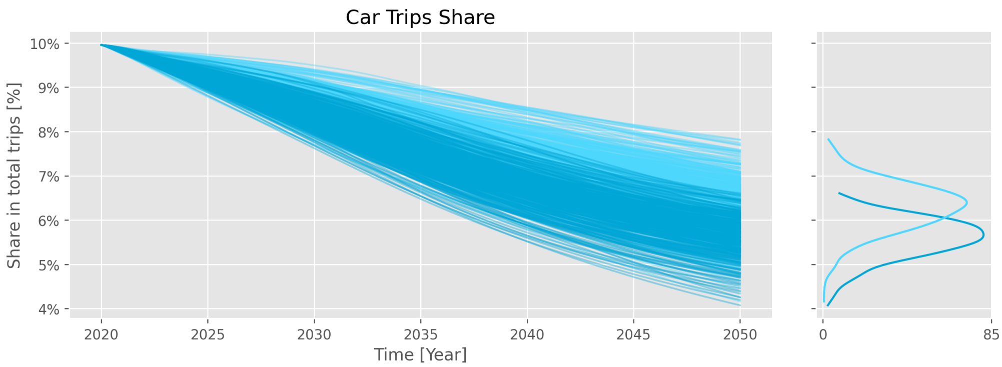


Figure D.7: The line charts in the left hand section of the figure display car trips share over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.8 shows the results for PT trips share.

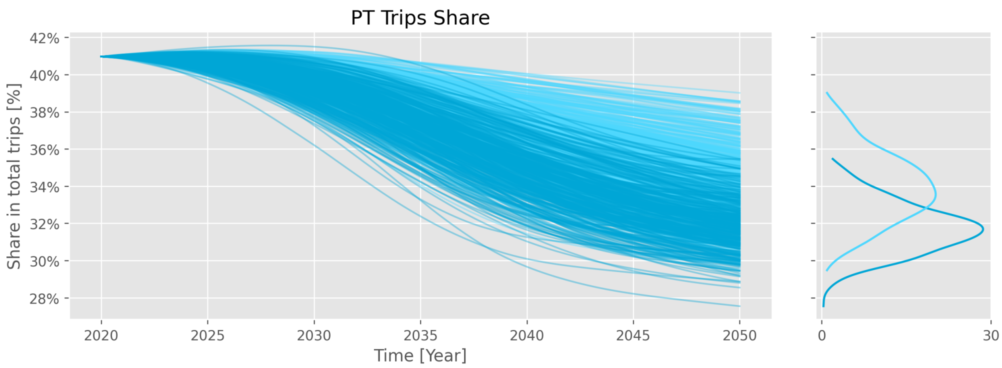


Figure D.8: The line charts in the left hand section of the figure display PT trips share over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.9 shows the results for bike trips share.

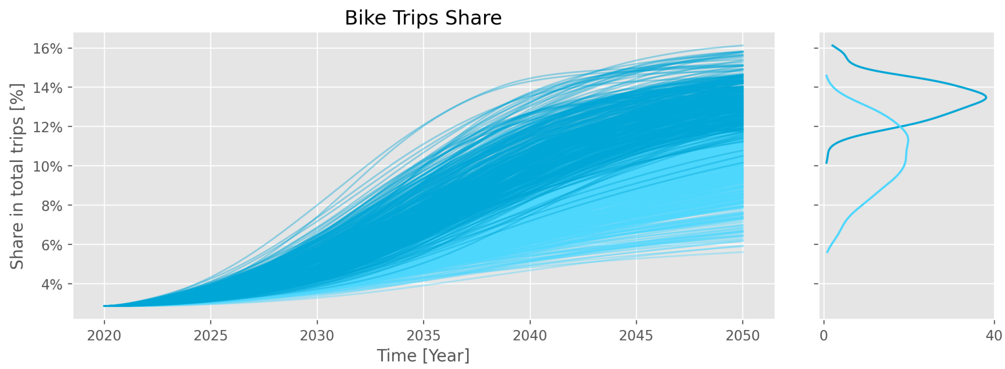


Figure D.9: The line charts in the left hand section of the figure display bike trips share over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.10 shows the results for fraction of city population with bike access.

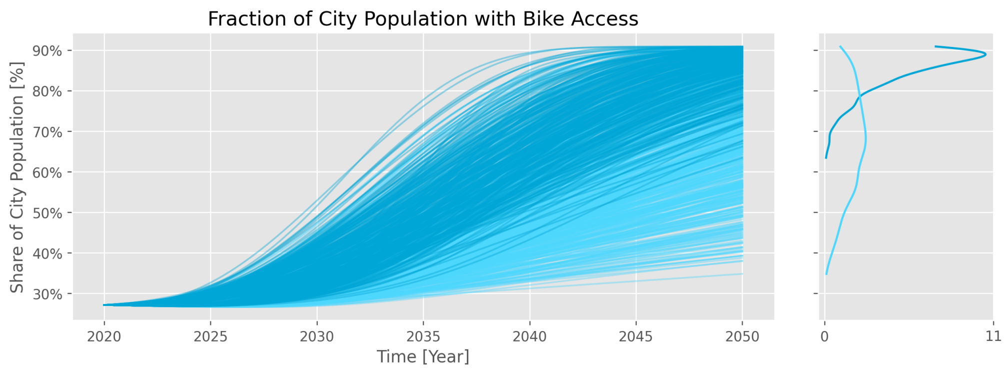


Figure D.10: The line charts in the left hand section of the figure display fraction of city population with bike access over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

Figure D.11 shows the results for population fraction with car access on long distance trips. The fraction of population with car access on long distance trips is a weighted average of car ownership in the city and in the ring based on the share of long-distance trips originating from each respective zone.

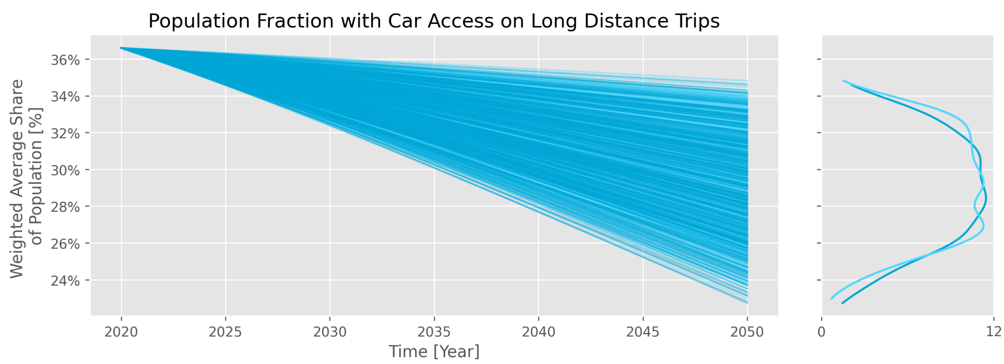
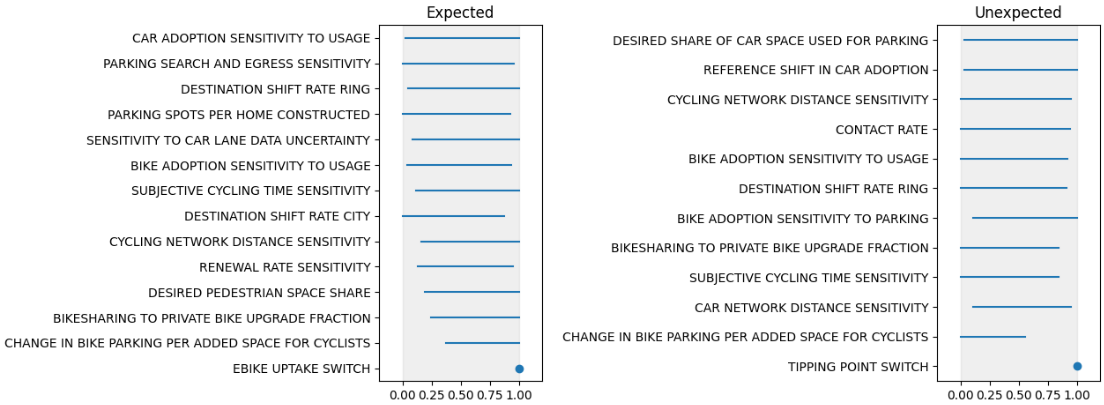


Figure D.11: The line charts in the left hand section of the figure display population fraction with car access on long distance trips over time and across 1000 scenarios. The scenarios are clustered based on whether or not distance traveled by bike exceeds distance traveled by car at final time. The density plot in the right hand section of the figure displays the distribution of the final time outcomes per cluster of scenarios.

PRIM

Figure D.12 shows the results from PRIM and presents which uncertain parameters explain variation between the two clusters of scenarios. The parameters constrained to narrower ranges are most important and inform the main results presented in this research.

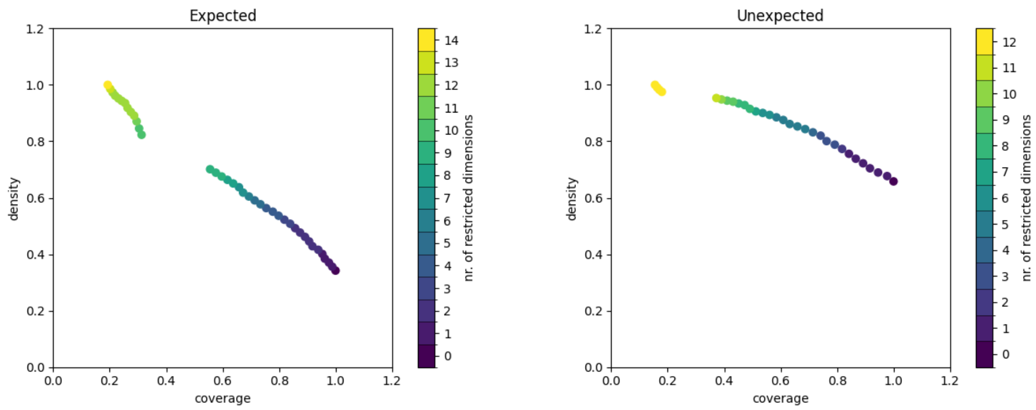


(a) Input space that explains expected results, where bike distance exceeds car distance by at least 50% at final time

(b) Input space that explains unexpected results, where bike distance does not exceed car distance by 50% at final time

Figure D.12: Outcomes from PRIM analysis of expected and unexpected results. The y-axis lists uncertain parameters the algorithm selected to obtain the constrained input space. The blue line on the x-axis represents the range across which uncertain parameters are constrained. The ranges are normalized to the parameters' minimum and maximum bounds, which are documented in Appendix C.

Figure D.13 shows the peeling trajectory of the algorithm, based on the trade-off between coverage and density as uncertain parameters are constrained.



(a) Peeling trajectory of the PRIM algorithm applied to expected results, where bike distance exceeds car distance by more than 50% at final time. The gap between (0.56, 0.70) and (0.31, 0.82) corresponds to constraining the categorical parameter EBIKE UPTAKE SWITCH.

(b) Peeling trajectory of the PRIM algorithm applied to unexpected results, where bike distance does not exceed car distance by more than 50% at final time. The gap between (0.37, 0.95) and (0.18, 0.98) corresponds to constraining the categorical parameter TIPPING POINT SWITCH

Figure D.13: Peeling trajectory of the PRIM algorithm applied to expected and unexpected results. The PRIM algorithm iteratively constrains the input space, with each set of constraints referred to as a "box". The x-axis in the figures shows coverage, which is the share of outcomes of interest in a given box. The y-axis shows density, which is the concentration of outcomes of interest in a given box. The color of the markers indicates the number of dimensions restricted to create the box. The algorithm optimizes for high density and high coverage.

Behavioral sensitivity tests

In one behavioral sensitivity test, subjective travel time of one mode of transport is doubled, and the effect on the reference mode is as expected (the share in total distance traveled falls, after a delay that matches the specified delay time) (Figure D.14).

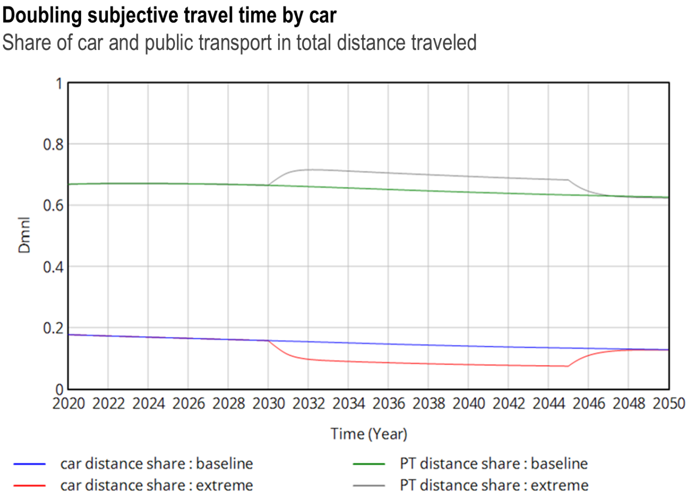


Figure D.14: Results from an extreme conditions test where subjective travel time by car is doubled between 2030 and 2045. The plotted lines represent the share of total distance traveled by car and by public transport in the baseline scenario, and in the extreme scenario when subjective travel time by car is doubled. The perception time (the delay time between a change in subjective travel time and a change in mode choice) in both scenarios 3 years.

In one behavioral sensitivity test, part of the road network is removed, and the effect on the distance traveled by car and congestion is as expected (the share in distance traveled falls, and congested speed during peak hour falls) (Figure D.15).

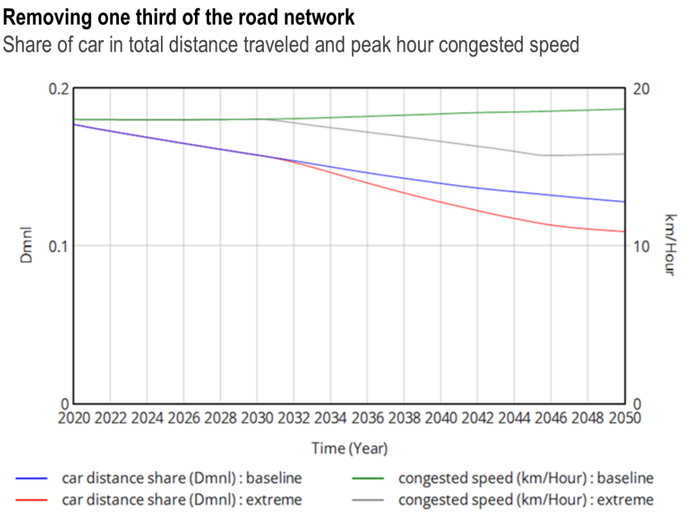


Figure D.15: Results from an extreme conditions test where one third of the road network is removed over the course of 15 years between 2030 and 2045. The plotted lines represent the share of total distance traveled by car and congested speed during peak hour in the baseline scenario, and in the extreme scenario when one third of the road network is removed. The perception time (the delay time between a change in subjective travel time and a change in mode choice) in both scenarios 3 years.

In one behavioral sensitivity test, the timing of the tipping point where the majority of the population becomes receptive to cycling is changed (Figure D.16). This is also an uncertainty included in the experiments. Bike adoption over time only incurs a delay of approximately 4 years, which is a surprising behavior in the model.

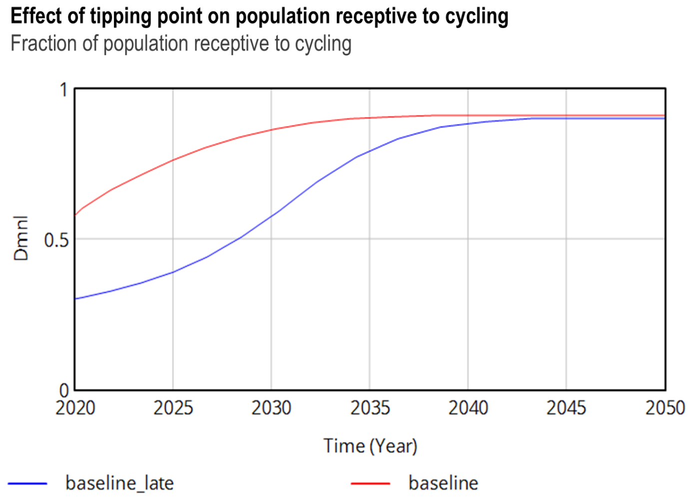


Figure D.16: Variation in population receptive to cycling over time as a result of the tipping point shifting. The plotted lines represent the fraction of population receptive to cycling over time in the baseline scenario (when the tipping point occurs between 20% and 60% of bike network completion and stabilizes at 80% completion), and in the baseline_late scenario (when the tipping point occurs between 40% and 60% of bike network completion and stabiliation occurs at 90% completion).

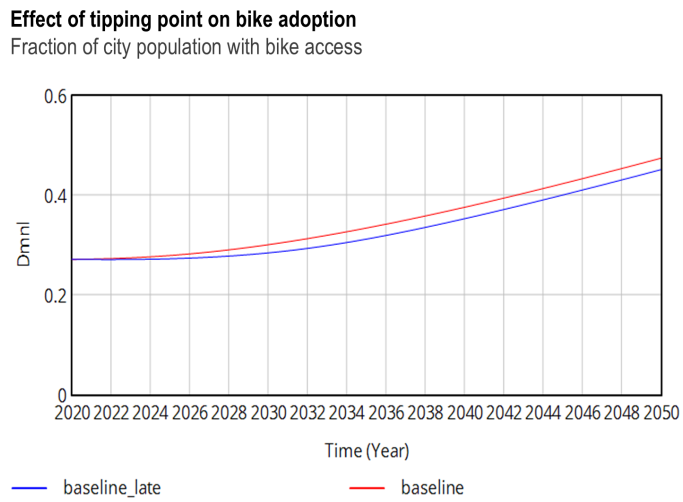


Figure D.17: Variation in bike adoption over time as a result of the tipping point shifting. The plotted lines represent bike adoption over time in the baseline scenario (when the tipping point occurs between 20% and 60% of bike network completion and stabilizes at 80% completion), and in the baseline_late scenario (when the tipping point occurs between 40% and 60% of bike network completion and stabilization occurs at 90% completion).

Alternative behavior prediction test

When the policy design leads to declining pedestrian space, the share of public transport is expected to fall due to declining walking attractiveness. Because destination choice is exogenous from the model, the model is not expected to show changes in the share of walking trips, which would require a shift in destination choice towards shorter distance trips. Figure D.18 shows the model displays the expected direction of change in public transport and car distance shares. Moreover, the bike distance share increases slightly due to public transport becoming less attractive on mid distance trips.

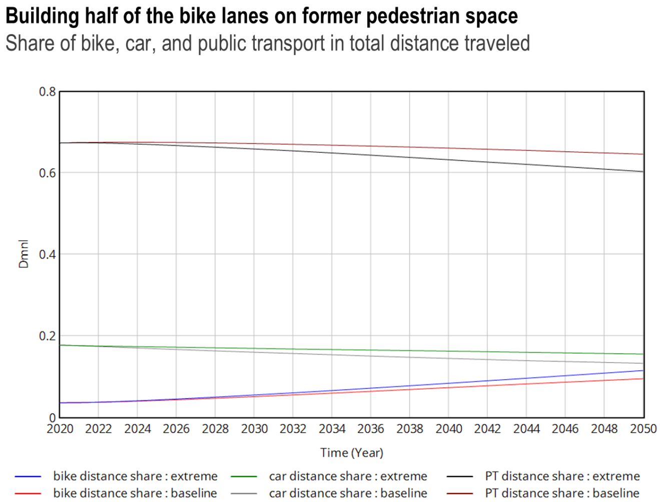


Figure D.18: Results from a validation test where half of the cycling network constructed as part of the proposed policy consumes space for pedestrians instead of space for motorists. The plotted lines represent the share of total distance traveled by car, by bike, and by public transport in the baseline scenario, and in the extreme scenario when half of the constructed cycling network consumes space for pedestrians.

E

Model

The model contains 318 variables. Some variables are subscripted. There are four subscript ranges with up to four levels:

- **zone**: city, ring
- **space use**: motor traffic, car parking, pedestrians, cyclists
- **car adoption status**: young adult, adult car, adult no car
- **user type**: private, sharing

The model file and an excel with the sources used for parameter estimation can be found on the GitHub Repository for this thesis.

Variables

previous space for cyclists = DELAY FIXED (Public space[cyclists],YEAR, Public space[cyclists])ha|

change in space for cyclists = (Public space[cyclists]-previous space for cyclists)/YEARha/Year|

CHANGE IN BIKE PARKING PER ADDED SPACE FOR CYCLISTS = 1Dmnl [0,2]|

bike parking added[user type] = change in space for cyclists*BIKE PARKING PER SPACE FOR CYCLISTS ADDED[user type]*CHANGE IN BIKE PARKING PER ADDED SPACE FOR CYCLISTSspots/Year|

DESIRED PEDESTRIAN SPACE SHARE = 0.584Dmnl [0.584,0.638]|

desired distribution of space[space use] = UNIT VECTOR PEDESTRIANS[space use]*net desired pedestrian space share+UNIT VECTOR CYCLISTS[space use]*DESIRED CYCLIST SPACE SHARE+UNIT VECTOR MOTOR TRAFFIC[space use]*desired motor traffic space share+UNIT VECTOR CAR PARKING[space use]*desired car parking space shareDmnl|(Unit vectors convert between vector and scalar variables)

DESIRED SHARE OF CYCLIST SPACE TAKEN FROM PEDESTRIAN SPACE = 0Dmnl [0,0.5]|

desired motorist space share = 1-DESIRED CYCLIST SPACE SHARE-net desired pedestrian space shareDmnl|

net desired pedestrian space share = DESIRED PEDESTRIAN SPACE SHARE-DESIRED SHARE OF CYCLIST SPACE TAKEN FROM PEDESTRIAN SPACEdesired change in cyclist spaceDmnl|

desired change in cyclist space = DESIRED CYCLIST SPACE SHARE-(INITIAL PUBLIC SPACE[cyclists]/SUM(INITIAL PUBLIC SPACE[space use!]))Dmnl|

mid distance car share = car users car share on mid distance trips*fraction of city population with car access(fraction of city population with car access+fraction of city population with bike access+fraction of city population with only PT access on mid distance trips)Dmnl|

mid distance PT share = (bike users PT share on mid distance trips*fraction of city population with bike access+car users PT share on mid distance trips*fraction of city population with car access+fraction of city population with only PT access on mid distance trips)/(fraction of city population with car access+fraction of city population with bike access+fraction of city population with only PT access on mid distance trips)Dmnl|

fraction of city population with bike access = fraction of population with bike access in each zone[city]Dmnl|

fraction of city population with only PT access on mid distance trips = 1-MAX(fraction of city population with car access,fraction of city population with bike access)Dmnl|

mid distance bike share = bike users bike share on mid distance trips*fraction of city population with bike access(fraction of city population with car access+fraction of city population with bike access+fraction of city population with only PT access on mid distance trips)Dmnl|

normalized fraction of city population with bike access = fraction of city population with bike access/REFERENCE FRACTION OF CITY POPULATION WITH BIKE ACCESSDmnl|

fraction of ring population with bike access = fraction of population with bike access in each zone[ring]Dmnl|

daily mid distance trips[trip distance band] = UNIT VECTOR MID DISTANCE[trip distance band]*daily trips in each trip distance band[trip distance band]trips/Day|(Unit vectors convert between vector and scalar variables)

physical travel time by bike[trip distance band] = (AVERAGE EUCLIDIAN DISTANCE[trip distance band]*cycling network to euclidian distance ratioaverage cycling speed*MINUTES PER HOUR+CYCLING PARKING TIME)*UNIT VECTOR MID DISTANCE[trip distance band]Minutes/trips|(Unit vectors convert between vector and scalar variables)

subjective travel time by PT[trip distance band] = (in vehicle time by PT[trip distance band]+subjective PT access egress time*UNIT VECTOR MID AND LONG DISTANCE[trip distance band]+SUBJECTIVE WAITING AND CHANGING TIME[trip distance band])*overcrowding multiplierMinutes/trips|(Unit vectors convert between vector and scalar variables)

variation in subjective travel time by car = (AVERAGE EUCLIDIAN DISTANCE[mid]*Smoothed subjective travel time by car[mid]/INITIAL SUBJECTIVE TRAVEL TIME BY CAR[mid]+AVERAGE EUCLIDIAN DISTANCE[long]*Smoothed subjective travel time by car[long]/INITIAL SUBJECTIVE TRAVEL TIME BY CAR[long])/(AVERAGE EUCLIDIAN DISTANCE[mid]+AVERAGE EUCLIDIAN DISTANCE[long])-1Dmnl|

variation in subjective travel time by PT = (AVERAGE EUCLIDIAN DISTANCE[mid]*Smoothed subjective travel time by PT[mid]/INITIAL SUBJECTIVE TRAVEL TIME BY PT[mid]+AVERAGE EUCLIDIAN DISTANCE[long]*Smoothed subjective travel time by PT[long]/INITIAL SUBJECTIVE TRAVEL TIME BY PT[long])/(AVERAGE EUCLIDIAN DISTANCE[mid]+AVERAGE EUCLIDIAN DISTANCE[long])-1Dmnl|

physical travel time by foot = AVERAGE EUCLIDIAN DISTANCE[short]/WALKING SPEED*MINUTES PER HOURMinutes/trips|

PT trips share = (daily mid distance PT trips+daily long distance PT trips)/total daily tripsDmnl|

daily walking distance = AVERAGE EUCLIDIAN DISTANCE[short]*Daily trips per city population within city[short]SUM(Population[city,car adoption status!])km/Day|

bike trips share = daily mid distance cycling trips/total daily tripsDmnl|

daily cycling distance = AVERAGE EUCLIDIAN DISTANCE[mid]*daily mid distance cycling tripskm/Day|

daily PT distance = daily mid distance PT trips*AVERAGE EUCLIDIAN DISTANCE[mid]+daily long distance PT tripsAVERAGE EUCLIDIAN DISTANCE[long]km/Day|

daily car distance = AVERAGE EUCLIDIAN DISTANCE[long]*daily long distance car trips+AVERAGE EUCLIDIAN DISTANCE[mid]*daily mid distance car tripskm/Day|

variation in subjective travel time by bike = Smoothed subjective travel time by bike[mid]/INITIAL SUBJECTIVE TRAVEL TIME BY BIKE[mid]-1Dmnl|

variation in pedestrian space = Public space[pedestrians]/INITIAL PUBLIC SPACE[pedestrians]-1Dmnl|

bike users PT share on mid distance trips = EXP(-beta 5*Smoothed subjective travel time by PT[mid]*TRIP PER MINUTE)/(EXP(-beta 5Smoothed subjective travel time by PT[mid]*TRIP PER MINUTE)+EXP(-beta 5*Smoothed subjective travel time by bike[mid]*TRIP PER MINUTE))Dmnl|

change in adults with cars[zone] = (Population[zone, adult car] - previous adults with cars[zone])/YEARpersons/Year|

bike network completion = separated bike lanes per road/NUMBER OF LANES PER ROAD FOR BIKE NETWORK COMPLETIONDmnl|

subjective parking search and out vehicle time = CAR PARKING SEARCH AND OUT VEHICLE STT LOOKUP(average parking search and out vehicle timeTRIP PER MINUTE)Minutes/trips|

subjective PT access egress time = PT ACCESS EGRESS STT LOOKUP(PT access egress time*TRIP PER MINUTE)Minutes/trips|

car users car share on long distance trips = EXP(-beta 8*Smoothed subjective travel time by car[long]*TRIP PER MINUTE)/(EXP(-beta 8Smoothed subjective travel time by car[long]*TRIP PER MINUTE)+EXP(-beta 8*Smoothed subjective travel time by PT[long]*TRIP PER MINUTE))Dmnl|

car users car share on mid distance trips = EXP(-beta 5*Smoothed subjective travel time by car[mid]*TRIP PER MINUTE)/(EXP(-beta 5Smoothed subjective travel time by car[mid]*TRIP PER MINUTE)+EXP(-beta 5*Smoothed subjective travel time by PT[mid]*TRIP PER MINUTE))Dmnl|

car users PT share on long distance trips = EXP(-beta 8*Smoothed subjective travel time by PT[long]*TRIP PER MINUTE)/(EXP(-beta 8Smoothed subjective travel time by car[long]*TRIP PER MINUTE)+EXP(-beta 8*Smoothed subjective travel time by PT[long]*TRIP PER MINUTE))Dmnl|

car users PT share on mid distance trips = EXP(-beta 5*Smoothed subjective travel time by PT[mid]*TRIP PER MINUTE)/(EXP(-beta 5Smoothed subjective travel time by PT[mid]*TRIP PER MINUTE)+EXP(-beta 5*Smoothed subjective travel time by car[mid]*TRIP PER MINUTE))Dmnl|

net annual network expansion = MAX(DELAY1(ROAD NETWORK EXPANSION RATE*Total length of street network,YEAR),-Total length of street networkYEAR)m*road/Year|

NUMBER OF LANES PER ROAD FOR BIKE NETWORK COMPLETION = 1lanes/road|

empty city parking spots per daily car trip = (parking spots city-Cars[city]*SPOT PER CAR)/daily car trips(spots*Day)/trips|

change in bike network completion = bike network completion/REFERENCE BIKE NETWORK COMPLETIONDmnl|

previous adults with cars[zone] = DELAY FIXED (Population[zone,adult car], YEAR, Population[zone,adult car])persons|

bike users bike share on mid distance trips = EXP(-beta 5*Smoothed subjective travel time by bike[mid]*TRIP PER MINUTE)/(EXP(-beta 5Smoothed subjective travel time by bike[mid]*TRIP PER MINUTE)+EXP(-beta 5*Smoothed subjective travel time by PT[mid]*TRIP PER MINUTE))Dmnl|

SPOT PER CAR = 1spots/cars|

TRIP PER MINUTE = 1trips/Minutes|

ebike share = IF THEN ELSE(EBIKE UPTAKE SWITCH=gentle,EBIKE GENTLE UPTAKE LOOKUP(Time/YEAR),EBIKE STEEP UPTAKE LOOKUP(Time/YEAR))Dmnl|

gentle = 0Dmnl|

potential adoption rate[zone] = fraction of population with bike access in each zone[zone]*fraction of population receptive to cycling and without bike access[zone]*CONTACT RATEDmnl|

REFERENCE FRACTION OF POPULATION RECEPTIVE TO CYCLING = IF THEN ELSE(TIPPING POINT SWITCH=early,0.58, 0.3)Dmnl|

fraction of population receptive to cycling and without bike access[zone] = fraction of population receptive to cycling-fraction of population with bike access in each zone[zone]Dmnl|

REFERENCE BIKE NETWORK COMPLETION = 0.4Dmnl|

contact fruitfulness[user type] = (EFFECT OF BIKE USAGE ON CONTACT FRUITFULNESS(normalized daily bike trips per user)^BIKE ADOPTION SENSITIVITY TO USAGE*EFFECT OF PARKING AVAILABILITY ON CONTACT FRUITFULNESS(actual relative to desired bike parking per user[user type])^BIKE ADOPTION SENSITIVITY TO PARKING)*REFERENCE CONTACT FRUITFULNESS[user type]Dmnl|

bike users discontinuing[zone, user type] = Bike users[zone,user type]*BIKE DISCONTINUATION FRACTION[user type]/PERIOD OF USE[zone user type]persons/Year|

people adopting bikes[zone, user type] = SUM(Bike users[zone,user type!])*potential adoption rate[zone]*contact fruitfulness[user type]/DECISION TIME BIKE ADOPTION[user type]persons/Year|

fraction of population receptive to cycling = IF THEN ELSE(TIPPING POINT SWITCH=early, EARLY EFFECT OF BIKE NETWORK COMPLETION ON POPULATION RECEPTIVE TO CYCLING(change in bike network completion), LATE EFFECT OF BIKE NETWORK COMPLETION ON POPULATION RECEPTIVE TO CYCLING(change in bike network completion))*REFERENCE FRACTION OF POPULATION RECEPTIVE TO CYCLINGDmnl|

BIKE ADOPTION SENSITIVITY TO USAGE = 1Dmnl [0.5,2]|

average physical time on long distance = physical travel time by car[long]*long distance car share+physical travel time by PT[long]*long distance PT shareMinutes/trips|

average physical time on mid distance = mid distance bike share*physical travel time by bike[mid]+mid distance car share*physical travel time by car[mid]+mid distance PT share*physical travel time by PT[mid]Minutes/trips|

REFERENCE IMMIGRATION RATE[zone] = 0.0259, 0.0187Dmnl/Year|

Daily trips per city population within city[trip distance band] = INTEG (net increase in self containment city*UNIT VECTOR MID DISTANCE[trip distance band]+net increase in proximity of destinationsUNIT VECTOR DESTINATION CHANGE[trip distance band]+net increase in trip frequency[trip distance band],INITIAL DAILY TRIPS PER CITY POPULATION WITHIN CITY[trip distance band])trips/(Day*persons)|(Unit vectors convert between vector and scalar variables)

net migration[zone] = (immigration rate[zone]-OUTMIGRATION RATE[zone])*SUM(Population[zone,car adoption status!])persons/Year|

REFERENCE POPULATION DENSITY[zone] = 101.1, 72.2persons/ha|

UNIT VECTOR MID DISTANCE[trip distance band] = 0, 1, 0Dmnl|(Converts between vector and scalar variables)

net increase in self containment city = DESTINATION SHIFT RATE CITY*Daily trips per city population to ringtrips/(Day*persons*Year)|

EFFECT OF POPULATION DENSITY ON IMMIGRATION RATE = [(0,0)-(8,2)],(0,1.55), (0.8,1.5), (1,1), (1.2,0.5), (2,0.45), (8.4,0))Dmnl|

normalized population density[zone] = population density[zone]/REFERENCE POPULATION DENSITY[zone]Dmnl|

net increase in proximity of destinations = DESTINATION SHIFT RATE CITY*Daily trips per city population within city[mid]trips/(Day*persons*Year)|

physical travel time by car[trip distance band] = UNIT VECTOR MID AND LONG DISTANCE[trip distance band]*average parking search and out vehicle time+in vehicle time by car[trip distance band]Minutes/trips|(Unit vectors convert between vector and scalar variables)

RELATIVE TIME GAIN DESTINATION SHIFT MID TO SHORT[trip distance band] = 0.005, 0, 0Dmnl|

population density[zone] = SUM(Population[zone, car adoption status!])/LAND AREA[zone]persons/ha|

immigration rate[zone] = EFFECT OF POPULATION DENSITY ON IMMIGRATION RATE(normalized population density[zone])*REFERENCE IMMIGRATION RATE[zone]Dmnl/Year|

Daily trips per ring population to city = INTEG (-net increase in self containment ring,INITIAL DAILY TRIPS PER RING POPULATION TO CITY)trips/(Day*persons)|

RELATIVE TIME GAIN DESTINATION SHIFT LONG TO MID[trip distance band] = 0, 0.2, 0Dmnl|

normalized empty city parking spots per daily car trip = empty city parking spots per daily car trip/REFERENCE EMPTY CITY PARKING SPOTS PER DAILY CAR TRIPDmnl|

net increase in trip frequency[trip distance band] = net increase in self containment city*RELATIVE TIME GAIN DESTINATION SHIFT LONG TO MID[trip distance band]+net increase in proximity of destinations*RELATIVE TIME GAIN DESTINATION SHIFT MID TO SHORT[trip distance band]trips/(Day*persons*Year)|

SENSITIVITY TO CAR LANE DATA UNCERTAINTY = 1Dmnl [0.5,1.5]|

added subjective cost of cycling time due to infrastructure = EFFECT OF BIKE LANES PER ROAD ON SUBJECTIVE VALUE OF CYCLING TIME(change in bike lanes per road)+EFFECT OF CAR LANES PER ROAD ON SUBJECTIVE VALUE OF CYCLING TIME(change in car lanes per road)*SENSITIVITY TO CAR LANE DATA UNCERTAINTY+EFFECT OF PARKING SPOTS PER METER ON SUBJECTIVE VALUE OF CYCLING TIME(change in parking spots per meter)Dmnl|

PT distance share = daily PT distance/total daily distance travelledDmnl|

annual public space entering maintenance[space use] = renewal rate of public space*Public space[space use]ha/Year|

EFFECT OF BIKE UPTAKE ON RENEWAL RATE = (0,0.667), (0.2,0.68), (0.4,0.72), (0.6,0.787), (0.8,0.88), (1,1), (1.169,1.12), (1.338,1.213), (1.507,1.28), (1.676,1.32), (1.845,1.333), (3.69,1.333))Dmnl|

renewal rate of public space = EFFECT OF BIKE UPTAKE ON RENEWAL RATE(normalized fraction of city population with bike access)^(RENEWAL RATE SENSITIVITY)*REFERENCE RENEWAL RATEDmnl/Year|

RENEWAL RATE SENSITIVITY = 1Dmnl [0.5,2]|

total daily distance travelled = daily car distance+daily cycling distance+daily PT distance+daily walking distancekm/Day|

REFERENCE FRACTION OF CITY POPULATION WITH BIKE ACCESS = 0.271Dmnl|

car distance share = daily car distance/total daily distance travelledDmnl|

bike distance share = daily cycling distance/total daily distance travelledDmnl|

REFERENCE RENEWAL RATE = 0.03Dmnl/Year|

walking distance share = daily walking distance/total daily distance travelledDmnl|

car network to euclidian distance ratio[trip distance band] = EFFECT OF CAR LANES PER ROAD ON NETWORK TO EUCLIDIAN DISTANCE RATIO(change in car lanes per road)^CAR NETWORK DISTANCE SENSITIVITY*REFERENCE CAR NETWORK TO EUCLIDIAN DISTANCE RATIO[trip distance band]Dmnl|

PT NETWORK TO EUCLIDIAN DISTANCE RATIO[trip distance band] = 0, 1.2, 1.2Dmnl|

subjective travel time by bike[trip distance band] = physical travel time by bike[trip distance band]*subjective cost of cycling timeMinutes/trips|

INITIAL SUBJECTIVE TRAVEL TIME BY BIKE[trip distance band] = 0, 57, 0Minutes/trips|

INITIAL SUBJECTIVE TRAVEL TIME BY CAR[trip distance band] = 0, 54, 65Minutes/trips|

INITIAL SUBJECTIVE TRAVEL TIME BY PT[trip distance band] = 0, 58, 74Minutes/trips|

AVERAGE EUCLIDIAN DISTANCE[trip distance band] = 1, 5, 8km/trips|

change in subjective travel time by bike[trip distance band] = (MIN(subjective travel time by bike[trip distance band],MAX STT[trip distance band])-Smoothed subjective travel time by bike[trip distance band])/PERCEPTION TIMEMinutes/(trips*Year)|

MAX STT[trip distance band] = 0, 80, 100Minutes/trips|

Smoothed subjective travel time by car[trip distance band] = INTEG (change in subjective travel time by car[trip distance band],INITIAL SUBJECTIVE TRAVEL TIME BY CAR[trip distance band])Minutes/trips|

Smoothed subjective travel time by PT[trip distance band] = INTEG (change in subjective travel time by PT[trip distance band],INITIAL SUBJECTIVE TRAVEL TIME BY PT[trip distance band])Minutes/trips|

change in subjective travel time by car[trip distance band] = (MIN(subjective travel time by car[trip distance band],MAX STT[trip distance band])-Smoothed subjective travel time by car[trip distance band])/PERCEPTION TIMEMinutes/(trips*Year)|

change in subjective travel time by PT[trip distance band] = (MIN(subjective travel time by PT[trip distance band],MAX STT[trip distance band])-Smoothed subjective travel time by PT[trip distance band])/PERCEPTION TIMEMinutes/(trips*Year)|

UNIT VECTOR MID AND LONG DISTANCE[trip distance band] = 0, 1, 1Dmnl|(Converts between vector and scalar variables)

in vehicle time by car[trip distance band] = car network to euclidian distance ratio[trip distance band]*AVERAGE EUCLIDIAN DISTANCE[trip distance band]/congested speed*MINUTES PER HOURMinutes/trips|

Smoothed subjective travel time by bike[trip distance band] = INTEG (change in subjective travel time by bike[trip distance band],INITIAL SUBJECTIVE TRAVEL TIME BY BIKE[trip distance band])Minutes/trips|

PT AVERAGE SPEED[trip distance band] = 30, 30, 50km/Hour|

SHARE OF TRIPS OCCURRING IN PEAK TIME = 0.4Dmnl|

PEAK TIME WINDOW = 4Hour/Day|

physical travel time by PT[trip distance band] = in vehicle time by PT[trip distance band]+PHYSICAL WAITING AND CHANGING TIME[trip distance band]Minutes/trips|

subjective travel time by car[trip distance band] = in vehicle time by car[trip distance band]+subjective parking search and out vehicle timeUNIT VECTOR MID AND LONG DISTANCE[trip distance band]Minutes/trips|(Unit vectors convert between vector and scalar variables)

SUBJECTIVE WAITING AND CHANGING TIME[trip distance band] = 0, 11.1719, 20.7945Minutes/trips|

CAR NETWORK DISTANCE SENSITIVITY = 1Dmnl [0.5,1.5]|

REFERENCE CAR NETWORK TO EUCLIDIAN DISTANCE RATIO[trip distance band] = 0, 1.26, 1.2Dmnl|

peak PT riders per hour = SHARE OF TRIPS OCCURRING IN PEAK TIME*daily PT trips/PEAK TIME WINDOW*PERSONS PER TRIPpersons/Hour|

in vehicle time by PT[trip distance band] = AVERAGE EUCLIDIAN DISTANCE[trip distance band]*PT NETWORK TO EUCLIDIAN DISTANCE RATIO[trip distance band]/PT AVERAGE SPEED[trip distance band]*MINUTES PER HOURMinutes/trips|

PHYSICAL WAITING AND CHANGING TIME[trip distance band] = 0, 4, 7.939Minutes/trips|

peak cars per hour = SHARE OF TRIPS OCCURRING IN PEAK TIME*daily car trips/CAR OCCUPANCY RATE/PEAK TIME WINDOWcars/Hour|

fraction of population with bike access in each zone[zone] = SUM(Bike users[zone,user type!])/SUM(Population[zone,car adoption status!])Dmnl|

daily long distance car trips = SUM(daily long distance trips[trip distance band!])*long distance car share-trips/Day|

daily long distance PT trips = SUM(daily long distance trips[trip distance band!])*long distance PT share-trips/Day|

daily long distance trips[trip distance band] = UNIT VECTOR LONG DISTANCE[trip distance band]*daily trips in each trip distance band[trip distance band]trips/Day|(Unit vectors convert between vector and scalar variables)

daily long trips = Daily trips per ring population to city*SUM(Population[ring,car adoption status!])+Daily trips per city population to ringSUM(Population[city,car adoption status!])trips/Day|

daily mid distance car trips = SUM(daily mid distance trips[trip distance band!])*mid distance car sharetrips/Day|

daily mid distance cycling trips = SUM(daily mid distance trips[trip distance band!])*mid distance bike sharetrips/Day|

long distance car share = population fraction with car access on long distance trips*car users car share on long distance tripsDmnl [0,?]|

long distance PT share = population fraction with car access on long distance trips*car users PT share on long distance trips+(1-population fraction with car access on long distance trips)Dmnl [0,?]|

DESTINATION SHIFT RATE RING = 0.005Dmnl/Year [0.001,0.01]|

daily trips in each trip distance band[trip distance band] = Daily trips per city population within city[trip distance band]*SUM(Population[city, car adoption status!])+daily long trips*UNIT VECTOR LONG DISTANCE[trip distance band]trips/Day|(Unit vectors convert between vector and scalar variables)

Daily trips per ring population within ring = INTEG (net increase in self containment ring,INITIAL DAILY TRIPS PER RING POPULATION WITHIN RING)trips/(Day*persons)|

Daily trips per city population to ring = INTEG (-net increase in self containment city,INITIAL DAILY TRIPS PER CITY POPULATION TO RING)trips/(Day*persons)|

total daily trips = SUM(daily trips in each trip distance band[trip distance band!])trips/Day|

city parking spots per car = parking spots city/SUM(Cars[zone!])spots/cars|

desired car parking space share = DESIRED SHARE OF CAR SPACE USED FOR PARKING*desired motorist space shareDmnl|

DESIRED SHARE OF CAR SPACE USED FOR PARKING = 0.19Dmnl [0,0.29]|

desired motor traffic space share = (1-DESIRED SHARE OF CAR SPACE USED FOR PARKING)*desired motorist space shareDmnl|

UNIT VECTOR LONG DISTANCE[trip distance band] = 0, 0, 1Dmnl|(Converts between vector and scalar variables) net change in cars[zone] = change in adults with cars[zone]*CARS PER ADULT WITH CAR[zone]cars/Year|

Cars[zone] = INTEG (net change in cars[zone],INITIAL CARS[zone])cars|

net increase in self containment ring = DESTINATION SHIFT RATE RING*Daily trips per ring population to citytrips/(Day*persons*Year)|

INITIAL DAILY TRIPS PER RING POPULATION WITHIN RING = 2.3457trips/(persons*Day)|

YEAR = 1Year|

INITIAL DAILY TRIPS PER CITY POPULATION TO RING = 0.3891trips/(persons*Day)|

daily mid distance PT trips = SUM(daily mid distance trips[trip distance band!])*mid distance PT share-trips/Day|

daily car trips per car = daily car trips/SUM(Cars[zone!])trips/(cars*Day)|

car trips share = (daily mid distance car trips+daily long distance car trips)/total daily tripsDmnl|

INITIAL DAILY TRIPS PER CITY POPULATION WITHIN CITY[trip distance band] = 2.2149, 1.2026, 0trips/(persons*Day)|

UNIT VECTOR CAR PARKING[space use] = 0, 1, 0, 0Dmnl|(Converts between vector and scalar variables)

population fraction with car access on long distance trips = Population[city,adult car]/SUM(Population[city, car adoption status!])*Daily trips per city population to ring(Daily trips per ring population to city+Daily trips per city population to ring)+Population[ring,adult car]/SUM(Population[ring, car adoption status!])*Daily trips per ring population to city(Daily trips per ring population to city+Daily trips per city population to ring)Dmnl|

UNIT VECTOR DESTINATION CHANGE[trip distance band] = 1, -1, 0Dmnl|(Converts between vector and scalar variables)

DESTINATION SHIFT RATE CITY = 0.003Dmnl/Year [0.001,0.005]|

INITIAL DAILY TRIPS PER RING POPULATION TO CITY = 0.445trips/(persons*Day)|

INITIAL CARS[zone] = 408081, 1.57975e+06cars|

REFERENCE EMPTY CITY PARKING SPOTS PER DAILY CAR TRIP = 0.322197(spots*Day)/trips|

EFFECT OF CAR LANES PER ROAD ON NETWORK TO EUCLIDIAN DISTANCE RATIO = [(0.8,0.8)-(1.7,2)],(0,1.5), (0.2,1.48), (0.4,1.42), (0.6,1.32), (0.8,1.18), (1,1), (1.133 0.942), (1.266,0.897), (1.399,0.865), (1.532,0.846), (1.665,0.839), (1.667,0.839))Dmnl|

CAR PARKING SEARCH AND OUT VEHICLE STT LOOKUP = (0,0), (1,2), (2,4.001), (3,6.003), (4,8.01), (5,10.027), (6,12.073), (7,14.189), (8,16.481) (9,19.205), (10,22.981), (10.5,25.669), (11,29.298), (11.5,34.382), (12,41.718), (12.5,52.533), (13,68.718), (13.5,93.178), (14,130.383), (14.5,145), (15,155), (15.5,160), (16,162), (25 162))Minutes/trips|

PT ACCESS EGRESS STT LOOKUP = [(0,0)-(10,100)],(0,0.844), (1,0.956), (2,2.228), (2.5,3.039), (3,4.009), (3.5,5.179), (4,6.6), (4.5,8.334), (5,10.458), (5.5,13.069), (6,16.283), (6.5,20.245), (7,25.132), (7.5,31.161), (8,38.599), (8.5,47.771), (9,59.076), (9.5,73.001), (10,90.139))Minutes/trips|

CYCLING PARKING TIME = 6Minutes/trips|

INITIAL PT CAPACITY = 887073persons/Hour|

LATE EFFECT OF BIKE NETWORK COMPLETION ON POPULATION RECEPTIVE TO CYCLING = [(0,0)-(4,4)],(0,0.01), (0.103,0.27), (0.205,0.458), (0.308,0.574), (0.41,0.658), (0.513,0.74), (0.615,0.809), (0.718,0.862), (0.821,0.91), (0.923,0.958), (1.026,1.016), (1.128,1.088), (1.231,1.18), (1.333,1.298), (1.436,1.465), (1.538,1.689), (1.641,1.971), (1.744,2.298), (1.846,2.574), (1.949,2.776), (2.051,2.906), (2.154,2.965), (2.256,3.002), (2.359,3.002), (2.462,3.002), (2.564,3.002), (2.667,3.002), (2.769,3.002), (2.872,3.002), (2.974,3.002), (3.077,3.002), (3.179,3.002), (3.282,3.002), (3.385,3.002), (3.487,3.002), (3.59,3.002), (3.692,3.002), (3.795,3.002), (3.897,3.002), (4,3.002))DmnlThe tipping point occurs between 40 and 60 percent completion and stabilizes at 90 percent completion|

net added capacity per year = NET ADDED PT CAPACITY PER YEAR*PT capacitypersons/(Hour*Year)|

NET ADDED PT CAPACITY PER YEAR = 0.001Dmnl/Year [0.0005,0.0015]|

SEAT CAPACITY TO TOTAL CAPACITY RATIO = 0.22Dmnl|

TIPPING POINT SWITCH = 0Dmnl [0,1,1]|

PT capacity = INTEG (net added capacity per year,INITIAL PT CAPACITY)persons/Hour|

construction rate[zone] = EFFECT OF HOME DENSITY ON CONSTRUCTION RATE(normalized home density[zone])*REFERENCE CONSTRUCTION RATE[zone]Dmnl/Year|

seat capacity = SEAT CAPACITY TO TOTAL CAPACITY RATIO*PT capacitypersons/Hour|

early = 0Dmnl|

standing capacity = (1-SEAT CAPACITY TO TOTAL CAPACITY RATIO)*PT capacitypersons/Hour|

total population = SUM(population per zone[zone!])persons|

population per zone[zone] = SUM(Population[zone,car adoption status!])persons|

actual relative to desired bike parking per user[user type] = bike parking per city user[user type]/DESIRED BIKE PARKING PER USER[user type]Dmnl|

REFERENCE CONTACT FRUITFULNESS[user type] = 0.1, 0.1Dmnl|

BIKE DISCONTINUATION FRACTION[user type] = 0.02, 0.005Dmnl|

bike parking per city user[user type] = Bike parking[user type]/Bike users[city, user type]spots/persons|

Bike parking[user type] = INTEG (bike parking added[user type],INITIAL BIKE PARKING[user type])spots|

BIKE PARKING PER SPACE FOR CYCLISTS ADDED[user type] = 434, 234spots/ha|

INITIAL BIKE PARKING[user type] = 59892, 32292spots|

CONTACT RATE = 2Dmnl [1,3]|

DESIRED BIKE PARKING PER USER[user type] = 0.3, 0.2spots/persons|

daily bike trips per city bike user = daily mid distance cycling trips/SUM(Bike users[city,user type!])trips/(persons*Day)|

UNIT VECTOR USER TYPE CHANGE[user type] = 1, -1Dmnl|(Converts between vector and scalar variables)

Bike users[zone, user type] = INTEG (people adopting bikes[zone,user type]-bike users discontinuing[zone, user type]+UNIT VECTOR USER TYPE CHANGE[user type]*bikesharing users upgrading to private bikes[zone],INITIAL BIKE USERS[zone, user type])persons|(Unit vectors convert between vector and scalar variables)

bikesharing users upgrading to private bikes[zone] = Bike users[zone,sharing]*BIKESHARING TO PRIVATE BIKE UPGRADE FRACTION/UPGRADE TIMEpersons/Year|

DECISION TIME BIKE ADOPTION[user type] = 3, 1;Year|

INITIAL BIKE USERS[zone,user type] = 283614, 294309; 1.41195e+06, 95691;persons|

PERIOD OF USE[zone,user type] = 10, 2; 10, 2;Year|

DESIRED CYCLIST SPACE SHARE = 0.174Dmnl|

UNIT VECTOR MOTOR TRAFFIC[space use] = 1, 0, 0, 0Dmnl|(Converts between vector and scalar variables)

Public space[space use] = INTEG (desired distribution of space[space use]*SUM(annual public space finishing maintenance[space use!])-annual public space entering maintenance[space use]+net annual street construction[space use],INITIAL PUBLIC SPACE[space use])ha|

UNIT VECTOR PEDESTRIANS[space use] = 0, 0, 1, 0Dmnl|(Converts between vector and scalar variables)

EARLY EFFECT OF BIKE NETWORK COMPLETION ON POPULATION RECEPTIVE TO CYCLING = (0,0.01), (0.103,0.014), (0.205,0.042), (0.308,0.094), (0.41,0.168), (0.513,0.264), (0.615 0.378), (0.718,0.512), (0.821,0.675), (0.923,0.871), (1.026,1.035), (1.128,1.142), (1.231 1.229), (1.333,1.313), (1.436,1.386), (1.538,1.445), (1.641,1.492), (1.744,1.528), (1.846 1.551), (1.949,1.561), (2.051,1.569), (2.154,1.569), (2.256,1.569), (2.359,1.569), (2.462 1.569), (2.564,1.569), (2.667,1.569), (2.769,1.569), (2.872,1.569), (2.974,1.569), (3.077 1.569), (3.179,1.569), (3.282,1.569), (3.385,1.569), (3.487,1.569), (3.59,1.569), (3.692 1.569), (3.795,1.569), (3.897,1.569), (4,1.569))DmnlThe tipping point occurs between 20 and 60 percent completion and stabilizes at 80 percent completion|

net annual street construction[space use] = IF THEN ELSE(net annual network expansion>0, desired distribution of space[space use], current distribution of public space[space use])* net annual network expansion*AVERAGE STREET WIDTH/M2 PER HA/ROADha/Year|

UNIT VECTOR CYCLISTS[space use] = 0, 0, 0, 1Dmnl|(Converts between vector and scalar variables)

parking spots city = public parking spots city+Residential car parking spots city+COMMERCIAL CAR PARKING SPOTS CITYspots|

CAR ADOPTION SENSITIVITY TO USAGE = 1Dmnl [0.5,2]|

deaths[zone] = DEATH RATE*SUM(Population[zone,car adoption status!])persons/Year|

car adoption status of young adults settling[zone, car adoption status] = normalized car adoption by adults[zone, car adoption status]+percentage point shift in car adoption by young adults relative to adults[car adoption status]Dmnl|

Population[zone,car adoption status] = INTEG (births[zone]*YOUTH CAR STATUS[car adoption status]+net migration[zone]*current car adoption status[zone,car adoption status]-young adults settling[zone]*YOUTH CAR STATUS[car adoption status]+young adults settling[zone]*car adoption status of young adults settling[zone,car adoption status]-deaths[zone]*normalized car adoption by adults[zone,car adoption status],INITIAL POPULATION[zone,car adoption status])persons|

COMMERCIAL CAR PARKING SPOTS CITY = 70540spots|

percentage point shift in car adoption by young adults relative to adults[car adoption status] = UNIT VECTOR CAR ADOPTION CHANGE[car adoption status]*REFERENCE SHIFT IN CAR ADOPTION*EFFECT OF CAR USAGE ON SHIFT IN CAR ADOPTION(normalized daily car trips per car)^CAR ADOPTION SENSITIVITY TO USAGEDmnl|(Unit vectors convert between vector and scalar variables)

relative car adoption by adults[zone,car adoption status] = UNIT VECTOR ADULT[car adoption status]*current car adoption status[zone,car adoption status]Dmnl|(Unit vectors convert between vector and scalar variables)

subjective cost of cycling time = REFERENCE SUBJECTIVE COST FACTOR+added subjective cost of cycling time due to infrastructureSUBJECTIVE CYCLING TIME SENSITIVITYDmnl|

REFERENCE HOME DENSITY[zone] = 66.2, 33.51homes/ha|

average private parking spots per home = Residential car parking spots city/Homes[city]spots/homes|

REFERENCE SHIFT IN CAR ADOPTION = 0.15Dmnl [0.05,0.25]|

normalized car adoption by adults[zone,car adoption status] = relative car adoption by adults[zone,car adoption status]/SUM(relative car adoption by adults[zone,car adoption status!])Dmnl|

residential parking constructed = PARKING SPOTS PER HOME CONSTRUCTED*home construction[city]spots/Year|

residential parking demolished = average private parking spots per home*home demolition[city]spots/Year|

normalized daily car trips per car = daily car trips per car/REFERENCE DAILY CAR TRIPS PER CARDmnl|

normalized home density[zone] = home density[zone]/REFERENCE HOME DENSITY[zone]Dmnl|

LAND AREA[zone] = 21100, 65400ha|

BIRTH RATE[zone] = 0.0126, 0.0156Dmnl/Year|

births[zone] = BIRTH RATE[zone]*SUM(Population[zone,car adoption status!])persons/Year|

OUTMIGRATION RATE[zone] = 0.0295, 0.0216Dmnl/Year|

daily car trips = daily mid distance car trips+daily long distance car tripstrips/Day|

EFFECT OF CAR USAGE ON SHIFT IN CAR ADOPTION = (0,1.3), (0.5,1.3), (0.6,1.29), (0.7,1.27), (0.8,1.23), (0.9,1.13), (1,1), (1.1,0.87), (1.2,0.77), (1.3,0.73), (1.4,0.71), (1.5,0.7), (4,0.7))Dmnl|

INITIAL POPULATION[zone, car adoption status] = 523323, 523181, 1.08661e+06; 1.21314e+06, 2.225e+06, 1.28119e+06;persons|

YOUTH CAR STATUS[car adoption status] = 1, 0, 0Dmnl|

REFERENCE CONSTRUCTION RATE[zone] = 0.014, 0.021Dmnl/Year|

CARS PER ADULT WITH CAR[zone] = 0.78, 0.71cars/persons|

home density[zone] = Homes[zone]/LAND AREA[zone]homes/ha|

fraction of city population with car access = Population[city,adult car]/SUM(Population[city,car adoption status!])Dmnl|

YOUTH AGING TIME = 20Year|

DEATH RATE = 0.0065Dmnl/Year|

INITIAL HOMES[zone] = 1.39675e+06,2.19182e+06homes|

UNIT VECTOR ADULT[car adoption status] = 0, 1, 1Dmnl|(Converts between vector and scalar variables)

current car adoption status[zone,car adoption status] = Population[zone,car adoption status]/SUM(Population[zone,car adoption status!])Dmnl|

Homes[zone] = INTEG (home construction[zone]-home demolition[zone],INITIAL HOMES[zone])homes|

home construction[zone] = DELAY1(construction rate[zone]*Homes[zone], CONSTRUCTION DELAY)homes/Year|

young adults settling[zone] = Population[zone,young adult]/YOUTH AGING TIMEpersons/Year|

home demolition[zone] = Homes[zone]/YEARS UNTIL DEMOLISHEDhomes/Year|

SUBJECTIVE CYCLING TIME SENSITIVITY = 1Dmnl [0.5,1.5]|

UNIT VECTOR CAR ADOPTION CHANGE[car adoption status] = 0, -1, 1Dmnl|(Converts between vector and scalar variables)

Built up area and greenfield = INTEG (-SUM(net annual street construction[space use!]),INITIAL GREENFIELD AND BUILT UP SPACE)ha|

overcrowding level = IF THEN ELSE(peak PT riders per hour<seat capacity, 1, MIN(2,1+(peak PT riders per hour-seat capacity)/standing capacity))Dmnl|

normalized daily bike trips per user = daily bike trips per city bike user/REFERENCE BIKE TRIPS PER USERDmnl|

average cycling speed = ebike share*EBIKE SPEED+(1-ebike share)*PEDAL BIKE SPEEDkm/Hour|

average parking search and out vehicle time = EFFECT OF PARKING SPOTS ON PARKING SEARCH AND EGRESS TIME TO CITY(normalized empty city parking spots per daily car trip)^PARKING SEARCH AND EGRESS SENSITIVITY*REFERENCE SEARCH AND EGRESS TIMEMinutes/trips|

PT access egress time = EFFECT OF SIDEWALK WIDTH ON PT ACCESS EGRESS TIME(normalized sidewalk width per road)^SENSITIVITY TO SIDEWALK DATA UNCERTAINTY*REFERENCE PT ACCESS EGRESS TIMEMinutes/trips|

change in parking spots per meter = parking spots per meter of road/REFERENCE PARKING SPOTS PER METER OF ROAD NETWORKDmnl|

BIKE ADOPTION SENSITIVITY TO PARKING = 1Dmnl [0.5,2]|

change in bike lanes per road = separated bike lanes per road/REFERENCE BIKE LANES PER ROAD-Dmnl|

change in car lanes per road = average car lanes per road/REFERENCE CAR LANES PER ROADDmnl|

REFERENCE BIKE TRIPS PER USER = 0.5trips/(persons*Day)|

normalized sidewalk width per road = sidewalk width per road/REFERENCE SIDEWALK WIDTH PER ROADDmnl|

cycling network to euclidian distance ratio = EFFECT OF BIKE LANES PER ROAD ON NETWORK TO EUCLIDIAN DISTANCE RATIO(change in bike lanes per road)^CYCLING NETWORK DISTANCE SENSITIV-ITY*REFERENCE NETWORK TO EUCLIDIAN DISTANCE RATIODmnl [?,?,0.1]|

CYCLING NETWORK DISTANCE SENSITIVITY = 1Dmnl [0.5,1.5]|

PARKING SEARCH AND EGRESS SENSITIVITY = 1Dmnl [0.5,2]|

SENSITIVITY TO SIDEWALK DATA UNCERTAINTY = 1Dmnl [0.5,2]|

EBIKE UPTAKE SWITCH = 0Dmnl [0,1,1]|

EBIKE STEEP UPTAKE LOOKUP = (2020,0.03), (2030,0.09), (2050,0.81), (2060,0.81))Dmnl|

separated bike lanes per road = total cycling lane length/Total length of street networklanes/road [0,?]|

annual public space finishing maintenance[space use] = Public space available for reallocation[space use]/ROAD WORKS DELAYha/Year|

average car lanes per road = MIN(4,total car lane length/Total length of street network)lanes/road [0,4]|

Public space available for reallocation[space use] = INTEG (annual public space entering maintenance[space use]-annual public space finishing maintenance[space use],INITIAL PUBLIC SPACE AVAILABLE FOR REALLO-CATION[space use])ha|

parking spots per meter of road = parking spots city/Total length of street networkspots/(road*m)|

sidewalk width per road = Public space[pedestrians]*M2 PER HA/Total length of street networkm/road|

AVERAGE STREET WIDTH = 17m|

Total length of street network = INTEG (net annual network expansion,INITIAL LENGHT OF ROAD NET-WORK)road*m|

total car lane length = Public space[motor traffic]*M2 PER HA/AVERAGE LANE WIDTHm*lanes|

total cycling lane length = Public space[cyclists]*M2 PER HA/AVERAGE LANE WIDTH*CYCLING LANE PER LANEm*lanes|

current distribution of public space[space use] = Public space[space use]/SUM(Public space[space use!])Dmnl|

INITIAL PUBLIC SPACE[space use] = 866, 197, 1515, 99ha|

INITIAL PUBLIC SPACE AVAILABLE FOR REALLOCATION[space use] = 6.11, 1.45, 11.37, 1.13ha|

public parking spots city = Public space[car parking]/PARKING SPOT AREAspots|

ROAD = 1road|

ROAD WORKS DELAY = 0.25Year|

beta 5 = 0.0878Dmnl|

beta 8 = 0.0799Dmnl|

MINUTES PER HOUR = 60Minutes/Hour|

REFERENCE NETWORK TO EUCLIDIAN DISTANCE RATIO = 1.4Dmnl [1,1.5,0.1]|

ROAD NETWORK EXPANSION RATE = 0Dmnl/Year|

EFFECT OF BIKE USAGE ON CONTACT FRUITFULNESS = [(0,0)-(2,2)],(0,0), (0.2,0.04), (0.4,0.16), (0.6,0.36), (0.8,0.64), (1,1), (1.2,1.36), (1.4 1.64), (1.6,1.84), (1.8,1.96), (2,2))Dmnl|

EFFECT OF PARKING AVAILABILITY ON CONTACT FRUITFULNESS = [(0,0)-(6,2)],(0,0), (0.2,0.04), (0.4,0.16), (0.6,0.36), (0.8,0.64), (1,1), (1.2,1.36), (1.4 1.64), (1.6,1.84), (1.8,1.96), (2,2), (6,2))Dmnl|

WALKING SPEED = 3km/Hour|

peak network density = MIN(peak cars per hour/total car lane length,COLLISION DENSITY)cars/(lanes*m*Hour)|

REFERENCE SIDEWALK WIDTH PER ROAD = 9.66m/road|

Residential car parking spots city = INTEG (residential parking constructed-residential parking demolished,INITIAL RESIDENTIAL PARKING SPOTS CITY)spots|

BIKESHARING TO PRIVATE BIKE UPGRADE FRACTION = 0.05Dmnl [0.01,0.1]|

PARKING SPOTS PER HOME CONSTRUCTED = 0.15spots/homes [0,0.3]|

EBIKE SPEED = 25km/Hour|

EBIKE GENTLE UPTAKE LOOKUP = (2020,0.03), (2030,0.09), (2050,0.27), (2060,0.27))Dmnl|

PEDAL BIKE SPEED = 18km/Hour|

REFERENCE PT ACCESS EGRESS TIME = 4.89Minutes/trips|

EFFECT OF SIDEWALK WIDTH ON PT ACCESS EGRESS TIME = [(0,0)-(2,4)],(0,4), (0.2,3.88), (0.4,3.52), (0.6,2.92), (0.8,2.08), (1,1), (1.2,0.82), (1.4 0.68), (1.6,0.58), (1.8,0.52), (2,0.5))Dmnl|

UPGRADE TIME = 2Year|

EFFECT OF BIKE LANES PER ROAD ON NETWORK TO EUCLIDIAN DISTANCE RATIO = [(0.8,0.8)-

(6,2)],(0,1.5), (0.2,1.48), (0.4,1.42), (0.6,1.32), (0.8,1.18), (1,1), (1.3,0.928), (1.6,0.872), (1.9,0.832), (2.2,0.808), (2.5,0.8), (6,0.8))Dmnl|

INITIAL RESIDENTIAL PARKING SPOTS CITY = 460179spots|

EFFECT OF CAR LANES PER ROAD ON SUBJECTIVE VALUE OF CYCLING TIME = (0,-0.1), (0.42,-0.1), (0.536,-0.09), (0.652,-0.075), (0.768,-0.055), (0.884,-0.03), (1,0) (1.134,0.03), (1.268,0.065), (1.402,0.1), (1.536,0.145), (1.67,0.2), (4,0.2))Dmnl|

REFERENCE SUBJECTIVE COST FACTOR = 1.96Dmnl|

REFERENCE CAR LANES PER ROAD = 2.4lanes/road|

EFFECT OF PARKING SPOTS PER METER ON SUBJECTIVE VALUE OF CYCLING TIME = [(-0.06,-0.06)-(1.6,0.06)],(0,-0.05), (0.2,-0.048), (0.4,-0.042), (0.6,-0.032), (0.8,-0.018), (1,0), (1.1,0.018), (1.2,0.032), (1.3,0.042), (1.4,0.048), (1.6,0.05), (25,0.05))Dmnl|

CYCLING LANE PER LANE = 1Dmnl|

REFERENCE BIKE LANES PER ROAD = 0.4lanes/road|

REFERENCE PARKING SPOTS PER METER OF ROAD NETWORK = 0.47spots/(m*road)|

EFFECT OF BIKE LANES PER ROAD ON SUBJECTIVE VALUE OF CYCLING TIME = (0,0.1), (0.2,0.096), (0.4,0.084), (0.6,0.064), (0.8,0.036), (1,0), (1.3,-0.036), (1.6,-0.085), (1.9,-0.14), (2.2,-0.19), (2.5,-0.2), (6,-0.2))Dmnl|

INITIAL LENGHT OF ROAD NETWORK = 1.567e+06road*m|

PERSONS PER TRIP = 1persons/trips|

CAR OCCUPANCY RATE = 1.2trips/cars|

INITIAL GREENFIELD AND BUILT UP SPACE = 18423ha|

daily PT trips = daily long distance PT trips+daily mid distance PT tripstrips/Day|

REFERENCE DAILY CAR TRIPS PER CAR = 0.548trips/(Day*cars)|

PERCEPTION TIME = 3Year [1,5]|

congested speed = MAX(WALKING SPEED,AVERAGE SPEED LIMIT*(1-peak network density/COLLISION DENSITY))km/Hour [0,?]|

EFFECT OF HOME DENSITY ON CONSTRUCTION RATE = [(0,0)-(8,2)],(0,1.55), (0.8,1.5), (1,1), (1.2,0.5), (2,0.45), (8.4,0))Dmnl|

REFERENCE SEARCH AND EGRESS TIME = 11.381Minutes/trips|

EFFECT OF PARKING SPOTS ON PARKING SEARCH AND EGRESS TIME TO CITY = [(0,0)-(15,2)],(0,1.23), (0.2,1.221), (0.4,1.193), (0.6,1.147), (0.8,1.083), (1,1), (1.2,0.91), (1.4,0.78), (1.6,0.68), (1.8,0.58), (2,0.52), (2.219,0.439), (15,0.439))Dmnl|

PARKING SPOT AREA = 0.00096ha/spots|

overcrowding multiplier = overcrowding level*overcrowding levelDmnl|

CONSTRUCTION DELAY = 5Year|

YEARS UNTIL DEMOLISHED = 100Year [60,110]|

AVERAGE LANE WIDTH = 2.2m/lanes|

M2 PER HA = 10000m*m/ha|

AVERAGE SPEED LIMIT = 30km/Hour|

COLLISION DENSITY = 0.05639cars/(lanes*m*Hour)|