Space Wars – Finding an Economically Efficient Allocation of Street Space Across Different Transport Modes

Jan Wessel*

July 2023

Abstract

This paper analyzes how street space should be allocated across cars, buses, bicycles, and parking in order to maximize economic efficiency. Accordingly, we set up a nested logit model reflecting user heterogeneity, cross-congestion effects between transport modes, and relevant transport demand elasticities. Simulations are conducted for Berlin, Germany and New York City, USA. We find that re-allocating street space from cars to buses and especially bicycles improves efficiency. Effect magnitudes and the extent of optimal re-allocations vary between cities. We also shed light on the channels through which re-allocations impact on efficiency.

JEL Codes: R48, L91, O18.
Keywords: transportation economics, urban economics, street space allocation, government policy, congestion.

*University of Münster, Institute of Transport Economics, Am Stadtgraben 9, 48143 Münster, Germany. E-Mail: jan.wessel@uni-muenster.de. I am grateful to Gernot Sieg and Hugo Silva for their helpful comments, especially with regard to the theoretical model. I also thank Thomas Hagedorn, Till Kösters, and Marlena Meier for their helpful comments; Alina Krämer, Johannes Höweler, Maria Kennel, Lars Rödermund, and Edita Selimaj for their valuable research assistance; and Brian Bloch for his editing.

1 Introduction

Space is a scarce resource in cities all over the world, so that it is crucial to use the available space as efficiently as possible. Maximizing the efficiency of the transportation system, subject to the available space, is therefore one of the key challenges for today's city planners and policy makers. Against this backdrop, a growing and ongoing debate has emerged in recent years about how space that is dedicated to the transportation system should be allocated to different modes of transport. In this paper, we tackle this question from an economic perspective and analyze how much of the available street space, i.e. the space dedicated to overground transportation, should be allocated to cars, buses, bikes, and parking in order to maximize the economic efficiency of a city's transportation system.

When it comes to optimizing the efficiency of transportation systems, the policy instruments that are traditionally at the forefront of public and scholarly debate include subsidization of public transport systems and optimizing fares and frequencies (e.g. Basso and Silva, 2014; Börjesson et al., 2017; Parry and Small, 2009), implementing congestion pricing for cars (e.g. Arnott et al., 1990; Lindsey and Verhoef, 2001; Vickrey, 1969), or setting parking fees (e.g. Anderson and de Palma, 2004; Inci, 2015). One particular policy instrument, however, is often neglected in the context of optimizing transportation systems: the re-allocation of available street space to the different transport modes. This instrument enables policy makers to alter the street capacity for transport modes, and thereby impact on transport-mode-specific travel times. Hence, re-allocating street space can lead to changes in the attractiveness of selected transport modes, and consequently, to changes in the performance of the entire transportation system.

In recent years, policymakers have seem to become more aware that re-allocating street space can indeed be an effective policy instrument. Prominent examples of such re-allocations are often related to increasing the attractiveness of the more sustainable modes of transport, especially walking and cycling. The city of Barcelona, for example, introduced so-called "superblocks" consisting of up to nine housing blocks, within which pedestrian and cycling traffic is prioritized by giving them more street space, while pushing car traffic back to the streets on the perimeter (Rueda, 2019). Increasing street space for cyclists was also a frequently applied policy instrument during the Covid-19 pandemic, when many cities installed provisional cycling lanes on street space that was formerly dedicated to cars (Buehler and Pucher, 2021a, 2022). These so-called "pop-up bike lanes" have been found to significantly increase cycling levels (Kraus and Koch, 2021).

Given the heightened awareness that re-allocating street space can be an effective policy instrument, there is increasing discussion on how street space should *ideally* be allocated. The complexity of this debate is outlined by Creutzig et al. (2020), who discuss 14 different street space allocation mechanisms in terms of normative and ethical principles. The discussed allocation mechanisms include allocating street space so that it equals modal shares, is equally distributed across transport modes ("Egalitarianism"), maximizes overall capacity, maximizes economic efficiency, or minimizes environmental damage. However, no clear winner emerges from their discussion, and depending on the weighting of the normative and ethical principles considered, certain allocation mechanisms could be favored over others.

This discussion is further complicated by the fact that for certain allocation mechanisms, it is unclear what the resulting street space allocation would look like. For allocation mechanisms such as egalitarianism or the modal-share-based one, it is straightforward to calculate the corresponding street space allocations for real-world cities. When it comes to maximizing economic efficiency, however, deriving the corresponding street shares is more complicated, due to the various channels through which the street space allocation impacts on efficiency. As economic efficiency is often used to evaluate the impact of transport policies (e.g. Bento et al., 2009; Parry and Small, 2009; Yang et al., 2020), a lack of knowledge on the economic effects of street space re-allocations creates an important gap in the literature. Against this backdrop, we contribute to the literature in the following ways.

To the best of our knowledge, we are the first to provide an analysis of the economic efficiency of street space allocations. More specifically, we derive the street space allocations that maximize economic efficiency in the respective cities, and we shed light on the channels through which street space re-allocations impact on economic efficiency. In this context, we also analyze the interplay between re-allocations and more traditional transport policies such as subsidization, adjusting frequencies, or implementing congestion tolls.

In order to derive our results, we extend the theoretical mode choice model outlined in Basso and Silva (2014). This model conforms to the principles of utility maximization and relates to economic efficiency through a measure of social welfare, which consists of consumer surplus and net revenue from the operation of the transportation system. While Basso and Silva (2014) and the related literature have focused on space for cars and buses (e.g. Basso et al., 2011; Börjesson et al., 2017; Currie et al., 2007; Zheng and Geroliminis, 2013), we additionally consider the space for cycling and parking in our model, because these two types of space are often at the forefront of discussions on street space re-allocations.

We then apply our theoretical model to two different cities, i.e. Berlin and New York City. The initial model calibration ensures that important real-world travel conditions and transport demand elasticities are reflected in the model. The simulations for both cities then show that re-allocating street space from cars and parking to buses and especially to bicycles increases the economic efficiency of the transportation system. The extent of proposed street space re-allocations and the subsequent efficiency gains are more pronounced in Berlin, mainly because transport mode preferences in Berlin are less car-centric and individuals are more willing to switch to other modes.

Our findings hence contribute an economic perspective to the ongoing debate on the allocation of street space. Historically, this allocation is heavily skewed towards cars and parking, but calls are being made for increasing the space for buses and especially for bicycles, in order to improve sustainability in the transportation sector. This is often accompanied by calls for greater "fairness of space" (Guzman et al., 2021). Our objective function includes no such sustainability or fairness aspects, but refers only to economic efficiency. Nonetheless, we find that more street space should be allocated to buses and bikes, underlining that such re-allocations would not only increase sustainability and fairness, but also economic efficiency in the transportation sector.

The remainder of this paper is structured as follows. In Section 2 we set up our theoretical model, and in Section 3 we analyze the economic efficiency of street space allocations by applying the model to Berlin and New York City. Section 4 discusses further aspects of street space allocations, the limitations of our model, and concludes.

2 Theoretical Model

2.1 Model introduction

In order to tackle the research question of an *economically efficient* allocation of street space, we build upon the model of Basso and Silva (2014) and also look at a representative kilometer of street space and one day of operation. This street space is used by utility-maximizing individuals, whose travel-related choices are reflected in a nested logit model. The individuals first choose between traveling in the peak or off-peak period. Then, they choose between traveling by car, bus, or bike. If individuals decide to travel by car and have no private parking space available, they also have to choose between on-street or off-street parking. Furthermore, individuals always have the outside option of not traveling at all.[1]

We then simulate various policy scenarios by applying the model to Berlin and New York City. One way for the social planner to maximize social welfare is by optimizing over a set of *traditional* policy variables. For car traffic, the planner can

[1] We label the outside option "no travel", but this option generally relates to the set of all alternatives with a fixed utility value. Hence, the outside option could also capture a subway system with fixed prices and service quality.

set a congestion toll in each period, the costs of on-street parking, and the costs of off-street parking. For bus traffic, the planner can set the bus frequency in each period, the bus fare in each period, the bus capacity, and the number of equidistant bus stops per km.

Most importantly for our research question, however, the social planner can also allocate the available street space across different transport modes. We define street space as the available area that city planners can use to accommodate different modes of transportation. In our model, the planner can then choose the share of street space that is exclusively allocated to cars, buses, cyclists, and parking. This allocation directly impacts on the travel times for each transport mode, as well as on the possibilities to park on-street. Therefore, a sensible allocation of street space is critical to maximizing the efficiency of the overall transportation system and, consequently, social welfare.

2.2 Model scope

As we focus on the allocation of street space, we only consider overground transportation in our model. For simplicity, we also assume that sidewalks are not part of the allocatable street space, more specifically that sidewalks have already been built and that this space cannot be allocated to other modes of transportation. First, this ensures that walking, e.g. to bus stations or off-street parking garages, is always possible. Second, sidewalks contribute to mobility equity, because they enable the more vulnerable groups to remain mobile (Clarke and Gallagher, 2013). For these individuals, enabling safe travel is more important than travel speed. Third, pedestrian spaces perform social and aesthetic functions that are unrelated to movement, for example providing space to communicate and relax (Nello-Deakin, 2019). Such essential functions of pedestrian street space would be difficult to capture in an economic model like ours.

In the course of our analysis, we mainly consider situations in which car traffic, bus traffic, and bicycle traffic are separated from each other. Even though mixed traffic, i.e. when two or more transport modes share the same street space, is still prevalent on many streets worldwide, there is evidence that separated traffic has advantages over mixed traffic. In particular, separated bike lanes are found to be safer (e.g. Lusk et al., 2013; Petegem et al., 2021), more inclusive for occasional and female cyclists (Aldred et al., 2017; Sanders and Judelman, 2018), and generally preferred by cyclists and potential cyclists (Winters et al., 2011). Even non-cycling drivers prefer separated bike lanes (Sanders, 2016). Additionally, exclusive bus lanes can reduce traffic accidents (Goh et al., 2013). They also reduce bus travel times and are found to be undersupplied from a welfare perspective (Russo et al., 2022). Hence, we mainly refrain from including mixed traffic in our model, because doing otherwise would run counter to our original goal of selectively allocating street space to specific modes of transport. We relax this restriction, however, in one sensitivity analysis.

2.3 Demand

In our model, we differentiate between two exogenously defined groups of individuals. Group 1 has no access to a private parking space, and Group 2 has such access. This differentiation is necessary to reflect the fact that individuals of Group 1 still have to decide where they park when choosing to go by car, whereas such a decision is not necessary for individuals of Group 2 who can simply park in their private parking space. The respective three-stage and two-stage decision processes of the two groups are outlined in Figure 1.

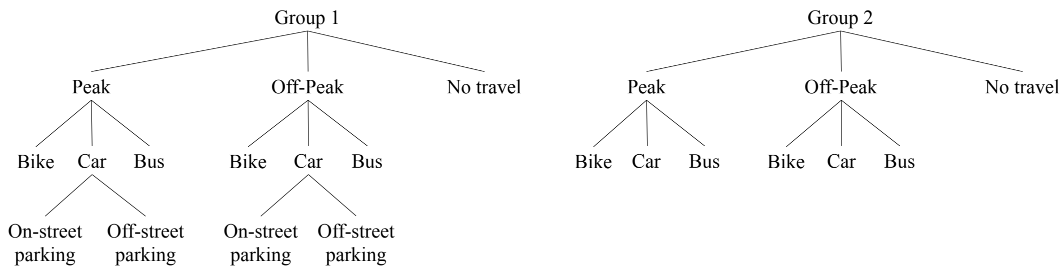


Figure 1: Decision Trees

At the upper level, the individual chooses between three nests: traveling in the peak period, traveling in the off-peak period, or not traveling at all. This decision is based on the expected utility of the respective nests. At the medium level, the individual then chooses between the three different transport modes, conditional on the earlier choice of the nest. The available transport modes are car, bus, and bike. This decision is based on the (expected) utility of each alternative. At the lower level, a car traveler of Group 1 additionally chooses between on-street parking or off-street parking. Again, this decision is based on the utility of each parking alternative.

In this section, we focus on the three-stage decision process for individuals of Group 1. We refrain from explicitly outlining the two-stage decision process for individuals of Group 2, as it is very similar, and only the parking decision at the lower level is missing.

Before outlining the relevant utility components at each of the three nesting levels, we would like to briefly discuss the chosen nesting structure. In nested multinomial logit (MNL) models, transport modes with similar characteristics are grouped in order to overcome problems caused by the Independence of Irrelevant Alternatives (IIA) assumption of non-nested MNL models. Koppelman and Bhat (2006), for example, show that transport modes such as bus and light rail might be grouped as a public transport nest, as they share certain characteristics. In our model, however, the three transport modes of car, bus, and bike are sufficiently distinct so that grouping transport modes would not be appropriate.[2] On the other hand, driving by car and parking on-street shares many characteristics with driving by car and parking off-street. Due to this high degree of similarity, these two alternatives are grouped together in a nest.

We now continue by describing the relevant utility components at each of the three nesting levels, beginning at the lowest level with the utility that an individual from Group 1 derives from parking. It can be written as

$$\begin{aligned} U^1_{q,Car,p} &= \lambda \cdot cost_{q,Car,p} + \beta_{q,Car} \cdot \phi_2 \cdot wt_p, \\ q &\in M_q = \{\text{Peak, Off-peak}\} \\ p &\in M_p = \{\text{On-street, Off-street}\} \end{aligned} \tag{1}$$

where $cost_{q,Car,p}$ are the monetary costs that accrue when parking, λ is the cost parameter, wt_p is the walking time associated with parking (e.g. walking from the parking space to the destination), $\beta_{q,Car}$ is the marginal utility of time for the transport mode car in time period q, and the parameter $\phi_2 > 1$ reflects the fact that time spent walking is perceived as worse than in-vehicle travel time.

The nested structure implies that the decision at each level is modeled as multinomial logit. Thus, the proportion of travelers that choose parking mode p, conditional on the choice of period q and choosing the transport mode car, is

$$\begin{aligned} \mathcal{P}^1_{p|(q,Car)} &= \frac{\exp\left(\frac{1}{\mu_l} \cdot U^1_{q,Car,p}\right)}{\sum_{s \in M_p} \exp\left(\frac{1}{\mu_l} \cdot U^1_{q,Car,s}\right)}, \\ q &\in M_q, \quad p \in M_p. \end{aligned} \tag{2}$$

Here, μ_l is the logsum parameter at the lower level and represents the heterogeneity of parking alternatives. The logsum parameter is generally bounded by zero and one, which ensures that it conforms to random utility maximization principles. When $\mu_l = 1$, there is no correlation between the parking alternatives. In such a case, the nested model would collapse to the non-nested model, which would be equivalent to having four alternatives at the medium level (i.e. car and on-street parking, car and off-street parking, bus, bike). For lower values of μ_l, the correlation between parking

[2] The three transport modes in our model differ with respect to costs, comfort, safety, and many other factors. Car drivers are, for example, not physically stressed (i.e. experience very little physical exhaustion), but shielded from direct contact to other traffic participants; bus passengers are neither physically stressed nor shielded from direct contact to other traffic participants; cyclists are physically stressed, but shielded from direct contact to other traffic participants.

alternatives increases and they become better substitutes. When μ_l converges to 0, both parking alternatives become perfect substitutes and everyone chooses the alternative with the higher value (Anderson and de Palma, 1992; Koppelman and Bhat, 2006).

Next, we can move to the medium level. For this level, the expected utility of the parking nest, which depends on the utilities of both parking alternatives, can be calculated with the logsum formula:

$$A^1_{q,Parking} = \mu_l \cdot \ln \left(\sum_{s \in M_p} \exp \left(\frac{1}{\mu_l} \cdot U^1_{q,Car,s} \right) \right) \tag{3}$$

The utility of choosing the car is then the utility of traveling by car, plus the expected utility of parking. This can be written as follows:

$$\begin{aligned} U^1_{q,Car} = \theta^1_{q,Car} + \lambda \cdot cost_{q,Car} + \beta_{q,Car} \cdot gt_{q,Car} + A^1_{q,Parking}, \\ q \in M_q, \end{aligned} \tag{4}$$

where $\theta^i_{q,Car}$ is the alternative-specific constant, $cost_{q,Car}$ are the monetary costs, and $gt_{q,Car}$ is the generalized travel time for traveling by car in period q. The monetary costs of the car consist of operational costs (maintenance, depreciation, fuel etc.) and a potential congestion toll. These costs are evenly allocated across all car passengers. Additionally, each transport mode is influenced by the alternative-specific constant θ^i_{qm}, which captures hard-to-measure factors such as comfort, perceived safety, or the general preferences for selected modes of transport. For Group 2, the utility of choosing the car is then very similar, but without the expected utility of parking:

$$\begin{aligned} U^2_{q,Car} = \theta^2_{q,Car} + \lambda \cdot cost_{q,Car} + \beta_{q,Car} \cdot gt_{q,Car}, \\ q \in M_q. \end{aligned} \tag{5}$$

For bus and bike, the utility for individuals of Group $i \in \{1, 2\}$ can similarly be written as:

$$\begin{aligned} U^i_{qm} = \theta^i_{qm} + \lambda \cdot cost_{qm} + \beta_{qm} \cdot gt_{qm},, \\ q \in M_q, \quad m \in \{\text{Bus, Bike}\}. \end{aligned} \tag{6}$$

When choosing the bus, the only monetary cost is the bus fare. For bikes, operational costs mainly consist of maintenance and depreciation. The generalized travel time consists of in-vehicle time for all modes, as well as waiting and walking time for the bus (from departure location to bus station and from bus station to destination).

The decision at the medium level is then again modeled as a multinomial logit and can be written as

$$\mathcal{P}^i_{m|q} = \frac{\exp\left(\frac{1}{\mu_m} \cdot U^i_{qm}\right)}{\sum_{r \in M_m} \exp\left(\frac{1}{\mu_m} \cdot U^i_{qr}\right)}, \tag{7}$$
$$q \in M_q, \quad m \in M_m.$$

where μ_m is the logsum parameter at the medium level, reflecting heterogeneity between transport modes. It is again bounded by zero and one, but it must also conform to $\mu_m \geq \mu_l$ in order to be consistent with utility maximization. This condition indicates that the parking alternatives in the lower nest are closer substitutes than the transport mode alternatives in the medium nest (Koppelman and Bhat, 2006).

We can now move to the upper level, where the decision is based on the expected utilities of the medium level. These utilities are again calculated with the logsum formula and can be written as:

$$A^i_q = \mu_m \cdot \ln\left(\sum_{r \in M_m} \exp\left(\frac{1}{\mu_m} \cdot U^i_{qr}\right)\right) \tag{8}$$

The expected utility from not traveling at all ($A^i_{notravel}$) is set to zero. The share of individuals who choose between traveling in period q or not traveling at all is given by

$$\mathcal{P}^i_n = \frac{\exp\left(\frac{1}{\mu_u} \cdot A^i_n\right)}{\sum_{r \in M_n} \exp\left(\frac{1}{\mu_u} \cdot A^i_r\right)} \tag{9}$$
$$n \in M_n = \{\text{Peak, Off-peak, no travel}\}$$

Here, μ_u represents the heterogeneity between periods. The logsum parameter μ_u is again bounded by zero and one, but must conform to $\mu_u \geq \mu_m$ so that transport mode alternatives in the medium nest are closer substitutes than alternatives in the upper nest (Koppelman and Bhat, 2006).

The number of individuals per hour and kilometer who choose transport mode m in period q can then be written as

$$Y_{qm} = \left(\sum_{i=1}^{2} Y^i \cdot \mathcal{P}^i_q \cdot \mathcal{P}^i_{m|q}\right) / H^q, \tag{10}$$
$$q \in M_q, \quad m \in M_m,$$

where Y^i is the number of individuals per kilometer who belong to Group i, and H^q

is the number of hours in period q. The number of individuals who do not travel is $Y_{notravel} = \sum_{i=1}^{2} Y^i \cdot \mathcal{P}^i_{notravel}$.

2.4 Monetary costs of traveling

In order to shed more light on the components of the utility functions in Equations 1, 4, 5, and 6, we now continue with a description of the actual monetary costs that are reflected in the *cost*-variables.

When an individual of Group 1 chooses to travel by car, he has to pay for parking. This parking fee per car and hour can differ between on-street parking (P_{parkon}) and off-street parking ($P_{parkoff}$). In combination with the average parking duration d_p and average car occupancy a, total parking costs per person amount to $P_{parkon} \cdot d_p/a$ for on-street parking, and $P_{parkoff} \cdot d_p/a$ for off-street parking.

In addition to the costs of parking, car travelers also have to pay operational costs (c_{car}), which include those for fuel, lubricants, maintenance, depreciation etc., and they have to pay a congestion charge ($P_{q,car}$) if congestion pricing is active. Both cost components are measured per kilometer and car. The individual driving costs (excluding parking costs) for a trip with length l and with equal cost allocation among passengers can then be written as $cost_{q,car} = (P_{q,car} + c_{car}) \cdot l/a$.

Bus travelers only pay a bus fare for each kilometer ($P_{q,bus}$), so that the costs for each bus trip are $cost_{q,bus} = P_{q,bus} \cdot l$. For cyclists, operational costs consist of maintenance and depreciation, so that $cost_{q,bike} = c_{bike} \cdot l$.

2.5 Transport times

The transport time functions that enter the utility functions in Equations 1, 4, 5, and 6 indicate that less dedicated street space or more people using that street space can lead to congestion, thereby reducing travel speed and increasing travel time.

2.5.1 Car

Parking We assume that on-street parking is always possible in the direct vicinity of the uniformly distributed departure and destination locations. Thus, on-street parking does not require additional walking time in our model, i.e. $wt_{parkon} = 0$. Off-street parking spaces such as parking garages are, however, not always in the immediate vicinity of the departure and destination locations. The average walking distance between the evenly distributed off-street parking spaces ($s_{parkoff}$) and the uniformly distributed departure locations is $1/(4s_{parkoff})$. The same holds for the distance between off-street parking spaces and destination locations. With an average walking speed of V_w, the average additional walking time for off-street parking is $wt_{parkoff} = 1/(2 \cdot s_{parkoff} \cdot V_w)$.

We assume that there is no cruising for parking in our model. This is due to the fact that the supply of parking spaces is always sufficient to serve parking demand (see also the explanations for Equations 18 and 24), and the assumption that cars are efficiently guided to open parking spaces through a smart parking guidance system.

In-vehicle travel time The walking time associated with parking is already accounted for at the lower level, so that we only need to include the remaining in-vehicle travel time at the medium level. Thus, the generalized travel time for a car driver at the medium level is defined as $gt_{q,car} = t_{q,car} \cdot l$, where $t_{q,car}$ is the in-vehicle travel time per kilometer in period q. This time depends on overall car flow, i.e. the number of cars per hour, and the capacity of the street space that is dedicated to cars. Car flow is defined as $l \cdot Y_{q,car}/a$, with $Y_{q,car}$ as the number of car travelers per hour and kilometer in period q, and a as the average car occupancy. The street space dedicated to cars is defined as the fraction *carlane* of available street space capacity C. The car travel time is calculated according to the well-established BPR formula (Bureau of Public Roads, 1964) and can be written as

$$t_{q,car} = t_f \cdot \left(1 + \alpha \cdot \left(\frac{l \cdot Y_{q,car}/a}{carlane \cdot C}\right)^{\beta}\right), \tag{11}$$

where t_f is the free-flow travel time in hours per kilometer, and α and β are parameter values for fitting the function. The exact parameterizations of BPR functions are based on the related literature and outlined in Appendix A.1.2.

2.5.2 Bus

Similar to Basso and Silva (2014), the generalized travel time for a bus user in period q is defined as $gt_{q,bus} = t_{q,bus} \cdot l + \phi_1 \cdot t_{q,w} + \phi_2 \cdot t_{acc}$, where $t_{q,bus}$ is the in-vehicle travel time, $t_{q,w}$ is the waiting time, and t_{acc} is the walking time to and from the bus stops. The parameters $\phi_1 > 1$ and $\phi_2 > 1$ indicate that the time spent waiting and walking is perceived as worse than the in-vehicle travel time.

Waiting and walking The time spent waiting for the bus ($t_{q,w}$) depends on the frequency of buses (f^q), and can be written as $t_{q,w} = \vartheta / f^q$, where ϑ is the fraction of the interval between two buses that constitutes waiting. We assume that $\vartheta = 0.5$, implying that arrival times at the bus stop are uniformly distributed.

Similar to the walking time that accrues when parking, the additional walking time when going by bus can be written as $t_{acc} = 1/(2 \cdot s_{busstop} \cdot V_w)$, where $s_{busstop}$ reflects the number of evenly distributed bus stops.

In-vehicle travel time The in-vehicle travel time for buses can be written as

$$t_{q,bus} = t_f \cdot \left(1 + \alpha \cdot \left(\frac{f^q \cdot b_{bus}(k)}{buslane \cdot C}\right)^{\beta}\right) + s_{busstop} \cdot \left(\frac{Y_{q,bus}}{f^q \cdot s_{busstop}} \cdot t_{sb} + t_d\right). \quad (12)$$

The first term on the right-hand side of this equation is again based on the BPR function. Here, travel time depends on the number of buses per hour (f^q) and the capacity of the street space that is dedicated to buses ($buslane \cdot C$). The overall street space capacity C is measured in car units and, as buses require more space than cars, the number of buses has to be converted into car units. This is done with the equivalence function $b_{bus}(k)$, which increases in bus capacity k, i.e. the size of the bus.

The second term reflects the additional time that a bus spends at each bus stop. It consists of boarding time and congestion at the bus stop, i.e. queuing to get in and out of the bus. The boarding time for each passenger is denoted as t_{sb}, and subsequently multiplied by the number of passengers boarding a bus at a bus stop, which is given by $Y_{q,bus}/(f^q \cdot s_{busstop})$. The congestion at the bus stop is given by t_d, which is a nonlinear function that depends on frequency, bus stop capacity, and numbers of passengers. The underlying formulas are not reported here for reasons of clarity, but they are based on microsimulations by Fernandez et al. (2002) and outlined in Basso and Silva (2014).

2.5.3 Bike

When traveling by bicycle, we assume that the generalized travel time for bikes consists only of the time actually spent riding the bike, so that $gt_{q,bike} = t_{q,bike} \cdot l$. This implies that bikes can always be parked at the desired location and that no additional walking is needed.
As outlined in an empirical study by Paulsen et al. (2019), congestion effects arise primarily from heterogeneity in cyclists' speed preferences, leading to a slowdown if scarce bike lane capacity prevents overtaking of slower cyclists. This can again can be modeled with a BPR function:

$$t_{q,bike} = t_f \cdot \left(1 + \alpha \left(\frac{l \cdot Y_{q,bike} \cdot b_{bike}}{bikelane \cdot C}\right)^{\beta}\right). \quad (13)$$

Hourly bicycle flow is given by $l \cdot Y_{q,bike}$ and, as bicycles require less space than cars, they are converted into car units with the factor b_{bike}. The capacity of the street space that is dedicated to bikes is $bikelane \cdot C$.

2.6 Revenue and operational costs

In the following, we calculate the daily revenue and costs that accrue when operating one kilometer of the entire transportation system. We again start by looking at the car, for which revenue can be generated from parking and tolls. Parking revenue is generated from the fees for on-street parking (P_{parkon}) and off-street parking ($P_{parkoff}$). In combination with the average parking duration and the number of parking cars per period, daily parking revenue per kilometer can be written as

$$\begin{aligned} rev_{park} =& P_{parkon} \cdot d_p \cdot \sum_q \left(Y_{q,car,parkon} \cdot H^q/a\right) \\ &+ P_{parkoff} \cdot d_p \cdot \sum_q \left(Y_{q,car,parkoff} \cdot H^q/a\right). \end{aligned} \tag{14}$$

If tolls are active, each car has to pay $P_{q,car}$ for each kilometer in period q. This would result in daily toll revenue per kilometer of

$$rev_{toll} = \sum_q P_{q,car} \cdot Y_{q,car} \cdot H^q \cdot l/a. \tag{15}$$

For buses, revenue can be generated from ticket fares $P_{q,bus}$ that each passenger has to pay per kilometer. The daily bus fare revenue per kilometer can be written as

$$rev_{bus} = \sum_q P_{q,bus} \cdot Y_{q,bus} \cdot H^q \cdot l. \tag{16}$$

In addition to generating money, the operation of the transport system also costs money. For parking, we consider costs for construction, operation, and maintenance of on-street and off-street parking spaces.[3] Parking costs can then be written as

$$cost_{parking} = c_{parkon} \cdot B_{parkon} + c_{parkoff} \cdot B_{parkoff} \tag{17}$$

where c_{parkon} and $c_{parkoff}$ are the daily costs for the construction, operation, and maintenance of each on-street and off-street parking space. B_{parkon} and $B_{parkoff}$ denote the number of on-street and off-street parking spaces that are needed to allow parking for each car. To calculate the maximum number of parked cars, we must consider that cars park for the duration d_p. The number of cars that are parked in a given hour is then determined by the cars that started parking in that hour, and the cars that started parking in the previous $d_p - 1$ hours. Consequently,

[3] We do not include costs for acquiring land in our model. First, against the backdrop of reallocating the available street space, we assume that our representative kilometer of street space is given, so that no costs would accrue for acquiring this land. Second, off-street parking is assumed to be in underground parking garages, for which no land costs would accrue (Litman and Doherty, 2009).

the maximum number of parked cars also depends on the sequence of peak and off-peak periods throughout the day. This number is usually determined by the sub-sequence of length d_p that contains the most peak hours (n^{max}_{Peak}), but it could also be determined by the sub-sequence that contains the most off-peak hours ($n^{max}_{Off-peak}$).[4] Hence, it follows that

$$B_p = max\Big\{\big(Y_{Peak,car,p} \cdot n^{max}_{Peak} + Y_{Off-peak,car,p} \cdot (d_p - n^{max}_{Peak})\big)/a,$$
$$\big(Y_{Off-peak,car,p} \cdot n^{max}_{Off-peak} + Y_{Peak,car,p} \cdot (d_p - n^{max}_{Off-Peak})\big)/a\Big\}. \tag{18}$$

The costs for running the congestion pricing system (e.g. traffic control, maintenance, etc.) are assumed to be the fraction η_{toll} of toll revenue (Basso and Silva, 2014).

The daily operation of the bus system costs

$$G = G_b(k) \cdot B_{bus} + G_v(k) \sum_q \cdot f^q \cdot H^q \cdot L. \tag{19}$$

The first term on the right-hand side consists of the costs for each bus per day ($G_b(k)$), which depends (linearly) on bus size k. This is multiplied by the required bus fleet $B_{bus} = max_q\{f^q \cdot t_{q,bus}\} \cdot L$, where L is the total distance that a bus has to drive during one cycle. The formula for B_{bus} also indicates that the required bus fleet depends on the period during which more travelers choose to go by bus, which consequently leads to idle capacity in the other period. The second term consists of the costs per vehicle kilometer $G_v(k)$, multiplied by the daily vehicle kilometers. As we generally report revenue and costs per kilometer and day, we still need to divide G by L. When doing so, L disappears from Equation 19, thereby also eliminating the need to estimate this parameter. The resulting costs per day and kilometer for operating the bus system are then defined as $cost_{bus} = G/L$.[5]

We do not include the operational costs for each driving lane that are caused by traffic control (e.g. traffic lights, signaling etc.), because these costs arise from the holistic optimization of the entire transportation system, and are therefore difficult to allocate to the individual modes of transport.

[4] If the parking duration d_p is 7 hours, we look for the 7-hour-sequence that contains the most peak periods, and the one that contains the most off-peak periods. Given a 20-hour sequence of (O,O,O,P,P,O,O,O,O,O,P,P,P,P,O,O,O,O,O,O; with P=peak and O=off-peak), a 7-hour-sequence would consist of a maximum of 4 peak periods ($n^{max}_{Off-peak} = 4$), and a maximum of 7 off-peak periods ($n^{max}_{Off-peak} = 7$). If the parking duration is not an integer value, we round it up and look at sub-sequences of length $\lceil d_p \rceil$. Additional information is provided in Appendix A.1.1.

[5] The underlying formulas for $G_b(k)$ and $G_v(k)$ are from Basso and Silva (2014).

2.7 Consumer surplus and social welfare function

Next, we calculate daily consumer surplus (CS) and social welfare (SW) for one kilometer of our representative street space. In the nested logit model, consumer surplus is calculated through the logsum formula (Anderson and de Palma, 1992):

$$CS = \sum_i \left(\frac{Y^i}{-\lambda^i} \cdot \mu_u \cdot \ln \left[\sum_n \exp \left(\frac{1}{\mu_u} \cdot A^i_n \right) \right] \right) \tag{20}$$

Finally, social welfare consists of consumer surplus, as well as the revenue and costs of operating the transport system for one kilometer and one day. It can be formalized as

$$\begin{aligned} SW = CS + \big(& rev_{park} + rev_{toll} \cdot (1 - \eta_{toll}) + rev_{bus} \\ & - cost_{park} - cost_{bus} \big) \cdot mcpf, \end{aligned} \tag{21}$$

Here, the net value of revenue minus costs is multiplied by the marginal costs of public funds ($mcpf$).

2.8 Optimization constraints

In our model, we optimize social welfare over various policy variables. As part of this optimization process, there are several constraints that must always hold, irrespective of the actual policy scenario that we analyze. The first set of these constraints stems from the fact that travel demand depends on travel times, but also impacts on travel times through congestion effects. Similar to Basso and Silva (2014), we solve this fixed-point problem by optimizing over demand, while including equilibrium equations as constraints. These constraints can be written as

$$\begin{aligned} 0 \leq Y^i_{nm} \leq Y^i & \qquad \forall\, i \in \{1,2\}, \quad \forall\, n \in M_n, \quad m \in M_m, \\ Y^i_{nm} = Y^i \cdot \mathcal{P}^i_n \cdot \mathcal{P}^i_{m|n} / H^q, & \qquad \forall\, i \in \{1,2\}, \quad \forall\, n \in M_n, \quad m \in M_m. \end{aligned} \tag{22}$$

When it comes to allocating street space, there are two constraints that have to be considered. First, the total size of the dedicated lanes cannot be larger than the overall available street space. Thus, the non-negative shares of each dedicated lane are constrained by

$$carlane + buslane + bikelane + parklane \leq 1. \tag{23}$$

In our model, the policy variables *carlane*, *buslane*, *bikelane*, and *parklane* correspond to fractions of total street space that are dedicated to each transport mode. Hence, these variables can take any value between 0 and 1, implying that street space can be divided continuously, similar to Zheng and Geroliminis (2013) or Börjesson et al. (2017). We think that such a continuous allocation is a reasonable assumption, because we explicitly model traffic for a representative kilometer of street space. This kilometer is then representative of a larger street network in which parallel streets can be grouped, so that some streets could be dedicated exclusively to buses, and parallel streets to cars. Of course, it is not necessary to always dedicate entire streets to one transport mode, because dedicating selected lanes (e.g. bus lanes or bike lanes) to certain transport modes is also possible. In some cities, comparable designs of street networks have already been put into practice, and the resulting wide range of possible street space allocations then underlines the generality of our continuous optimization of street space allocation. We verify the general results from this continuous street space allocation, however, by also running a scenario where we impose a minimum share of street space that must be allocated to each purpose (please refer to Footnote 8 for a more detailed description of this scenario and its results).

Second, we must ensure that there is always enough on-street parking space to accommodate every car driver who chooses to park on-street. Hence, the available street space in each hour must be at least equal to the space required by on-street parking cars. This can be formalized as

$$B_{parkon} \cdot s_{req} \leq parklane \cdot w \cdot 1000, \tag{24}$$

where s_{req} is the space that a car requires for parking [m^2/car], and w is the width of the street [m], so that $w \cdot 1000$ equals the area of our representative kilometer of street space in m^2.

Moreover, bus fares, congestion tolls, and parking fees are constrained to be non-negative. Bus frequency must be positive, but less than the capacity of bus stops.[6] Additionally, the bus size has to be sufficiently large so that all passengers can be transported in both periods. Thus, bus capacity must be

$$k \geq \frac{Y_{q,bus} \cdot l}{f^q} \qquad \forall\, q \in M_q. \tag{25}$$

This constraint is binding in at least one period, but there might be idle capacity in the other period (usually the off-peak period).

[6]To calculate bus stop capacity, we follow the microsimulations that are outlined in Basso and Silva (2014).

3 Analysis

3.1 Setting

We apply our theoretical model to the cities of Berlin and New York City. These cities are chosen because they share important characteristics that motivate the analysis of street space allocation. First, they are severely affected by congestion, as shown by travel times during peak hours in 2019, which were 32 % and 37 % longer, respectively, than under uncongested conditions (TomTom, 2019). Second, street space in both cities is strongly skewed towards cars and parking, which take up more than 50 % of total street space, and more than 90 % of the street space considered in this model, i.e. cars, parking, buses, and bikes (Agentur für Clevere Städte, 2014; Transportation Alternatives, 2021). Third, both cities have conducted larger projects to re-allocate street space from cars to bikes and pedestrians, especially during the Covid-19 pandemic (Buehler and Pucher, 2021a, 2022). These characteristics highlight the relevance and importance of studying the effects of street space re-allocations for both cities.

Additionally, however, these two cities are also chosen because they differ with respect to their attitude towards cycling. Considering only trips by car, bus, and bike, the share of cycling is 34.8 % in Berlin, and only 4.3 % in New York City, indicating that cycling is a more established transport mode in Berlin. This difference allows us to study whether the role of cycling might influence the economic effects of street space re-allocations, and the analyses of these two cities may therefore be informative for policymakers in cities with varying degrees of cycling intensities.

3.2 Model calibration

To ensure that our model reflects the actual choice behavior and travel conditions in Berlin and New York City, we conduct separate calibrations for both cities in a manner similar to Basso and Silva (2014) and Börjesson et al. (2017). More precisely, we undertake three main steps, which are briefly summarized below and outlined in more detail in Appendix A.

First, we set many model parameters according to the values that we calculated from city-specific travel surveys or found in the relevant transport literature.

Second, we calibrate the remaining model parameters in such a way that choice behavior in our model would reflect real-world choice behavior as closely as possible. In particular, the calibration ensures that the actually observed values for our policy variables would lead to the actually observed modal shares in the cities, and that important travel elasticities are similar to the values reported in the literature.

Third, we check the validity of our calibration by computing various travel elasticities and cross-elasticities from our calibrated model and comparing them to the values from the literature. This comparison shows that our calibrated choice model indeed reflects real-world choice behavior very well.

The calibrated models for Berlin and New York City are subsequently used to evaluate the economic effects of street space re-allocations in both cities.

3.3 Main scenarios

In order to get a better understanding of the economic effects of street space re-allocations, we analyze four counterfactual scenarios:

1. Reference: The street space allocation and most traditional policy variables are similar to the real-world situations in Berlin and New York City.[7] The main deviation from reality is then our focus on separated traffic. Hence, this counterfactual scenario is an ideal starting point for evaluating the effects of various transport policies and street space allocations under separated traffic.

2. Traditional: The street space allocation is still similar to the real-world situation, but the social planner can now optimize welfare over traditional policy variables. This allows us to evaluate by how much efficiency could be improved if the street space allocation remained fixed.

3. Space: Most traditional policy variables are similar to the real-world situation, but the social planner can now optimize welfare over the street space allocation. This allows us to evaluate by how much efficiency could be improved if traditional policy variables remained fixed.

4. Traditional + Space: In this scenario, the social planner can optimize welfare over the choice of the street space allocation, as well as over traditional policy variables. From a welfare perspective, this scenario then reflects an *ideal* allocation of street space.

Besides the optimization constraints that must always be satisfied (see Section 2.8), we then include additional constraints to model the above scenarios. These additional constraints generally fix the street space allocation or selected policy variables to specific values, dependent on the respective scenarios.

[7]Traditional policy variables include car tolls, bus fares, and bus frequencies for peak and off-peak hours; parking fees for on-street and off-street parking; bus size and the number of bus stops per kilometer. We label these variables as "traditional" because there already is extensive literature on their economic effects. In Scenarios 1 and 3, the parking fees and bus size cannot be fixed to their real-world values, but have to be chosen by the model. Otherwise, the inefficient usage of parking space and bus capacity would lead to a model optimization failure.

3.4 The impact of street space allocation on economic efficiency

An overview of the simulation results for the four main scenarios in Berlin and New York City is illustrated in Figure 2, where street space allocations and their efficiency gains with respect to the REFERENCE scenario are depicted. In the REFERENCE scenario in Berlin, 4.9 % of street space is allocated to bikes, 1.3 % to buses, 62.6 % to driving cars, and 31.2 % to parking (based on Agentur für Clevere Städte, 2014). In New York City, 1.2 % is allocated to bikes, 1.7 % to buses, 69.4 % to driving cars, and 27.7 % to parking (based on Transportation Alternatives, 2021).

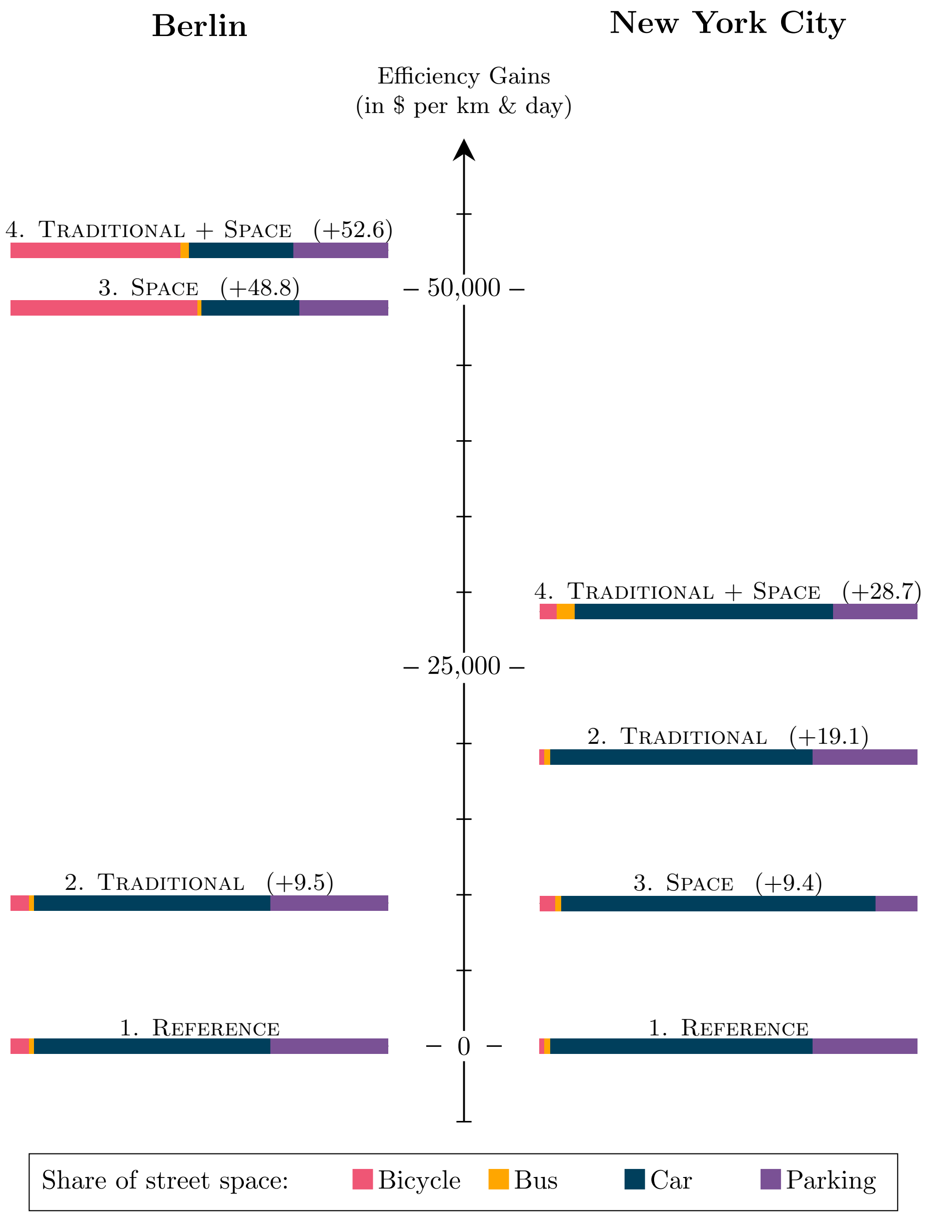


Figure 2: Efficiency gains of main scenarios

If policy makers have to take the current street space allocation as given and can optimize only over traditional policy variables (Scenario 2), the efficiency of the transportation system can be improved by \$9,455 per kilometer and day in Berlin, and by \$19,111 in New York City.

In Scenario 3, the traditional policy variables are fixed to their real-world values and policy makers can optimize only over the street space allocation. This would result in strong re-allocations in Berlin, with efficiency gains of \$48,795. On the other hand, the optimal re-allocations in New York City are less extreme and result in lower efficiency gains of \$9,428.

The greatest efficiency gains are realized in Scenario 4, in which policy makers can optimize over traditional policy variables as well as over street space allocation. In Berlin, the street space for bikes increases to 45.0 % and for buses to 2.2 %, whereas the space for driving cars decreases to 27.7 %, and for parking to 25.2 %. This allocation then leads to efficiency gains of \$52,610 per kilometer and day, relative to the Reference scenario. In New York City, the maximum attainable efficiency gain is \$28,715, and thus less extreme than in Berlin. This is due to the fact that the accompanying street space re-allocations are also less extreme. The street space for cars is only reduced to 67.3 % and for parking to 23.3 %. The space for buses increases to 4.8 %, and for bikes to 4.6 %.[8] The results for both cities underline the importance of street space re-allocation as an effective policy instrument. Leaving the allocation of street space untouched wastes significant potential for improving the efficiency of transportation systems.

3.5 Main results for Berlin

3.5.1 Analysis of the underlying economic channels of impact

We now proceed by shedding more light on the underlying economic channels that lead to the efficiency effects illustrated in Figure 2. We explain and discuss these channels by looking at the changes between the respective scenarios. This also includes an examination of policy variables, modal shares, travel speed, and monetary outcomes of the transportation system, which are outlined in Table 1. All monetary values in the subsequent analyses, including the monetary values from other sources, are presented in 2020 US dollars.

[8] The continuous allocation of our representative street space allows for very small values, e.g. 2.2 % or 4.6 %. To test the results of this continuous allocation, we run a scenario where we impose a minimum share of 1/8 that must be allocated to each purpose. This minimum would correspond to one entire lane of two parallel three-lane corridors with adjacent parking lanes. In Berlin, allocating 44.2 % to bicycles, 12.5 % to buses, 25.5 % to cars, and 17.8 % to parking increases social welfare by \$50,647. In New York City, an allocation of 12.5 % to bicycles, 12.5 % to buses, 59.6 % to cars, and 15.4 % to parking increases social welfare by \$22,474. Hence, imposing a minimum share that must be allocated to each purpose does not change the direction of our overall results.

Table 1: Main results (Berlin)

Scenario	Reference	Traditional	Space	Traditional + Space
Social welfare	0.000	9455.253	48795.292	52610.463
Consumer surplus	0.000	161.766	21780.789	28276.423
People	12500	12500	12500	12500
Travelers	11906.277	11902.592	12057.977	12093.767
Share of space for bicycles	0.049	0.049	0.492	0.450
Share of space for buses	0.013	0.013	0.013	0.022
Share of space for cars	0.626	0.626	0.260	0.277
Share of space for parking	0.312	0.312	0.235	0.252
Bus fare (peak)	0.324	0.000	0.324	0.000
Bus fare (off-peak)	0.324	0.000	0.324	0.000
Car toll (peak)	0.000	0.716	0.000	0.672
Car toll (off-peak)	0.000	0.000	0.000	0.000
Parking fee (on-street)	1.208	1.063	1.530	1.156
Parking fee (off-street)	0.000	0.000	0.728	0.447
Bus frequency (peak)	12.000	16.464	12.000	19.952
Bus frequency (off-peak)	8.000	13.545	8.000	17.369
Bus size	62.185	72.731	45.560	43.325
Number of bus stops	3.800	2.945	3.800	2.746
Share of peak travelers	0.379	0.333	0.509	0.482
Share of off-peak travelers	0.573	0.619	0.455	0.486
Share of non-travelers	0.047	0.048	0.035	0.032
Modal share of car (peak)	0.654	0.496	0.193	0.156
Modal share of bus (peak)	0.160	0.293	0.087	0.146
Modal share of bicycle (peak)	0.186	0.212	0.720	0.698
Modal share of car (off-peak)	0.655	0.617	0.318	0.357
Modal share of bus (off-peak)	0.095	0.151	0.089	0.138
Modal share of bike (off-peak)	0.251	0.232	0.593	0.505
Speed of cars (peak)	17.947	41.088	20.400	39.412
Speed of buses (peak)	22.706	20.688	24.415	27.460
Speed of bicyles (peak)	8.379	8.345	19.012	18.999
Speed of cars (off-peak)	42.426	41.540	45.898	40.225
Speed of buses (off-peak)	25.833	25.983	26.797	30.859
Speed of bicycles (off-peak)	11.680	11.675	19.997	19.997
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000
Used parking spaces (on-street, minimum)	0.674	0.960	0.661	0.960
Share of on-street parking (peak, all travelers)	0.095	0.125	0.181	0.220
Share of on-street parking (off-peak, all travelers)	0.090	0.119	0.174	0.212
Net revenue of operating transport systems	-20552.954	-12471.661	2937.918	607.081
Parking system: revenue	4221.988	4275.866	10770.518	8026.291
Parking system: costs	25772.224	19271.295	8559.526	7686.651
Toll system: net revenue	0.000	4362.352	0.000	1867.419
Bus system: revenue	2128.230	0.000	1702.326	0.000
Bus system: costs	1130.948	1838.583	975.399	1599.978

The street space shares are adjusted for car, bus, bike, and parking. Space for pedestrians and others is excluded, but takes up 33 % and 6 % of total street space in reality.
The modal shares are adjusted for the three overground transport modes car, bus, and bike. Overground transport makes up 50.6 % of overall traffic.

Reference First, it should be noted that our Reference does not aim to represent the real world as accurately as possible, but intentionally deviates from reality and should therefore be considered a counterfactual scenario.

The most important deviation from the real world stems from the fact that we only model separated traffic, which was motivated and discussed in Section 2.2. Hence, buses and bikes actually have less street space in our model than in reality, because they cannot use the space allocated to cars. At the same time, cars have more space in our model and are no longer slowed down by frictions with other modes of transport, so that driving by car is more attractive and the modal share of cars is roughly 15 pp higher than in reality. This effect is even stronger in the off-peak period, because congestion constrains the increase in car travel speed in the peak period. As a result, traveling in off-peak periods is more attractive, and the share of off-peak travelers is about 10 pp higher than in reality.

The second deviation from reality is more technical. Most policy variables in our Reference scenario are set to their real-world values, but parking fees and bus size have to be chosen by the model. Taking real-world values would lead to an inefficient usage of parking space and bus capacity, and subsequently to a model optimization failure, as the model is geared towards efficiency.

Despite these deviations, the Reference scenario reflects most real-world policy choices and results in a situation that would appear reasonable for completely separated traffic. Consequently, this scenario can indeed serve as an adequate reference point for evaluating the efficiency gains of the other scenarios.

Traditional The allocation of street space remains fixed, but policy makers can now optimize over all other policy variables. In this scenario, as well as in all other scenarios with flexible policy variables, bus tickets are always completely subsidized. Free tickets and slightly higher frequencies than in the Reference scenario increase the attractiveness of buses, thus shifting people to this transport mode and subsequently relieving car congestion. To increase the capacity of the entire bus transportation system, the size of buses is increased.

The fixed street space allocation reduces the ability of policy makers to impact on travel speed and modal shares. Therefore, a congestion toll of \$0.72 per kilometer is introduced to account for congestion externalities in peak hours. This reduces the modal share of cars in peak periods, thereby increasing car speed. Moreover, the congestion toll helps to harmonize the absolute number of cars between peak and off-peak hours, resulting in a much better utilization of on-street parking space in lower-demand periods.

To compensate for the congestion toll, the on-street parking fee is slightly reduced. Interestingly, the fee for on-street parking is at \$1.06 per hour, while off-street parking is free. At first glance, this might seem surprising, as the monetary costs of constructing and maintaining one on-street parking space are much lower than those of one off-street parking space in an underground parking garage. However, the total costs of on-street parking spaces include not only the monetary costs, but also the negative externalities on the travel times of all transport modes. These externalities appear to be very costly, thus driving up the fees for on-street parking.

Off-street parking is free, so that using the car is still attractive enough.

The use of public funds is significantly reduced in this scenario, mainly due to congestion pricing and the reduction in the number of necessary parking spaces.

Space The traditional policy variables remain fixed, but policy makers can now optimize over the allocation of street space. The result is a very strong re-allocation of street space from cars and parking to bicycles, with a tenfold increase in space for cyclists. This enhances cycling conditions, so that cycling speed more than doubles in the peak period, and also increases substantially in the off-peak period. Consequently, the modal share of cycling increases to 72.0 % in peak hours, and 59.3 % in off-peak hours.

On the other hand, the space for cars is substantially reduced. This reduction would increase congestion and slow cars down, but the above-outlined shift to bikes counteracts this effect and increases speed again. In this case, the former effect is weaker than the latter, so that car speed increases modestly in contrast to the Reference scenario. The re-allocation of street space from cars to bicycles thus helps to relieve car congestion. As policymakers have no instrument to differentiate between periods, however, street space for cars cannot be used efficiently in both the peak and the off-peak period, which is underlined by the speed difference between the two periods.

Space for on-street parking is also reduced, which is reflected in the highest on-street parking fee ($1.53 per hour). This fee accounts for the negative externality that an additional on-street parking space has on car travel speed, an externality that increases if the space for cars becomes scarcer. Additionally, off-street parking is now priced at $0.73 per hour. This would not have been sensible in the previous scenario, because bikes were already severely affected by congestion. An off-street parking fee would then have exacerbated bike congestion by shifting car users to these modes. In this scenario, however, bikes have more space, thus reducing their congestion problems and enabling charging off-street parking fees.

The operation of the entire transport system now results in positive net revenues, mainly due to higher parking fees and the reduction in the number of necessary parking spaces. This clearly outweighs the reduction in congestion pricing revenue.

Traditional + Space Economic efficiency is maximized in this scenario. Now, most traditional policy variables are set comparable to the Traditional scenario. The largest efficiency gain compared to the previous Space scenario then comes from the congestion toll, which harmonizes car traffic between peak and off-peak hours. As a result, street space for cars is now used efficiently and congestion is significantly reduced in both periods.

Regarding the street space allocation, the space for buses is set to 2.2 % of street space. This allocation leads to an increase in bus space compared to the Reference scenario (+0.9 pp). In general, the rather small percentage of street space that is allocated to buses underlines the space-efficiency of this transport mode.

Bikes are allocated 45.0 % of street space, reflecting a substantial increase from the Reference scenario (+40.1 pp). Allocating that much street space to cycling reduces congestion for cyclists and ensures fast cycling, thereby increasing the attractiveness of cycling and inducing modal shifts.

The space for cars is reduced to 52.9 %, a substantial reduction from the Reference scenario (−40.9 pp). The remaining space for cars is divided approximately half-half between driving (27.7 %) and on-street parking (25.2 %). Although on-street parking spaces have a negative externality on driving speed, they are still provided as they have much lower construction and maintenance costs compared to off-street parking. The negative speed externality is then reflected in the on-street parking fee, which is again higher than the off-street parking fee.

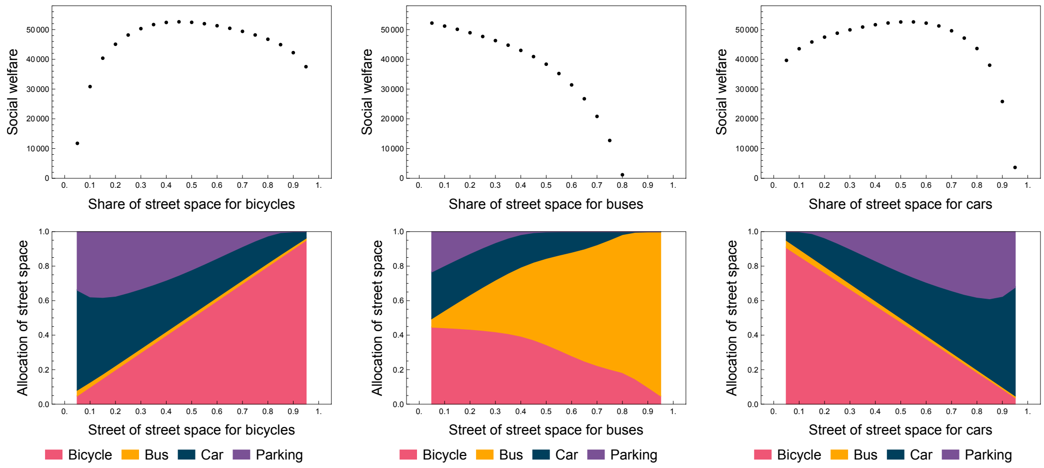
Again, the operation of the entire transport system results in positive net revenues. The costs of the bus system are more than covered by the positive net revenues from the parking and toll system.

Transport-mode-specific impact of allocated space on economic efficiency After looking at the main scenarios, we now extend our discussion on the underlying economic channels by illustrating how the share of street space that is allocated to a specific transport mode impacts on social welfare.

The upper part of Figure 3a shows the maximum obtainable social welfare, dependent on the share of street space allocated to bikes. The lower part then depicts the corresponding street space allocation.[9] If the street space for bikes is scarce, the marginal benefit of re-allocating space to bikes is rather high, because it can greatly help to make cycling more attractive, thereby inducing modal shifts and also mitigating congestion for cars. If street space for bikes is between 30 % and 65 %, social welfare is less than 1 % below the optimum in Scenario 4. Allocating even more street space to bikes reduces social welfare, but at a slower pace than the previous gains. Hence, it appears that too little space for bikes is worse than too much.

Scenario 4 has shown that it is efficient to only allocate 2.2 % of street space to buses. This is also emphasized in Figure 3b, where social welfare clearly decreases with more space that is allocated to buses. As buses only need relatively little space

[9]To generate these Figures, we maximize social welfare over the choice of traditional policy variables and the street space allocation (similar to Scenario 4), but we gradually constrain the share of street space allocated to a given mode of transport. For Figure 3a, for example, we begin by allocating 5 % of street space to bicycles, and proceed in steps of 5 pp until 95 % of street space is allocated to bicycles.



(a) Street space for bike (b) Street space for bus (c) Street space for car

Figure 3: Transport-mode-specific impact of allocated space on economic efficiency (Berlin)

to generate decent passenger throughput, re-allocating more than 2.2 % of street space to buses only worsens the conditions for cars and bikes without improving those for buses. As a consequence, social welfare would decrease.

Figure 3c then shows that social welfare is dependent on street space allocated to cars. If street space for cars is very scarce, it is entirely used for driving, and all cars must be parked off-street. At 15 %, the parking lane is still only 1 % of total street space, because the negative externality on car speed would be relatively strong and outweigh the higher costs of off-street parking spaces. From then onwards, however, this externality decreases, and the parking lane increases stronger than the driving lane. Thereby, more cars can park on-street, and expensive off-street parking spaces can be reduced. In the optimum, the driving lane is 27.7 %, and the parking lane is 25.2 % of overall street space. Both lanes only equalize when about 60 % of the total street space is allocated to cars, and allocating even more street space to cars further decreases social welfare, with reductions becoming progressively stronger from 75 %.

3.5.2 The efficient street space allocation in Berlin

To sum up the most efficient scenario, the space for cars is reduced significantly and a congestion toll makes using the car more expensive. Nonetheless, car drivers benefit from much faster speeds. Bus passengers benefit from free tickets and faster travel times due to higher frequencies and less congestion. The space for bikes is increased significantly, so that cyclists benefit from cycling speeds that are close to free-flow speeds. Moreover, the transportation system now even generates revenue, mainly due to the reduction in parking space capacity (especially off-street), consistent pricing of all parking spaces, and the introduction of a peak congestion toll.

Comparing the resulting street space allocation with the current allocation is not straightforward, because we model only separated traffic, whereas mixed traffic is still prevalent on many streets. In reality, bikes can therefore use more street space than the 4.9 % they are currently exclusively allocated, and the *real* increase in street space for cyclists is consequently less extreme than suggested by the model results. Nevertheless, the street space re-allocation from cars to bikes should still be substantial, as indicated by the almost tenfold increase in bike space and the approximate halving of car space.[10] The scope of such an ambitious re-allocation would approximately correspond to Barcelona's *superblock* project that re-allocates roughly 70 % of car space to pedestrians and cyclists (Rueda, 2019), and is expected to improve health by reducing air pollution, noise, and heat (Mueller et al., 2020).

Previous papers have not analyzed how much street space should be allocated to bikes, so we cannot directly relate our results to the literature. Even so, Zheng and Geroliminis (2013) as well as Börjesson et al. (2017) analyze the street space allocation for cars (without parking spaces) and buses. Both find that buses should be allocated around 10 % of the street space for these two transport modes. In our analysis, buses are allocated roughly 7 % of the street space for cars (without parking spaces) and buses. It should be noted, however, that Zheng and Geroliminis (2013) use a different objective function and minimize passenger-hours traveled, whereas Börjesson et al. (2017) and we ourselves maximize over social welfare.

The average daily modal share for bikes is 60.1 % in the efficient scenario. This value refers, however, to the adjusted modal share of the three transport modes of car, bus, and bike. They account for only 50.6 % of overall traffic, so that the actual modal share of bikes would be reduced to 30.4 %. This is a significant increase from the actually observed 17.6 % (Gerike et al., 2019) and would place Berlin between Copenhagen (29 %) and Amsterdam (36 %), arguably the two most renowned cycling cities. In both of these cities, the expansion and improvement of bicycle infrastructure, often separated from other modes, is regarded as the basis for the success of cycling (Koglin et al., 2021).

The parking prices in our model are, at first glance, relatively low, with \$1.16 per hour for on-street parking and \$0.45 for off-street parking. These prices are, however, based on the assumption that there is no longer any discounted parking for residents, and that each parking space is priced consistently. This is in stark contrast to Berlin

[10] It should be noted that we generally consider street space to be the same as capacity, and indeed, re-allocating street space is the most obvious way to re-allocate capacity. We could, however, also re-allocate capacity by changing how selected modes of transport are prioritized by traffic lights (e.g. Qadri et al., 2020). The herein presented changes in the street space allocation might therefore be less pronounced if part of the capacity re-allocation were achieved through changes in traffic light systems.

in 2020, where residents only had to pay \$11.65 per year to use residential parking, which amounts to a meagre \$0.03 per day. In our model, the daily cost for on-street parking would increase to \$27.84, and \$10.80 for off-street parking. The high price for on-street parking is driven by the scarcity of street space, as well as the negative externality on travel speeds. Off-street parking spaces are relatively cheaper and cost less than the willingness to pay for a daily residential parking permit, which van Ommeren et al. (2011) estimate to be \$15.75 in Amsterdam. A permanent parking space in an underground garage in Berlin would then cost roughly \$320 per month. This is more expensive than the prices found in reality, but it should be kept in mind that the real prices for parking spaces in Berlin are distorted downwards by the supply of cheap residential parking permits.

The peak car toll of \$0.67 per kilometer would, on average, result in about \$3.95 per trip. Thus, it is close to the real-world values for Stockholm (between \$3.28 and \$4.91 per one-hour trip during peak, and maximum \$14.71 per day), but slightly below the real-world values for London (\$19.52 per day).[11]

The bus service is fully subsidized, so that riding the bus is free. Basso and Silva (2014) also find an optimal subsidy of 100 % for London, and Parry and Small (2009) find that large subsidies are warranted from a welfare-perspective. On the other hand, Börjesson et al. (2017) find that the optimal subsidy for Stockholm lies around 30-40 %.

In conclusion, we find that the policy variables and traffic outcomes in the efficient scenario generally take on quite realistic values. The re-allocation of street space from cars to bikes would surely be substantial, but still comparable in scale to Barcelona's *superblock* project.

3.6 Main results for New York City

3.6.1 Analysis of the underlying economic channels of impact

The detailed results for New York City are presented in Table 2. In general, the underlying channels through which street space re-allocations impact on social welfare are similar to those in Berlin, so we continue by focusing only on the main similarities and differences between the cities.

Similar to Berlin, we find that even if the street space allocation is fixed, economic efficiency can still be improved by providing free bus transport at higher frequencies, and introducing a congestion toll while slightly lowering on-street parking prices. These policies shift people from cars to buses, thereby reducing car congestion and travel times.

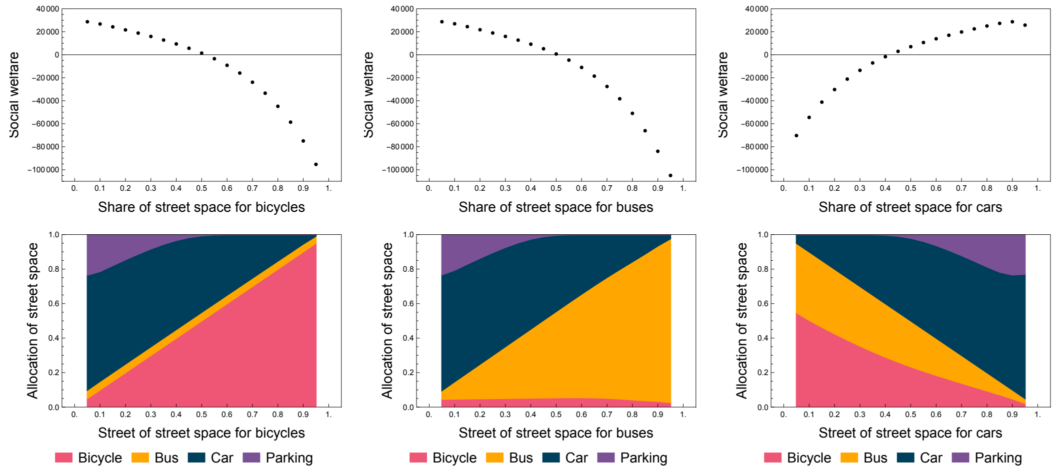
[11] Monetary values for Stockholm and London were taken from the official web pages of the congestion pricing system, and subsequently converted to 2020 US dollars.

Table 2: Main results (New York City)

Scenario	Reference	Traditional	Space	Traditional + Space
Social welfare	0.000	19111.225	9428.178	28715.077
Consumer surplus	0.000	3423.127	19919.588	7732.785
People	14800	14800	14800	14800
Travelers	14572.187	14581.722	14607.195	14590.688
Share of space for bicycles	0.012	0.012	0.042	0.046
Share of space for buses	0.017	0.017	0.015	0.048
Share of space for cars	0.694	0.694	0.832	0.673
Share of space for parking	0.277	0.277	0.112	0.233
Bus fare (peak)	0.508	0.000	0.508	0.000
Bus fare (off-peak)	0.508	0.000	0.508	0.000
Car toll (peak)	0.000	0.686	0.000	0.949
Car toll (off-peak)	0.000	0.000	0.000	0.000
Parking fee (on-street)	3.148	2.958	4.154	3.013
Parking fee (off-street)	0.000	0.000	0.000	0.010
Bus frequency (peak)	12.000	23.148	12.000	48.862
Bus frequency (off-peak)	8.000	19.986	8.000	41.356
Bus size	49.768	46.480	42.226	26.392
Number of bus stops	3.900	2.950	3.900	2.868
Share of peak travelers	0.650	0.630	0.689	0.635
Share of off-peak travelers	0.335	0.356	0.298	0.350
Share of non-travelers	0.015	0.015	0.013	0.014
Modal share of car (peak)	0.831	0.717	0.822	0.625
Modal share of bus (peak)	0.131	0.243	0.105	0.289
Modal share of bicycle (peak)	0.039	0.039	0.073	0.086
Modal share of car (off-peak)	0.888	0.819	0.889	0.797
Modal share of bus (off-peak)	0.073	0.145	0.070	0.165
Modal share of bike (off-peak)	0.039	0.036	0.041	0.038
Speed of cars (peak)	19.769	30.017	27.231	35.849
Speed of buses (peak)	23.622	23.073	24.200	27.581
Speed of bicyles (peak)	12.917	13.098	19.370	19.320
Speed of cars (off-peak)	42.300	43.317	53.229	43.844
Speed of buses (off-peak)	26.296	27.396	26.697	30.837
Speed of bicycles (off-peak)	18.846	19.025	19.998	19.998
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000
Used parking spaces (on-street, minimum)	0.573	0.701	0.460	0.782
Share of on-street parking (peak, all travelers)	0.051	0.062	0.019	0.060
Share of on-street parking (off-peak, all travelers)	0.049	0.059	0.018	0.057
Net revenue of operating transport systems	-31968.737	-18326.913	-41091.702	-13723.267
Parking system: revenue	9196.959	9275.070	4571.517	8691.240
Parking system: costs	43200.863	35789.135	47321.820	31478.263
Toll system: net revenue	0.000	10311.055	0.000	12520.165
Bus system: revenue	3100.865	0.000	2656.675	0.000
Bus system: costs	1065.699	2123.903	998.074	3456.408

The street space shares are adjusted for car, bus, bike, and parking. Space for pedestrians is excluded, but takes up 23.7 % of total street space in reality.
The modal shares are adjusted for the three overground transport modes car, bus, and bike. Overground transport makes up 43.6 % of overall traffic.

In contrast to Berlin, however, optimizing over the street space allocation in New York City leads to lower efficiency gains than optimizing over traditional policy variables. The main reason for this difference is the general preference for the three modes of transportation, which are reflected in the alternative-specific constants. The city-specific calibration of the theoretical model results in alternative-specific constants that are slightly higher for bikes than for cars in Berlin, whereas they are much lower for bikes than for cars in New York City.[12] This implies that there is a strong preference for cars in New York City, so that shifting people away from cars can quickly become welfare-reducing. This is also illustrated in Figures 4a and 4b, where welfare basically decreases if more than 5 % of street space is allocated to either buses or bikes. Figure 4c then also underlines that those two modes are roughly equally attractive, independent of the space for cars.



(a) Street space for bike (b) Street space for bus (c) Street space for car

Figure 4: Transport-mode-specific impact of allocated space on economic efficiency (New York City)

The general preference for cars in New York City also results in an efficient street space allocation that is not too different from the real situation. The space for driving cars is reduced only slightly to 67.3 % (−2.1 pp), and the space for parking is reduced to 23.3 % (-4.4 pp). The space for buses increases to 4.8 % (+3.1 pp), and for bikes to 4.6 % (+3.4 pp). At first glance, these changes might seem small, but the space for buses is nearly tripled, and for bikes even more than tripled. However, as individuals in New York City are less willing to switch to buses or bikes, it would not be sensible to reduce the space for cars too much. This ensures that individuals who do not want to switch to buses or bikes are not affected too negatively by longer car travel times, thereby providing a rationale for the mitigated effectiveness of street space re-allocations in New York City.

3.6.2 The efficient street space allocation in New York City

The extent of the proposed street space re-allocations is significantly less pronounced than in Berlin, because the current situation is already rather close to the optimum

[12]In Section 4.3, we further discuss the role of the alternative-specific constants in our model.

for New York City. As a consequence, the proposed re-allocations are feasible, but they are also less effective in improving efficiency.

In Scenario 4, the adjusted modal share of cycling increases to 6.9 % (+2.6 pp), compared to reality. Given the general preference for cars, this modest increase appears reasonable in our model context. The underlying assumption that the general transport preferences are constant is, however, further discussed in Section 4.3.

Most of the other model results are also reasonable and in line with findings from Berlin. Again, the space for buses is roughly 7 % of that for driving cars and buses, and bus tickets in New York City are free as well. The peak congestion toll for an average trip amounts to $4.95, and is thus higher than the congestion toll that was simulated for Berlin. This substantially increases the costs for cars, which in turn can explain the very low monthly price for parking in an off-street parking garage, now at only about $7.30. Expensive congestion charges *and* high parking fees would shift more car drivers to modes of transport they do not like, thereby reducing their utility from traveling. Hence, off-street parking serves as a cheap parking alternative, whereas on-street parking is more expensive due to its negative speed externality.

3.7 Sensitivity analysis

3.7.1 Additional scenarios

To test whether the economically efficient street space allocations in Berlin and New York City are similar if we impose political constraints or change modeling assumptions, we conduct additional sensitivity analyses. Below, we focus on the motivation, description, and main findings of these scenarios, while the mathematical implementations of Scenarios 6 and 8 are outlined in Appendix B.1, and detailed results for the scenarios are presented in Tables 4 and 5 in Appendix B.2.

5. Political Constraints: First, we test the robustness of Scenario 4 to changes in the set of available policy measures.

    (a) *No Congestion Toll*: The introduction of congestion pricing is often met with widespread opposition among a majority of voters, and could affect low-income individuals differently than high-income individuals (De Borger and Proost, 2012). Therefore, politicians might shy away from implementing congestion pricing.

    (b) *No Subsidies*: As outlined by Basso and Silva (2014), there are several arguments both for and against subsidizing public transit. Against this backdrop, we analyze a scenario in which the transportation system under consideration has to be completely self-financed.

6. Mixed Traffic: As argued by Anderson and Geroliminis (2020), dedicated bus lanes might underutilize street space, especially if bus frequency is rather low. Against this backdrop, we analyze whether allowing for mixed traffic of cars and buses on a shared lane can increase welfare.

7. Capacity Reduction: Recently, there is intensified discussion on turning "streets for traffic" into "streets for people". Thus, we model a scenario where (arbitrarily) 20 % of street space is now used for other purposes, e.g. public seating or community gathering places. As the economic effects of such conversions are unclear, we aim for a lower-bound estimate by assuming that the 20 % of re-purposed street space has no impact on social welfare. This scenario thus basically corresponds to a reduction in street space capacity of 20 %.

8. Bike Parking: Until now, parking space for bikes has not been explicitly incorporated into our model. Instead, it was implicitly assumed that there is always enough off-street space where bikes can be parked, e.g. along the edges of sidewalks, in courtyards, private sheds, or in bicycle cellars. As a sensitivity analysis, we run Scenarios 1 and 4 again, but now consider that all individuals of Group 1 need to park their bike on-street.[13] The two new scenarios are then denoted as:

   (a) *Reference (With Bike Parking)*

   (b) *Traditional + Space (With Bike Parking)*

   These two scenarios allow us to verify whether the efficiency gains between the original Scenarios 1 and 4 are robust to the inclusion of bike parking. The results also demonstrate how street space should be allocated if policymakers aim to provide enough adequate bike parking facilities on-street.

3.7.2 Results

Political constraints (Sensitivity) If policy makers cannot set a congestion toll, they increase parking fees to maintain an adequate modal share of cars. However, they lose the ability to specifically price car traffic in peak periods, leading to higher congestion levels in these periods, but only a minor reduction in efficiency, compared to Scenario 4.

A self-financed transportation system is already achieved in the welfare-maximizing Scenario 4 in Berlin, because the net revenues from toll and parking exceed the costs of the bus system. In New York City, however, operational net revenue is

[13] Assuming that all individuals of Group 1 (83 % in Berlin, 83.6 % in New York City) have to park their bike on-street, is arguably a rather extreme case. In reality, this share is likely to be lower, because many individuals can park their bike in courtyards, private sheds, or in bicycle cellars.

negative, mostly due to the costs of providing a lot of expensive off-street parking. Hence, policy makers increase the congestion toll and parking fees, and slightly reduce the space for cars. This reduces the modal share of cars and the necessary number of expensive off-street parking spaces. The efficiency remains very close to the optimum in Scenario 4. It should be noted, however, that self-financing is achieved at the expense of consumer surplus.

Both analyzed constraints only have a small effect on street space allocation, which is still very similar to that of Scenario 4. Thus, the efficient street space allocation appears to be rather robust to changes in the availability of policy instruments.

Mixed Traffic (Sensitivity) Mixed traffic of cars and buses leads to a small reduction in efficiency compared to Scenario 4, which is mainly due to the slightly reduced speed of buses. To accommodate cars and buses on the same lane, the parking lane is slightly reduced, so that the new shared lane is even larger than the sum of car and bus lanes in Scenario 4. This additional space helps to mitigate speed reductions from frictions between cars and buses on the same lane.

Capacity Reduction (Sensitivity) Reducing street space by 20 % still increases efficiency compared to the Reference scenario, and it is only slightly lower than in Scenario 4. This is achieved by mainly reducing the space for parking, but also for driving cars. The reduction in on-street parking spaces is accompanied by a strong increase in on-street parking fees. In New York City, off-street parking fees are additionally increased, and the congestion toll is lowered at the same time. The outlined price changes generally shift people to buses and bikes, ensuring that car travel speed does not decrease excessively.

If the 20 % of former street space are used relatively efficiently for alternative purposes, it is easy to imagine that social welfare might become even higher than in Scenario 4. Examples of such alternative purposes include the provision of community gathering places, public seating, or planting trees and flowers to provide for additional shade and enhance the cityscape (Mehta and Bosson, 2021).

Bike Parking (Sensitivity) If we introduce on-street bike parking in our model, we find that re-allocating street space can still lead to significant efficiency gains. In Berlin, the inclusion of bike parking mainly reduces the space for bikes by ca. 15 pp compared to Scenario 4, and increases the parking space accordingly. Nearly all of the on-street parking space is now used by bikes, and cars are shifted to parking off-street by adjusting parking fees. Again, off-street parking spaces are more expensive to build and maintain, thus significantly increasing operational costs. This, however, appears to be better than losing cyclists to cars due to insufficient bike parking spaces.

In New York City, the introduction of bike parking has different effects. Bike parking generally creates a negative external effect on travel speeds, because each bike consumes on-street parking space. To internalize this effect, cycling must become relatively less attractive, and in New York City this is achieved by increasing the space for cars by 6.3 pp compared to Scenario 4. In Berlin, the pressure on making cycling relatively more expensive was mitigated by the generally high attractiveness of cycling.

4 Discussion and Conclusion

4.1 Impact on congestion

Despite our focus on economic efficiency, we can also draw interesting conclusions about the impact on congestion. Comparing the Reference scenarios – where cars were significantly slowed down by congestion during peak hours in both cities – to the respective Space scenarios enables us to analyze the isolated impact of street space re-allocations on congestion. Although street space is re-allocated from cars and parking to buses and bicycles, the speed of cars does not decrease. Instead, it increases slightly in Berlin and even a little more in New York City. This underlines that taking space away from the car need not lead to a worsening of congestion problems, but it can even help to alleviate congestion problems. While this might be counterintuitive at first glance, there is a simple explanation: the re-allocation improves the conditions for the travel alternatives, making them more attractive and thus inducing significant modal shifts. These modal shifts reduce the number of cars, and the remaining car drivers can benefit from less congested streets.

When it comes to tackling congestion, there is, however, one limitation of street space re-allocations. Usually, the implemented allocation is static throughout the day.[14] More capacity and better utilization in peak hours might therefore lead to idle capacity in off-peak hours, which is underlined by the very different congestion levels in our scenarios without a congestion toll. Our analyses then confirm that time-dependent congestion tolls are an effective policy instrument to tackle congestion in peak hours, without generating idle capacity in off-peak hours. Hence, re-allocations can be supported well by congestion tolls.

[14] Technically, a dynamic street space allocation could be realized, for example, through lane control signs indicating that selected lanes are only open for buses or bicycles, or through automatic rising bollards that physically block out cars and buses from selected lanes. Such tools are relatively easy to implement and rather cheap (Valença et al., 2021), but currently barely used.

4.2 Further implications of efficient street space allocation

In our model, we mainly focus on time and monetary costs. There are, however, additional implications associated with the re-allocation of street space and the subsequent modal shifts.

Importantly, the proposed shift from cars to bikes should entail benefits that are not captured by our model, such as positive effects on health, injury risks, and the environment. First, the physical activity that comes with cycling can lead to lower levels of obesity or reduce the risk of cardiovascular disease (Garrard et al., 2021). Second, a cyclist's risk of injury decreases when trips are longer and more frequent, and each cyclists also benefits from a general increase in bicycle ridership, which reduces the risk of injury as well. These two effects are labeled *safety in kilometers* and *safety in numbers*, respectively. Moreover, separating bike lanes from motorized traffic increases traffic safety (Elvik, 2021). The shift from cars to bikes also leads to reductions in air and noise pollution, and can thereby contribute to a more sustainable transport system (Garrard et al., 2021).

When re-allocating street space to cyclists, it is important to pay attention to the design of the new bike lanes, because well-designed and safe infrastructure can help to promote cycling for women, children, and elderly people, thereby improving the equity of the overall transportation system (Buehler and Pucher, 2021b). Also, the inclusiveness of the transportation system is significantly improved by the provision of free public transport at higher frequencies.

Moreover, discouraging the use of cars and supporting cycling can increase social interaction, thereby generating positive effects on livability and amenities within cities (Garrard et al., 2021).

4.3 Model limitations

In our model, the alternative-specific constants θ_{qm} capture hard-to-measure factors such as perceived safety, comfort, or general preferences for selected modes of transport. Their values are calibrated so that real-world policy values would lead to real-world modal shares. As their name suggests, we assume that alternative-specific constants are really *constant*. In reality, however, their values might change due to street-space re-allocations. More space and a higher modal share of cycling could, for example, enhance perceived safety and comfort, thus increasing the value of the alternative-specific constant for bikes. Due to missing information on the actual determinants of alternative-specific constants, however, we refrain from modeling such changes. As more space for one transport mode would most likely increase its alternative-specific constant, the inclusion of such relationships might amplify the simulated re-allocations and modal shifts. This might be especially relevant for

New York City, where transport preferences are currently more car-centric. Hence, economic efficiency in New York City might be further improved by re-allocating even more street space to buses and bikes than suggested by our model simulation.

Street space re-allocations would not only impact on the transport system, but also on other sectors of the city's economy. One area that might be affected are housing prices. On the one hand, housing prices might increase with less traffic and a higher livability, due to the re-allocation of street space from cars to bikes. On the other hand, potential decreases in accessibility and higher costs due to congestion pricing and worse parking conditions might reduce housing prices. This ambiguity is also underlined by Polloni (2019), who finds no clear direction of effects, but strong effect heterogeneity between different traffic-calming projects.

Another area that might be affected is the impact on local businesses. A recent review on the effects of comparable street experiments finds that there are no negative effects on local businesses, and some businesses even report positive effects (Bertolini, 2020). Moreover, we do not explicitly include delivery traffic in our model. The volume of this type of traffic is often fixed, because stores have to be supplied and packages delivered at relatively fixed intervals and times to maintain operations. Hence, explicitly including delivery traffic in our model would probably correspond to a reduction of street capacity, which is in fact analyzed in Scenario 7.

Moreover, we only account for private time and monetary costs, but not for the external effects of street space re-allocations and subsequent modal shifts. As outlined in Gössling et al. (2019), the external costs of driving by car are around \$0.13 per kilometer, whereas cycling creates external benefits of around \$0.21 per kilometer. This suggests that accounting for external effects would be likely to increase the changes proposed by the model, and thus poses as an interesting area for future research.

4.4 Conclusion

We find that street space re-allocations are an effective policy instrument for increasing the efficiency of the transportation system. If policy makers can optimize over the street space allocation, the efficiency of the transportation system can be significantly improved. These gains are mainly achieved by reducing the space for cars and parking, and increasing the space for buses and especially for bikes.

In Berlin, the extent of proposed street space re-allocations is greater than in New York City, because cycling is considered a more established mode of transport, and people are generally more inclined to switch to cycling. Hence, re-allocations in Berlin are more effective in inducing modal shifts, and the attainable efficiency gains are much higher than in New York City. This underlines that city-specific characteristics and people's transport preferences should be taken into account when re-allocating street space.

Our findings hence contribute an economic perspective to the ongoing debate on the allocation of street space, which historically, is heavily skewed towards cars and parking. There are increasing demands to re-allocate street space to buses and especially to bicycles in order to improve the sustainability and fairness of space in the transportation sector. We demonstrate that sustainability and fairness are not the only incentives for such re-allocations, and that maximizing economic efficiency is just as good a reason.

References

Agentur für Clevere Städte (2014). *Wem gehört die Stadt? Der Flächen-Gerechtigkeits-Report. Mobilität und Flächengerechtigkeit. Eine Vermessung Berliner Straßen.* Agentur für Clevere Städte, Heinrich Strößenreuther.

Aldred, Rachel, Bridget Elliott, James Woodcock, and Anna Goodman (Jan. 2017). "Cycling provision separated from motor traffic: a systematic review exploring whether stated preferences vary by gender and age". In: *Transport reviews* 37.1, pp. 29–55. DOI: 10.1080/01441647.2016.1200156.

Anderson, Paul and Nikolas Geroliminis (2020). "Dynamic lane restrictions on congested arterials". In: *Transportation Research Part A: Policy and Practice* 135, pp. 224–243. DOI: 10.1016/j.tra.2020.03.009.

Anderson, Simon P. and André de Palma (1992). "Multiproduct Firms: A Nested Logit Approach". In: *The Journal of Industrial Economics* 40.3, pp. 261–276. DOI: 10.2307/2950539.

Anderson, Simon P. and André de Palma (2004). "The economics of pricing parking". In: *Journal of Urban Economics* 55.1, pp. 1–20. DOI: 10.1016/j.jue.2003.06.004.

Arnott, Richard, André de Palma, and Robin Lindsey (1990). "Economics of a bottleneck". In: *Journal of Urban Economics* 27.1, pp. 111–130. DOI: 10.1016/0094-1190(90)90028-L.

Basso, Leonardo J., Cristián Angelo Guevara, Antonio Gschwender, and Marcelo Fuster (2011). "Congestion pricing, transit subsidies and dedicated bus lanes: Efficient and practical solutions to congestion". In: *Transport Policy* 18.5, pp. 676–684. DOI: 10.1016/j.tranpol.2011.01.002.

Basso, Leonardo J. and Hugo E. Silva (2014). "Efficiency and Substitutability of Transit Subsidies and Other Urban Transport Policies". In: *American Economic Journal: Economic Policy* 6.4, pp. 1–33. DOI: 10.1257/pol.6.4.1.

Bento, Antonio M., Lawrence H. Goulder, Mark R. Jacobsen, and Roger H. von Haefen (2009). "Distributional and Efficiency Impacts of Increased US Gasoline Taxes". In: *American Economic Review* 99.3, pp. 667–99. DOI: 10.1257/aer.99.3.667.

Bertolini, Luca (Nov. 2020). "From 'streets for traffic' to 'streets for people': can street experiments transform urban mobility?" In: *Transport Reviews* 40.6, pp. 734–753. DOI: 10.1080/01441647.2020.1761907.

Börjesson, Maria, Chau Man Fung, and Stef Proost (2017). "Optimal prices and frequencies for buses in Stockholm". In: *Economics of Transportation* 9, pp. 20–36. DOI: 10.1016/j.ecotra.2016.12.001.

Buehler, Ralph and John Pucher (2021a). "COVID-19 Impacts on Cycling, 2019–2020". In: *Transport Reviews* 41.4, pp. 1–8. DOI: 10.1080/01441647.2021.1914900.

Buehler, Ralph and John Pucher (2021b). "Cycling to a More Sustainable Transport Future". In: *Cycling for Sustainable Cities*. Ed. by Ralph Buehler and John Pucher. The MIT Press, pp. 425–440. DOI: 10.7551/mitpress/11963.003.0025.

Buehler, Ralph and John Pucher (2022). "Cycling through the COVID-19 Pandemic to a More Sustainable Transport Future: Evidence from Case Studies of 14 Large Bicycle-Friendly Cities in Europe and North America". In: *Sustainability* 14.12. DOI: 10.3390/su14127293.

Bureau of Public Roads (1964). *Traffic assignment manual for application with a large, high speed computer*. Washington: U.S. Dept. of Commerce, Bureau of Public Roads, Office of Planning, Urban Planning Division.

Clarke, Philippa and Nancy Ambrose Gallagher (2013). "Optimizing Mobility in Later Life: The Role of the Urban Built Environment for Older Adults Aging in Place". In: *Journal of Urban Health* 90.6, pp. 997–1009. DOI: 10.1007/s11524-013-9800-4.

Creutzig, Felix, Aneeque Javaid, Zakia Soomauroo, Steffen Lohrey, Nikola Milojevic-Dupont, Anjali Ramakrishnan, Mahendra Sethi, Lijing Liu, Leila Niamir, Christopher Bren d'Amour, Ulf Weddige, Dominic Lenzi, Martin Kowarsch, Luisa Arndt, Lulzim Baumann, Jody Betzien, Lesly Fonkwa, Bettina Huber, Ernesto Mendez, Alexandra Misiou, Cameron Pearce, Paula Radman, Paul Skaloud, and J. Marco Zausch (2020). "Fair street space allocation: ethical principles and empirical insights". In: *Transport Reviews* 40.6, pp. 711–733. DOI: 10.1080/01441647.2020.1762795.

Currie, Graham, Majid Sarvi, and Bill Young (2007). "A new approach to evaluating on-road public transport priority projects: balancing the demand for limited road-space". In: *Transportation* 34.4, pp. 413–428. DOI: 10.1007/s11116-006-9107-3.

De Borger, Bruno and Stef Proost (2012). "A political economy model of road pricing". In: *Journal of Urban Economics* 71.1, pp. 79–92. DOI: 10.1016/j.jue.2011.08.002.

Elvik, Rune (2021). "Cycling Safety". In: *Cycling for Sustainable Cities*. Ed. by Ralph Buehler and John Pucher. The MIT Press, pp. 57–79. DOI: 10.7551/mitpress/11963.003.0008.

Fernandez, R., E. Valenzuela, and T. Gálvez. (2002). "Incorporación de la capacidad y rendimiento de paraderos en el programa TRANSYT". In: *Actas del XI Congreso Panamericano de Ingeniería Tránsito y Transporte*.

Garrard, Jan, Chris Rissel, Adrian Bauman, and Billie Giles-Corti (2021). "Cycling and Health". In: *Cycling for Sustainable Cities*. Ed. by Ralph Buehler and John Pucher. The MIT Press, pp. 35–55. DOI: 10.7551/mitpress/11963.003.0007.

Gerike, Regine, Stefan Hubrich, Frank Ließke, Sebastian Wittig, and Rico Wittwer (2019). *Tabellenbericht zum Forschungsprojekt "Mobilität in Städten – SrV 2018" in Berlin*. Technische Universität Dresden, Professur für Integrierte Verkehrsplanung und Straßenverkehrstechnik.

Goh, Kelvin Chun Keong, Graham Currie, Majid Sarvi, and David Logan (2013). "Road Safety Benefits from Bus Priority: An Empirical Study". In: *Transportation Research Record* 2352.1, pp. 41–49. DOI: 10.3141/2352-05.

Gössling, Stefan, Andy Choi, Kaely Dekker, and Daniel Metzler (2019). "The Social Cost of Automobility, Cycling and Walking in the European Union". In: *Ecological Economics* 158, pp. 65–74. DOI: 10.1016/j.ecolecon.2018.12.016.

Guzman, Luis A., Daniel Oviedo, Julian Arellana, and Victor Cantillo-García (2021). "Buying a car and the street: Transport justice and urban space distribution". In: *Transportation Research Part D: Transport and Environment* 95, p. 102860. DOI: 10.1016/j.trd.2021.102860.

Inci, Eren (2015). "A review of the economics of parking". In: *Economics of Transportation* 4.1, pp. 50–63. DOI: 10.1016/j.ecotra.2014.11.001.

Koglin, Till, Marco te Brömmelstroet, and Bert van Wee (2021). "Cycling in Copenhagen and Amsterdam". In: *Cycling for Sustainable Cities*. Ed. by Ralph Buehler and John Pucher. The MIT Press, pp. 347–370. DOI: 10.7551/mitpress/11963.003.0022.

Koppelman, Frank S and Chandra Bhat (2006). *A self instructing course in mode choice modeling: multinomial and nested logit models*. FTA US Department of Transportation.

Kraus, Sebastian and Nicolas Koch (2021). "Provisional COVID-19 infrastructure induces large, rapid increases in cycling". In: *Proceedings of the National Academy of Sciences* 118.15. DOI: 10.1073/pnas.2024399118.

Lindsey, Robin and Erik Verhoef (2001). "Traffic Congestion And Congestion Pricing". In: *Handbook of Transport Systems and Traffic Control*. Ed. by Kenneth J. Button and David A. Hensher. Vol. 3. Emerald Group Publishing Limited, pp. 77–105. DOI: 10.1108/9781615832460-007.

Litman, Todd and Eric Doherty (2009). "Parking Costs". In: *Transportation Cost and Benefit Analysis: Techniques, Estimates and Implications*. 2nd ed. Victoria Transport Policy Institute. Chap. 5.4, pp. 5.4.1–5.4.29.

Lusk, Anne C., Patrick Morency, Luis F. Miranda-Moreno, Walter C. Willett, and Jack T. Dennerlein (2013). "Bicycle Guidelines and Crash Rates on Cycle Tracks in the United States". In: *American Journal of Public Health* 103.7, pp. 1240–1248. DOI: 10.2105/AJPH.2012.301043.

Mehta, Vikas and Jennifer K. Bosson (2021). "Revisiting Lively Streets: Social Interactions in Public Space". In: *Journal of Planning Education and Research* 41.2, pp. 160–172. DOI: 10.1177/0739456X18781453.

Mueller, Natalie, David Rojas-Rueda, Haneen Khreis, Marta Cirach, David Andrés, Joan Ballester, Xavier Bartoll, Carolyn Daher, Anna Deluca, Cynthia Echave, Carles Milà, Sandra Márquez, Joan Palou, Katherine Pérez, Cathryn Tonne, Mark Stevenson, Salvador Rueda, and Mark Nieuwenhuijsen (2020). "Changing the urban design of cities for health: The superblock model". In: *Environment International* 134, p. 105132. DOI: 10.1016/j.envint.2019.105132.

Nello-Deakin, Samuel (Sept. 2019). "Is there such a thing as a 'fair' distribution of road space?" In: *Journal of Urban Design* 24.5, pp. 698–714. DOI: 10.1080/13574809.2019.1592664.

Parry, Ian W. H. and Kenneth A. Small (2009). "Should Urban Transit Subsidies Be Reduced?" In: *American Economic Review* 99.3, pp. 700–724. DOI: 10.1257/aer.99.3.700.

Paulsen, Mads, Thomas Kjær Rasmussen, and Otto Anker Nielsen (2019). "Fast or forced to follow: A speed heterogeneous approach to congested multi-lane bicycle traffic simulation". In: *Transportation Research Part B: Methodological* 127, pp. 72–98. DOI: 10.1016/j.trb.2019.07.002.

Petegem, Jan Hendrik van, Paul Schepers, and Gert Jan Wijlhuizen (2021). "The safety of physically separated cycle tracks compared to marked cycle lanes and mixed traffic conditions in Amsterdam". In: *European Journal of Transport and Infrastructure Research* 21.3, pp. 19–37. DOI: 10.18757/ejtir.2021.21.3.5283.

Polloni, Stefano (2019). "Traffic calming and neighborhood livability: Evidence from housing prices in Portland". In: *Regional Science and Urban Economics* 74, pp. 18–37. DOI: 10.1016/j.regsciurbeco.2018.11.004.

Qadri, Syed Shah Sultan Mohiuddin, Mahmut Ali Gökçe, and Erdinç Öner (2020). "State-of-art review of traffic signal control methods: challenges and opportunities". In: *European Transport Research Review* 12.1, p. 55. DOI: 10.1186/s12544-020-00439-1.

Rueda, Salvador (2019). "Superblocks for the Design of New Cities and Renovation of Existing Ones: Barcelona's Case". In: *Integrating Human Health into Urban and Transport Planning: A Framework*. Ed. by Mark Nieuwenhuijsen and Haneen Khreis. Springer International Publishing, pp. 135–153. DOI: 10.1007/978-3-319-74983-9_8.

Russo, Antonio, Martin W. Adler, and Jos N. van Ommeren (2022). "Dedicated bus lanes, bus speed and traffic congestion in Rome". In: *Transportation Research Part A: Policy and Practice* 160, pp. 298–310. DOI: 10.1016/j.tra.2022.04.001.

Sanders, Rebecca L. (2016). "We can all get along: The alignment of driver and bicyclist roadway design preferences in the San Francisco Bay Area". In: *Transportation Research Part A: Policy and Practice* 91, pp. 120–133. DOI: 10.1016/j.tra.2016.06.002.

Sanders, Rebecca L. and Belinda Judelman (2018). "Perceived Safety and Separated Bike Lanes in the Midwest: Results from a Roadway Design Survey in Michigan". In: *Transportation Research Record* 2672.36, pp. 1–11. DOI: 10.1177/0361198118758395.

TomTom (2019). *TomTom Traffic Index 2019*. TomTom International BV.

Transportation Alternatives (2021). *NYC 25x25 – A Challenge to New York City's Next Leaders to Give Streets Back to People*. Transportation Alternatives, New York City.

Valença, Gabriel, Filipe Moura, and Ana Morais de Sá (2021). "Main challenges and opportunities to dynamic road space allocation: From static to dynamic urban designs". In: *Journal of Urban Mobility* 1, p. 100008. DOI: 10.1016/j.urbmob.2021.100008.

van Ommeren, Jos, Derk Wentink, and Jasper Dekkers (2011). "The real price of parking policy". In: *Journal of Urban Economics* 70.1, pp. 25–31. DOI: 10.1016/j.jue.2011.02.001.

Vickrey, William S. (1969). "Congestion Theory and Transport Investment". In: *The American Economic Review* 59.2, pp. 251–260.

Winters, Meghan, Gavin Davidson, Diana Kao, and Kay Teschke (2011). "Motivators and deterrents of bicycling: comparing influences on decisions to ride". In: *Transportation* 38.1, pp. 153–168. DOI: 10.1007/s11116-010-9284-y.

Yang, Jun, Avralt-Od Purevjav, and Shanjun Li (2020). "The Marginal Cost of Traffic Congestion and Road Pricing: Evidence from a Natural Experiment in Beijing". In: *American Economic Journal: Economic Policy* 12.1, pp. 418–53. DOI: 10.1257/pol.20170195.

Zheng, Nan and Nikolas Geroliminis (2013). "On the distribution of urban road space for multimodal congested networks". In: *Transportation Research Part B: Methodological* 57, pp. 326–341. DOI: 10.1016/j.trb.2013.06.003.

Appendix

A Model Calibration

The calibration of our model consists of three main steps, which are explained in detail below. First, we set model parameters based on city-specific travel surveys and the relevant literature (Section A.1). Second, we calibrate the remaining parameters so that our model closely matches real-world choice behavior (Section A.2). Third, we validate our calibration by computing travel elasticities and cross-elasticities from our calibrated model and comparing them with the related literature (Section A.3).

A.1 Parameter values from travel surveys and the related literature

In the first step, we set many parameters according to values calculated from city-specific travel surveys or found in the literature. All monetary values of our analysis are presented in 2020 US dollars. If sources report monetary values in different currencies or base years, those values are converted to 2020 US dollars. An overview of the main parameter values for Berlin and New York City can be found in Table 3.

A.1.1 General parameters

Similar to Basso and Silva (2014), we choose a setting with a capacity of 3,600 vehicles per hour for our representative kilometer of street space. This capacity was already reduced by a factor of 0.6 in order to account for traffic lights. The corresponding width of our representative kilometer of street space is 10.5 meters.

We then set the number of individuals in such a way that congestion is generated. More specifically, we set total travel demand Y so that using the actually observed values for our policy variables in our model leads to the actually observed car speed during peak hours.

In our model, we differentiate between people who have access to private parking space, and those who have to use public on-street or off-street parkings spaces. In Berlin, 33.3 % of inhabitants own a car, and 50.9 % of car owners have a private parking space (Gerike et al., 2019). Thus, we assume that $0.509 \cdot 0.333 \approx 17\,\%$ of our considered individuals own a private parking space and belong to Group 2; the remaining 83 % do not own a private parking space and belong to Group 1. For New York City, we use data from the 2019 Citywide Mobility Survey and find that 83.6 % belong to Group 1, and 16.4 % to Group 2 (NYC DOT, 2019).

In Berlin, the average trip length is 5.9 km and the average walking speed 3.9 km/h (Gerike et al., 2019). In line with Basso and Silva (2014), we define 6

Table 3: Main parameter values

Parameter	Variable	Berlin	New York City
Road capacity [veh/hr]	C	3,600	3,600
Street width [m]	w	10.5	10.5
Total travel demand [pax/day]	Y	12,500	14,800
Share Group 1 (public parking)	Y^1/Y	0.83	0.836
Share Group 2 (private parking)	Y^2/Y	0.17	0.164
Average trip length [km]	l	5.9	5.22
Considered hours per day		20	20
Peak duration [hr]	H^{Peak}	6	11
Off-Peak duration [hr]	$H^{\text{Off-Peak}}$	14	9
Car occupancy [pax/veh]	a	1.3	1.51
Car operating costs [$/km]	c_{car}	0.46	0.46
Bike operating costs [$/km]	c_{bike}	0.06	0.06
Parking space area for cars [m²]	s_{req}	16	16
Parking space area for bike [m²]	$s_{req}/10$	1.6	1.6
Cost per on-street car parking space [$/day]	c_{parkon}	3.43	3.43
Cost per off-street car parking space [$/day]	$c_{parkoff}$	14.88	14.88
Cost per on-street bicycle parking space [$/day]	$c_{parkbike}$	0.08	0.08
Parking garages [garages/km]	$s_{parkoff}$	2	2
Average parking duration [hr]	d_p	6.33	7.09
Bus stops [stops/km]	$s_{busstop}$	3.8	3.8
Value of peak car travel time [$/h]		8.03	17.80
Value of peak bus travel time [$/h]		5.85	17.80
Value of peak bike travel time [$/h]		20.01	32.40
Value of off-peak car travel time [$/h]		7.05	15.61
Value of off-peak bus travel time [$/h]		5.14	15.61
Value of off-peak bike travel time [$/h]		17.55	28.42
Weight of waiting time	ϕ_1	2.00	2.00
Weight of walking time	ϕ_2	2.50	2.50
Free flow speed, car and bus [km/h]	$1/t_f$	60	60
Free flow speed, bike [km/h]	$1/t_f$	20	20
Parameters for car and bus BPR functions	$\alpha; \beta$	2.0; 4.0	2.0; 4.0
Parameters for bike BPR functions	$\alpha; \beta$	0.5; 5.0	0.5; 5.0
Time for boarding the bus [seconds/pax]	t_{sb}	2.5	2.5
Equivalence factor bus (at $b_{bus}(k = 75)$)	b_{bus}	2.0	2.0
Equivalence factor bike	b_{bike}	0.25	0.25
Walking speed [km/h]	V_w	3.9	4.77
Marginal costs of public funds	$mcpf$	1.15	1.15
Operational costs of congestion pricing [share of revenue]	η_{toll}	0.35	0.35

peak hours and 14 off-peak hours. Based on Gerike et al. (2019), peak hours are from 7:00 to 8:59 and from 14:00 to 17:59. During this time, hourly traffic volume is at least 6.9 % of daily traffic volume. Hourly off-peak traffic volume is never more than 6.5 % of daily traffic volume. The time from 0:00 to 3:59 only features 0.1 % of daily traffic volume, and is subsequently excluded. Hence, the aggregated traffic volume during the 6 peak hours is 50.2 % of daily traffic volume, and the 14 off-peak hours contain 49.6 % of daily traffic volume.

In New York City, the average trip length is 5.22 km and walking speed is 4.77 km/h (NYC DOT, 2019). Traffic levels are generally high, so that morning and evening peak hours are not so clearly discernible. Based on data from NYC DOT (2019), we then define 11 peak hours (7:00 to 9:59 and 11:00 to 18:59) and 9 off-peak hours (4:00 to 6:59, 10:00 to 10:59, and 19:00 to 23:59). The excluded hours from 0:00 to 3:59 only feature 1.4 % of daily traffic volume, the aggregated traffic volume during the 11 peak hours is 71.7 % of daily traffic volume, and the 9 off-peak hours observe 26.9 % of daily traffic volume.

For cars, the average occupancy is 1.3 passengers per vehicle in Berlin (Gerike et al., 2019), and 1.51 in New York City (NYC DOT, 2019). Operating costs per kilometer are \$0.46 for each car, and \$0.06 for bikes (Gössling et al., 2019). The cost function for buses is from Basso and Silva (2014) and converted to 2020 US dollars. Based on values by Litman and Doherty (2009), we assume that each car requires 16 m^2 when parking, and each bike parking space requires a tenth of the parking space for a car, i.e. 1.6 m^2. The costs for construction, operation, and maintenance for parking spaces are \$3.43 per day for an on-street parking space, and \$14.88 for an off-street parking space in an underground parking garage (Litman and Doherty, 2009).[15] Based on real-world observations, we assume that there are two underground parking garages per street kilometer. The construction costs for one bicycle parking space are \$0.08 per day, assuming a lifespan of 20 years (Bushell et al., 2013).

In reality, cars are in motion for roughly 1 hour, and parked for the rest of the day (Gerike et al., 2019). For our model, this would imply an average parking duration of $20 - 1 = 19$ hours per car. However, our model assumes that each individual makes only one trip per day, whereas in reality, people make several trips per day, and use the same car for some of these trips. In order to account for the fact that cars are used for more than one trip per day, we divide the average parking duration by the daily number of trips per car, which is 3.0, based on an approximation with

[15] In our context, the costs for parking spaces are not influenced by land costs. For on-street parking spaces, the required land is taken from the exogenously given street space, so that no additional costs in acquiring the land would accrue. For simplification, we set land costs for the given street space to zero. For off-street parking spaces in underground parking garages, no land costs accrue (Litman and Doherty, 2009).

data from Germany's largest mobility survey "Mobilität in Deutschland" (Nobis and Kuhnimhof, 2018).[16] Not doing so would inflate the number of parking cars, leading to incorrect parking space requirements. Hence, the average parking duration d_p is set to $19/3 = 6.33$. In New York, the daily number of trips per car is 2.68, so that the average parking duration d_p is set to $19/2.68 = 7.09$

For Germany, the values of time (VOT) are taken from Steck et al. (2018), and for New York City from the U.S. Department of Transportation (2022). We use information from Wardman et al. (2016) to differentiate between peak and off-peak hours.

A.1.2 Transport time parameters

For cars, we assume that the free flow speed is 60 km/h, so that t_f is 1/60. Similar to Basso and Silva (2014), we set $\beta = 4$ and assume that $\alpha = 2$, so that the free flow speed is reduced to 1/3 at capacity.

For buses, the values for t_f, α, and β are assumed to be the same as for cars. The equivalence function is $b_{bus} = 0.0114 \cdot k + 1.15$, so that a bus with 75 passengers would correspond to 2 cars (Basso and Silva, 2014).

For cyclists, we assume a free flow speed of 20 km/h, so that $t_f = 1/20$. This value is based on a study by Paulsen et al. (2019).[17] Congestion effects for cyclists arise mainly due to heterogeneous speed preferences of cyclists, which again can be modeled with a BPR function. Paulsen et al. (2019) estimated such a BPR function for cyclists, and in line with their findings, we set $\alpha = 0.5$ and $\beta = 5$. As bicycles have different space requirements than cars, we use the equivalence factor $b_{bike} = 0.25$ to convert cyclists to passenger car units (Agarwal et al., 2013).

A.1.3 Welfare function parameters

In line with Parry and Small (2009) and Basso and Silva (2014), we set the marginal costs of public funds to 1.15. The operational costs of the congestion pricing system are assumed to be the share η_{toll} of the revenue from congestion pricing. In London, the operational costs of the congestion pricing system were, on average, 35 % of the revenue between 2012 and 2019. Accordingly, we set $\eta_{toll} = 0.35$.

[16] We use the regional dataset *Mobilität in Deutschland B3*, and only consider those journeys that start and end in Berlin, thereby ensuring that the respective journeys are within Berlin.

[17] Older studies appear to report free-flow speeds that are, on average, slightly lower than 20 km/h. Allen et al. (1998), for example, report that values lie between 12 km/h and 20 km/h. Given the increasing usage of pedelecs, however, we think that it is appropriate to set the free-flow speed at 20 km/h. An even higher value for the average speed (21.6 km/h) is reported by Greibe and Buch (2016) for Copenhagen, Denmark. To test the robustness of our model, we also run a simulation with a free-flow speed of 15 km/h and find that the main model insights remain valid; detailed results are available upon request.

A.1.4 Street space allocation

To derive the actual street space allocation in Berlin, we use the data reported in Agentur für Clevere Städte (2014) and adjust the street space allocation to cars, bicycles, and parking. We then use publicly available information on the length of the road network and the length of bus lanes to calculate how much of the space for cars is taken up by bus lanes. We find that 62.6 % of street space in Berlin is allocated to cars, 31.2 % to parking, 1.3 % to buses, and 4.9 % to bicycles.

For New York City, we proceed in a similar manner, with Transportation Alternatives (2021) as the main data source. Here, 69.4 % of street space is allocated to cars, 27.7 % to parking, 1.7 % to buses, and 1.2 % to bicycles.

A.2 Parameter calibration

In the second step, we calibrate the remaining parameters so that the choice behavior in our model reflects real-world choice behavior as closely as possible. This calibration is conducted separately for Berlin and New York City. The remaining parameters to be calibrated are the six period-specific modal constants (θ^i_{qm}), the six period-specific marginal utilities of time (β_{qm}), the marginal utility of money (λ), three scale parameters (μ), as well as the number of individuals considered (Y^i).

We begin by calibrating these parameters for individuals of Group 1. To do this, we recreate real-world conditions in our model by setting travel speeds, travel costs, and policy variables similar to the values observed in Berlin and New York City. The average travel speeds are calculated with data from "Mobilität in Deutschland" (Nobis and Kuhnimhof, 2018) and NYC DOT (2019). Information on travel costs and policy variables are from Gerike et al. (2019), NYC DOT (2019) and other publicly available sources. The calibration of the remaining parameters then ensures that the following relationships are satisfied exactly under real-world conditions:

- The modal shares for peak and for off-peak hours are similar to those observed in Berlin.
- The ratio between peak and off-peak travel is similar to that observed in Berlin.
- The $\mathrm{VOT}_{\mathrm{qm}}$ for a given transport m mode in period q is equal to the ratio of the respective marginal utility of travel time β_{qm} and the marginal utility of income λ.
- The total travel elasticity with respect to bus peak fare is set to -0.002, similar to Parry and Small (2009) and Basso and Silva (2014).
- The car peak elasticity with respect to the peak travel time is set to -0.41, similar to Basso and Silva (2014) and in line with Litman (2022).

- Logsum parameters conform to $1 \geq \mu_u \geq \mu_m \geq \mu_l \geq 0$ in order to be consistent with utility maximization (Koppelman and Bhat, 2006).
- The number of individuals considered is set so that Equation 11 results in the observed travel speed for cars.[18]

For individuals of Group 2, we use the calibrated parameters from Group 1, but change the car modal constants for peak and off-peak hours in such a way that real-world conditions lead to the observed modal shares.[19]

A.3 Checking the validity of the calibration

In the third step, we check the validity of our calibration by computing various elasticities and cross-elasticities from our calibrated models for Berlin and New York City, and comparing them to the related literature.

- The car peak elasticity with respect to the bus peak fare (0.034 in Berlin; 0.079 in New York City) lies between the values for a single ticket (0.116) and a travel pass (0.02) that were estimated by Hensher (1998) and reported in the review by Litman (2022).
- The car peak elasticity with respect to the off-street parking fee (−0.215; −0.171) and the on-street parking fee (−0.343; −0.263) are in accordance with the typical values reported in a meta-analysis by Lehner and Peer (2019). Both elasticities also lie within the confidence interval of their estimated baseline elasticity of parking volumes with respect to price changes.
- The cross-price elasticity of off-street parking with respect to on-street parking fees is 0.77 in both cities, which is the same as estimated by Gragera and Albalate (2016).
- The bus elasticity with respect to the bus fare is −0.45 in both cities, which is in line with results reported in Dunkerley et al. (2018), Börjesson et al. (2017) and also in the review by Litman (2022).
- The bus peak elasticity with respect to the bus off-peak fare is 0.029 in Berlin and 0.027 in New York City, implying a rather low inter-temporal substitution. Börjesson et al. (2017) use a value of 0.1, but our elasticity is similar to findings

[18] Apart from the share of car space that is used in Equation 11, the real-world street space allocation does not impact on the calibration.

[19] Of course, individuals from Groups 1 and 2 might differ with respect to modal shares, elasticities, and other characteristics. Unfortunately, the available data on mobility behavior in Berlin and New York City, as well as the literature-based elasticities are usually not reported separately for these two groups, but as aggregated values over all travelers. We therefore have to calibrate the model in such a way that modal shares and elasticities are the same for both groups.

in Guzman et al. (2018), who show that elasticity values below 0.03 can also be realistic.

- The bike peak elasticity with respect to car (0.13) and bus (0.03) peak costs as well as with respect to car (0.13) and bus (0.06) peak travel times are close to the ones (0.15; 0.02; 0.18; 0.08) reported in Holmgren and Ivehammar (2020).

This comparison shows that the elasticities and cross-elasticities from our calibrated model are indeed in line with empirically estimated values from the related literature. Therefore, we can conclude that the choice behavior in our calibrated model reflects real-world choice behavior very well, thus enhancing the validity of our model results.

B Sensitivity analyses

B.1 Model implementation

B.1.1 Mixed traffic for cars and buses

In this scenario, we get rid of dedicated bus lanes and allow buses to use the street space for cars. We follow Basso and Silva (2014) for modeling the speed of cars and buses in these mixed traffic conditions. For buses, the speed function is rather similar to that of separated traffic (Equation 12), with the only notable difference being in the term of the BPR function. Now, the street space capacity is not only used by buses, but also by cars.

$$\begin{aligned} t_{q,bus} = t_f \cdot \left(1 + \alpha \cdot \left(\frac{l \cdot Y_{q,car}/a + f^q \cdot b_{bus}(k)}{carlane \cdot C}\right)^{\beta}\right) \\ + s_{busstop} \cdot \left(\frac{Y_{q,bus}}{f^q \cdot p} \cdot t_{sb} + t_d\right). \end{aligned} \tag{26}$$

The same change in the BPR function also applies to cars. Moreover, cars are now slowed down by bus stop operations, but it is assumed that they only experience a fraction of the delay for buses. This fraction is then modeled by $\epsilon(f^q) = 1 - 1.01^{-f^q}$, implying that higher bus frequencies lead to greater impediments to cars. The speed function for cars then changes to

$$\begin{aligned} t_{q,car} = t_f \cdot \left(1 + \alpha \cdot \left(\frac{l \cdot Y_{q,car}/a + f^q \cdot b_{bus}(k)}{carlane \cdot C}\right)^{\beta}\right) \\ + \epsilon(f^q) \cdot s_{busstop} \cdot \left(\frac{Y_{q,bus}}{f^q \cdot p} \cdot t_{sb} + t_d\right). \end{aligned} \tag{27}$$

B.1.2 Bike parking

In order to include bike parking in our model, we change the on-street parking space requirements of Equation 24 to

$$B_{parkon} \cdot s_{req} + B_{parkbike} \cdot (s_{req}/10) \leq parklane \cdot w \cdot 1000, \tag{28}$$

where $B_{parkbike}$ denotes the number of parking spaces that are needed to allow parking for each bike, and $(s_{req}/10)$ indicates that one bike only requires a tenth of a car parking space. The maximum number of parked bikes is calculated as

$$\begin{aligned} B_{parkbike} = max\Big\{ \big(Y_{Peak,bike} \cdot n^{max}_{Peak} + Y_{Off-peak,bike} \cdot (d_p - n^{max}_{Peak})\big), \\ \big(Y_{Off-peak,bike} \cdot n^{max}_{Off-peak} + Y_{Peak,bike} \cdot (d_p - n^{max}_{Off-Peak})\big) \Big\}. \end{aligned} \tag{29}$$

The parking cost function of Equation 17 changes to

$$cost_{parking} = c_{parkon} \cdot B_{parkon} + c_{parkoff} \cdot B_{parkoff} + c_{parkbike} \cdot B_{parkbike}, \tag{30}$$

with $c_{parkbike}$ as the daily costs for construction and maintenance of each bike parking spot. For simplicity, we assume that the parking duration for cars and bikes is the same, and that only individuals of Group 1 park their bike on-street. Moreover, policymakers do not charge parking fees for cyclists.

B.2 Results

B.2.1 Berlin

Table 4: Sensitivity analysis (Berlin)

Scenario	Political Constraints		Mixed Traffic	Capacity Reduction	Bike Parking	
	No Congestion Toll	*No Subsidies*			*Reference*	*Traditional + Space*
Social welfare	51473.507	52610.463	51625.507	48247.020	0.000	45483.299
Consumer surplus	27497.546	28276.423	26560.746	25060.533	0.000	25951.568
People	12500	12500	12500	12500	12500	12500
Travelers	12089.455	12093.767	12090.272	12076.615	11899.362	12067.796
Share of space for bicycles	0.463	0.450	0.453	0.433	0.049	0.309
Share of space for buses	0.022	0.022	-0.964	0.021	0.013	0.013
Share of space for cars	0.256	0.277	0.311	0.236	0.626	0.287
Share of space for parking	0.258	0.252	0.235	0.110	0.312	0.390
Bus fare (peak)	0.000	0.000	0.000	0.000	0.324	0.000
Bus fare (off-peak)	0.000	0.000	0.000	0.000	0.324	0.000
Car toll (peak)	0.000	0.672	0.678	0.672	0.000	0.687
Car toll (off-peak)	0.000	0.000	0.000	0.000	0.000	0.000
Parking fee (on-street)	1.424	1.156	1.237	1.615	1.421	2.622
Parking fee (off-street)	0.686	0.447	0.504	0.495	0.000	0.282
Bus frequency (peak)	20.230	19.952	18.515	20.176	12.000	17.859
Bus frequency (off-peak)	17.394	17.369	14.240	17.508	8.000	13.917
Bus size	43.125	43.325	46.785	44.654	62.884	48.976
Number of bus stops	2.743	2.746	2.472	2.762	3.800	2.604
Share of peak travelers	0.508	0.482	0.483	0.483	0.379	0.449
Share of off-peak travelers	0.459	0.486	0.484	0.483	0.573	0.517
Share of non-travelers	0.033	0.032	0.033	0.034	0.048	0.035
Modal share of car (peak)	0.190	0.156	0.153	0.140	0.652	0.180
Modal share of bus (peak)	0.140	0.146	0.146	0.152	0.162	0.159
Modal share of bicycle (peak)	0.670	0.698	0.701	0.709	0.186	0.662
Modal share of car (off-peak)	0.308	0.357	0.351	0.323	0.652	0.363
Modal share of bus (off-peak)	0.148	0.138	0.137	0.145	0.096	0.132
Modal share of bike (off-peak)	0.543	0.505	0.512	0.532	0.252	0.505
Speed of cars (peak)	20.582	39.412	38.902	36.553	16.736	31.999
Speed of buses (peak)	27.509	27.460	24.602	27.072	12.105	21.266
Speed of bicyles (peak)	19.072	18.999	18.995	18.696	8.352	16.892
Speed of cars (off-peak)	46.245	40.225	41.608	37.085	39.394	33.741
Speed of buses (off-peak)	30.876	30.859	27.341	30.566	21.983	23.308
Speed of bicycles (off-peak)	19.997	19.997	19.997	19.995	11.626	19.972
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000	0.663	0.030
Used parking spaces (on-street, minimum)	0.659	0.960	0.960	0.960	0.445	0.029
Share of on-street parking (peak, all travelers)	0.202	0.220	0.210	0.107	0.063	0.010
Share of on-street parking (off-peak, all travelers)	0.194	0.212	0.202	0.103	0.060	0.009
Net revenue of operating transport systems	295.708	607.081	1242.490	-390.792	-22785.912	-5801.798
Parking system: revenue	10213.237	8026.291	8497.759	7194.363	3287.896	4272.669
Parking system: costs	8305.246	7686.650	7539.467	7614.462	26496.224	10439.917
Toll system: net revenue	0.000	1867.419	1848.851	1674.273	0.000	2043.649
Bus system: revenue	0.000	0.000	0.000	0.000	2159.492	0.000
Bus system: costs	1612.282	1599.978	1564.653	1644.966	1737.076	1678.198
Share of Car Parking Space					0.663	0.030
Share of Bike Parking Space					0.337	0.970
Share of Car Parking Space (in p.p.)					0.207	0.012
Share of Bike Parking Space (in p.p.)					0.105	0.378
Number of Car Parking Spaces					135.756	7.725
Number of Bike Parking Spaces					689.937	2482.576

The street space shares are adjusted for car, bus, bike, and parking. Space for pedestrians and others is excluded, but takes up 33 % and 6 % of total street space in reality. The modal shares are adjusted for the three overground transport modes car, bus, and bike. Overground transport makes up 50.6 % of overall traffic.

B.2.2 New York City

Table 5: Sensitivity analysis (New York City)

Scenario	Political Constraints		Mixed Traffic	Capacity Reduction	Bike Parking	
	No Congestion Toll	*No Subsidies*			*Reference*	*Traditional + Space*
Social welfare	26890.761	28373.912	19148.983	17956.160	0.000	22860.450
Consumer surplus	8857.119	-8390.137	-8704.843	-7899.173	0.000	13126.067
People	14800	14800	14800	14800	14800	14800
Travelers	14591.377	14560.947	14578.813	14561.527	14571.503	14588.697
Share of space for bicycles	0.046	0.051	0.048	0.049	0.012	0.048
Share of space for buses	0.049	0.051	3.578	0.049	0.017	0.016
Share of space for cars	0.703	0.634	0.743	0.607	0.694	0.770
Share of space for parking	0.202	0.264	0.209	0.095	0.277	0.165
Bus fare (peak)	0.000	0.000	0.000	0.000	0.508	0.000
Bus fare (off-peak)	0.000	0.000	0.000	0.000	0.508	0.099
Car toll (peak)	0.000	1.005	1.304	0.750	0.000	0.698
Car toll (off-peak)	0.000	0.000	0.000	0.000	0.000	0.000
Parking fee (on-street)	3.799	3.060	3.028	4.194	3.258	4.053
Parking fee (off-street)	0.462	0.290	0.000	0.302	0.000	0.002
Bus frequency (peak)	49.466	50.033	38.930	50.251	12.000	33.677
Bus frequency (off-peak)	41.161	41.517	23.240	42.229	8.000	16.666
Bus size	25.859	29.326	33.906	29.055	49.904	27.344
Number of bus stops	2.866	2.872	2.373	2.884	3.900	2.031
Share of peak travelers	0.703	0.638	0.615	0.651	0.650	0.645
Share of off-peak travelers	0.283	0.345	0.370	0.332	0.335	0.341
Share of non-travelers	0.014	0.016	0.015	0.016	0.015	0.014
Modal share of car (peak)	0.663	0.574	0.600	0.586	0.830	0.709
Modal share of bus (peak)	0.259	0.327	0.306	0.319	0.131	0.203
Modal share of bicycle (peak)	0.078	0.099	0.095	0.095	0.039	0.087
Modal share of car (off-peak)	0.746	0.763	0.812	0.754	0.887	0.834
Modal share of bus (off-peak)	0.207	0.193	0.151	0.200	0.073	0.127
Modal share of bike (off-peak)	0.047	0.044	0.038	0.046	0.040	0.039
Speed of cars (peak)	28.887	37.011	34.819	32.061	18.346	29.926
Speed of buses (peak)	27.685	26.995	24.648	26.908	12.998	22.918
Speed of bicyles (peak)	19.382	19.272	19.308	19.162	12.905	19.426
Speed of cars (off-peak)	54.471	43.744	39.099	44.032	39.246	44.098
Speed of buses (off-peak)	30.869	30.524	27.195	30.420	22.150	29.916
Speed of bicycles (off-peak)	19.998	19.998	19.998	19.998	18.834	19.999
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000	0.900	0.597
Used parking spaces (on-street, minimum)	0.444	0.806	0.940	0.717	0.516	0.397
Share of on-street parking (peak, all travelers)	0.042	0.073	0.058	0.025	0.046	0.022
Share of on-street parking (off-peak, all travelers)	0.041	0.070	0.056	0.024	0.044	0.021
Net revenue of operating transport systems	-16287.310	0.000	-7748.019	-9485.839	-33300.858	-24836.178
Parking system: revenue	25159.266	19734.713	8060.636	15674.249	8569.177	4521.784
Parking system: costs	37980.812	28318.754	28821.939	30986.344	43400.547	37717.160
Toll system: net revenue	0.000	12244.085	15986.128	9508.951	0.000	10628.328
Bus system: revenue	0.000	0.000	0.000	0.000	3113.623	247.246
Bus system: costs	3465.764	3660.043	2972.844	3682.695	1583.111	2516.376
Share of Car Parking Space					0.900	0.597
Share of Bike Parking Space					0.100	0.403
Share of Car Parking Space (in p.p.)					0.249	0.099
Share of Bike Parking Space (in p.p.)					0.028	0.067
Number of Car Parking Spaces					163.679	64.707
Number of Bike Parking Spaces					181.023	437.320

The street space shares are adjusted for car, bus, bike, and parking. Space for pedestrians is excluded, but takes up 23.7 % of total street space in reality.
The modal shares are adjusted for the three overground transport modes car, bus, and bike. This overground transport makes up 43.6 % of overall traffic.

References

Agarwal, A, M Zilske, K Rao, and K Nagel (2013). "Person-based dynamic traffic assignment for mixed traffic conditions". In: *Conference on Agent-Based Modeling in Transportation Planning and Operations*, pp. 12–11.

Agentur für Clevere Städte (2014). *Wem gehört die Stadt? Der Flächen-Gerechtigkeits-Report. Mobilität und Flächengerechtigkeit. Eine Vermessung Berliner Straßen.* Agentur für Clevere Städte, Heinrich Strößenreuther.

Allen, D. Patrick, Nagui Rouphail, Joseph E. Hummer, and Joseph S. Milazzo (1998). "Operational Analysis of Uninterrupted Bicycle Facilities". In: *Transportation Research Record* 1636.1, pp. 29–36. DOI: 10.3141/1636-05.

Basso, Leonardo J. and Hugo E. Silva (2014). "Efficiency and Substitutability of Transit Subsidies and Other Urban Transport Policies". In: *American Economic Journal: Economic Policy* 6.4, pp. 1–33. DOI: 10.1257/pol.6.4.1.

Börjesson, Maria, Chau Man Fung, and Stef Proost (2017). "Optimal prices and frequencies for buses in Stockholm". In: *Economics of Transportation* 9, pp. 20–36. DOI: 10.1016/j.ecotra.2016.12.001.

Bushell, Max A., Bryan W. Poole, Charles V. Zegeer, and Daniel A. Rodriguez (2013). *Costs for Pedestrian and Bicyclist Infrastructure Improvements. A Resource for Researchers, Engineers, Planners, and the General Public.* UNC Highway Safety Research Center.

Dunkerley, Fay, Mark Wardman, Charlene Rohr, and Nils Fearnley (2018). *Bus fare and journey time elasticities and diversion factors for all modes: A rapid evidence assessment.* Santa Monica, CA: RAND Corporation. DOI: 10.7249/RR2367.

Gerike, Regine, Stefan Hubrich, Frank Ließke, Sebastian Wittig, and Rico Wittwer (2019). *Tabellenbericht zum Forschungsprojekt "Mobilität in Städten – SrV 2018" in Berlin.* Technische Universität Dresden, Professur für Integrierte Verkehrsplanung und Straßenverkehrstechnik.

Gössling, Stefan, Andy Choi, Kaely Dekker, and Daniel Metzler (2019). "The Social Cost of Automobility, Cycling and Walking in the European Union". In: *Ecological Economics* 158, pp. 65–74. DOI: 10.1016/j.ecolecon.2018.12.016.

Gragera, Albert and Daniel Albalate (2016). “The impact of curbside parking regulation on garage demand”. In: *Transport Policy* 47, pp. 160–168. DOI: 10.1016/j.tranpol.2016.02.002.

Greibe, Poul and Thomas Skallebæk Buch (2016). “Capacity and Behaviour on One-way Cycle Tracks of Different Widths”. In: *Transportation Research Procedia* 15, pp. 122–136. DOI: 10.1016/j.trpro.2016.06.011.

Guzman, Luis A., Carlos A. Moncada, and Santiago Gómez (2018). “Fare discrimination and daily demand distribution in the BRT system in Bogotá”. In: *Public Transport* 10.2, pp. 191–216. DOI: 10.1007/s12469-018-0181-7.

Hensher, David A. (1998). “Establishing a Fare Elasticity Regime for Urban Passenger Transport”. In: *Journal of Transport Economics and Policy* 32.2, pp. 221–246.

Holmgren, Johan and Pernilla Ivehammar (2020). “Mode choice in home-to-work travel in mid-size towns: The competitiveness of public transport when bicycling and walking are viable options”. In: *Transportation Research Procedia* 48, pp. 1635–1643. DOI: 10.1016/j.trpro.2020.08.204.

Koppelman, Frank S and Chandra Bhat (2006). *A self instructing course in mode choice modeling: multinomial and nested logit models*. FTA US Department of Transportation.

Lehner, Stephan and Stefanie Peer (2019). “The price elasticity of parking: A meta-analysis”. In: *Transportation Research Part A: Policy and Practice* 121, pp. 177–191. DOI: 10.1016/j.tra.2019.01.014.

Litman, Todd (2022). *Understanding Transport Demands and Elasticities. How Prices and Other Factors Affect Travel Behavior*. Victoria Transport Policy Institute.

Litman, Todd and Eric Doherty (2009). “Parking Costs”. In: *Transportation Cost and Benefit Analysis: Techniques, Estimates and Implications*. 2nd ed. Victoria Transport Policy Institute. Chap. 5.4, pp. 5.4.1–5.4.29.

Nobis, Claudia and Tobias Kuhnimhof (2018). *Mobilität in Deutschland – MiD Ergebnisbericht*. Infas, DLR, IVT, und infas 360 im Auftrag des Bundesministers für Verkehr und digitale Infrastruktur (FE-NR. 70.904/15).

NYC DOT (2019). *Citywide Mobility Survey 2019 – Survey User Guide*. New York City, Department of Transportation.

Parry, Ian W. H. and Kenneth A. Small (2009). "Should Urban Transit Subsidies Be Reduced?" In: *American Economic Review* 99.3, pp. 700–724. DOI: 10.1257/aer.99.3.700.

Paulsen, Mads, Thomas Kjær Rasmussen, and Otto Anker Nielsen (2019). "Fast or forced to follow: A speed heterogeneous approach to congested multi-lane bicycle traffic simulation". In: *Transportation Research Part B: Methodological* 127, pp. 72–98. DOI: 10.1016/j.trb.2019.07.002.

Steck, Felix, Viktoriya Kolarova, Francisco Bahamonde-Birke, Stefan Trommer, and Barbara Lenz (2018). "How Autonomous Driving May Affect the Value of Travel Time Savings for Commuting". In: *Transportation Research Record* 2672.46, pp. 11–20. DOI: 10.1177/0361198118757980.

Transportation Alternatives (2021). *NYC 25x25 – A Challenge to New York City's Next Leaders to Give Streets Back to People*. Transportation Alternatives, New York City.

U.S. Department of Transportation (2022). *Benefit-Cost Analysis Guidance for Discretionary Grant Programs*. Office of the Secretary, U.S. Department of Transportation.

Wardman, Mark, V. Phani K. Chintakayala, and Gerard de Jong (2016). "Values of travel time in Europe: Review and meta-analysis". In: *Transportation Research Part A: Policy and Practice* 94, pp. 93–111. DOI: 10.1016/j.tra.2016.08.019.