

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

Jan Wessel*

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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, and analyze the efficiency of often-discussed allocation mechanisms.

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 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 are – to the best of our knowledge – the first to provide an economic analysis on the efficiency of street space allocations. More specifically, we contribute to the literature in the following ways.

First, we extend the theoretical mode choice model outlined in Basso and Silva (2014), which conforms to the principles of utility maximization and features an objective function that reflects a measure of social welfare. 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. Generally, it is argued that cycling should receive more space due to its sustainability, and that on-street parking space should be reduced due to its inefficiency (Creutzig et al., 2020).

Second, we 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.

Third, we evaluate the economic efficiency of two allocation mechanisms that are often called for in public debates, i.e. egalitarianism and allocating street space according to modal shares. We find that both mechanisms *can*, but *need not* lead to greater economic efficiency. Their effectiveness in enhancing efficiency is influenced by city-specific characteristics and people’s general transport preferences, especially the strength of preference for cars. From an economic perspective, therefore, caution is advised when calling for these rather intuitive, yet simple allocation mechanisms.

Fourth, 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.

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. Further aspects of street space allocation are discussed in Section 4, and Section 5 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 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

¹We 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.

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.

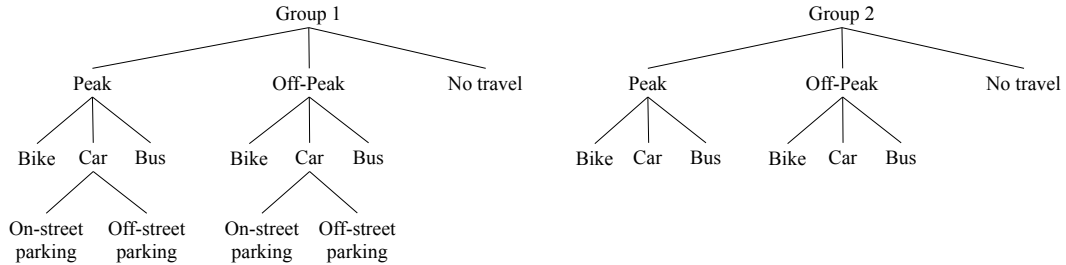


Figure 1: Decision Trees

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

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

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

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

²The 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.

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 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:

$$A_{q, Parking}^1 = \mu_l \cdot \ln \left(\sum_{s \in M_p} \exp \left(\frac{1}{\mu_l} \cdot U_{q, Car, s}^1 \right) \right) \quad (3)$$

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:

$$U_{q, Car}^1 = \theta_{q, Car}^1 + \lambda \cdot cost_{q, Car} + \beta_{q, Car} \cdot gt_{q, Car} + A_{q, Parking}^1, \quad (4)$$

$$q \in M_q,$$

where $\theta_{q, Car}^i$ 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_{qm}^i , 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:

$$U_{q, Car}^2 = \theta_{q, Car}^2 + \lambda \cdot cost_{q, Car} + \beta_{q, Car} \cdot gt_{q, Car}, \quad (5)$$

$$q \in M_q.$$

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

written as:

$$U_{qm}^i = \theta_{qm}^i + \lambda \cdot cost_{qm} + \beta_{qm} \cdot gt_{qm}, \quad (6)$$

$$q \in M_q, \quad m \in \{\text{Bus, Bike}\}.$$

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

$$\mathcal{P}_{m|q}^i = \frac{\exp\left(\frac{1}{\mu_m} \cdot U_{qm}^i\right)}{\sum_{r \in M_m} \exp\left(\frac{1}{\mu_m} \cdot U_{qr}^i\right)}, \quad (7)$$

$$q \in M_q, \quad m \in M_m.$$

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:

$$A_q^i = \mu_m \cdot \ln \left(\sum_{r \in M_m} \exp \left(\frac{1}{\mu_m} \cdot U_{qr}^i \right) \right) \quad (8)$$

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

$$\mathcal{P}_n^i = \frac{\exp\left(\frac{1}{\mu_u} \cdot A_n^i\right)}{\sum_{r \in M_n} \exp\left(\frac{1}{\mu_u} \cdot A_r^i\right)} \quad (9)$$

$$n \in M_n = \{\text{Peak, Off-peak, no travel}\}$$

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

$$Y_{qm} = \left(\sum_{i=1}^2 Y^i \cdot \mathcal{P}_q^i \cdot \mathcal{P}_{m|q}^i \right) / H^q, \quad (10)$$

$$q \in M_q, \quad m \in M_m,$$

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 $Y_{notravel} = \sum_{i=1}^2 Y^i \cdot \mathcal{P}_{notravel}^i$.

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

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

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.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 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

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

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 kilometers of

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

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

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

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

$$cost_{parking} = c_{parkon} \cdot B_{parkon} + c_{parkoff} \cdot B_{parkoff} \quad (17)$$

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, 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_{Peak}^{max}), but it could also be determined by the sub-sequence that contains the most off-peak hours ($n_{Off-peak}^{max}$).⁴ Hence, it follows that

$$B_p = \max \left\{ (Y_{Peak,car,p} \cdot n_{Peak}^{max} + Y_{Off-peak,car,p} \cdot (d_p - n_{Peak}^{max})) / a, \right. \\ \left. (Y_{Off-peak,car,p} \cdot n_{Off-peak}^{max} + Y_{Peak,car,p} \cdot (d_p - n_{Off-peak}^{max})) / a \right\}. \quad (18)$$

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

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

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

³We do not include costs for acquiring land in our model. First, against the backdrop of re-allocating 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).

⁴If 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 ($n_{Off-peak}^{max} = 4$), and a maximum of 7 off-peak periods ($n_{Off-peak}^{max} = 7$). 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.

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.

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):

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

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

$$SW = CS + (rev_{park} + rev_{toll} \cdot (1 - \eta_{toll}) + rev_{bus} - cost_{park} - cost_{bus}) \cdot mcpf, \quad (21)$$

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

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

equilibrium equations as constraints. These constraints can be written as

$$\begin{aligned} 0 \leq Y_{nm}^i \leq Y^i \quad & \forall i \in \{1, 2\}, \quad \forall n \in M_n, \quad m \in M_m, \\ Y_{nm}^i = Y^i \cdot \mathcal{P}_n^i \cdot \mathcal{P}_{m|n}^i / H^q, \quad & \forall i \in \{1, 2\}, \quad \forall n \in M_n, \quad m \in M_m. \end{aligned} \quad (22)$$

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

$$carlane + buslane + bikelane + parklane \leq 1. \quad (23)$$

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.

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

$$B_{parkon} \cdot s_{req} \leq parklane \cdot w \cdot 1000, \quad (24)$$

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

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

Additionally, the bus size has to be sufficiently large so that all passengers can be transported in both periods. Thus, bus capacity must be

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

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

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). 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. This indicates that cycling is a more established transport mode in Berlin, and these general preferences could subsequently impact on the efficient street space allocation of the respective cities.

To ensure that our model reflects the actual travel conditions in these cities, we calibrate it in a manner similar to Basso and Silva (2014) and Börjesson et al. (2017). More precisely, we undertake two main steps. First, we set the model parameters according to the values that we found in the relevant transport literature. Second, we calibrate the model in such a way that the actually observed values for our policy variables would lead to the actually observed modal shares in the cities. In addition, the calibration ensures that important travel elasticities and cross-elasticities are similar to the values reported in the literature. For the sake of clarity, the chosen parameter values and the model calibration are outlined in more detail in Appendix A.

3.2 Main scenarios

We continue by describing the main scenarios that we analyze. In particular, we analyze the economic efficiency of the current street space allocation (Scenarios 1 and 2) and of two allocations that are often called for to increase the fairness of street space allocation (3 and 4). Then, we determine the street space allocation that maximizes social welfare (5).

1. **REFERENCE:** The street space allocation is similar to the real-world situations in Berlin and New York City. Bus frequencies, bus ticket prices, and car tolls are set to their real-world values. Hence, street space allocation and most traditional policy variables reflect the actual conditions in Berlin and New York City, thereby making this scenario an ideal starting point for evaluating the effects of various transport policies and street space allocations.
2. **FIXED LANES:** The street space allocation is still similar to the real-world situation, but the social planner can now optimize welfare over all other policy variables.⁷ This allows us to evaluate by how much efficiency could be improved if the street space allocation remained fixed.
3. **EGALITARIANISM:** Each of the three considered transport mode receives 1/3 of available street space. The social planner can allocate the street space for cars optimally between driving and parking. In addition, the social planner can optimize welfare over all other policy variables.
4. **MODAL SHARE:** Each transport mode receives the share of available street space that equals the modal share of the respective transport mode. The social planner can allocate the street space for cars optimally between driving and parking. In addition, the social planner can optimize welfare over all other policy variables.
5. **FREE LANES:** In this scenario, the social planner can optimize welfare over the choice of the street space allocation, as well as over all other 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.

⁷These 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. As the social planner maximizes over welfare, the optimal values for these policy variables are endogenously determined by the model.

3.3 The impact of street space allocation on economic efficiency

An overview of the simulation results for the five 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).

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 5.0 % in Berlin, and by 4.6 % in New York City.

The greatest efficiency gains are, however, realized in Scenario 5, where 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 27.7 %, relative to the REFERENCE scenario. In New York City, the maximum attainable efficiency gain is 6.9 %, 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 %. 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.

The results also show that re-allocating street space according to egalitarianism or modal shares – two allocation mechanisms that are usually proposed in order to pursue fairness of space – do not necessarily improve efficiency. While both allocation mechanisms lead to substantial efficiency gains in Berlin, they are less suited for allocating street space in New York City, where egalitarianism even leads to lower efficiency than in the REFERENCE scenario.

3.4 Main results for Berlin

3.4.1 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

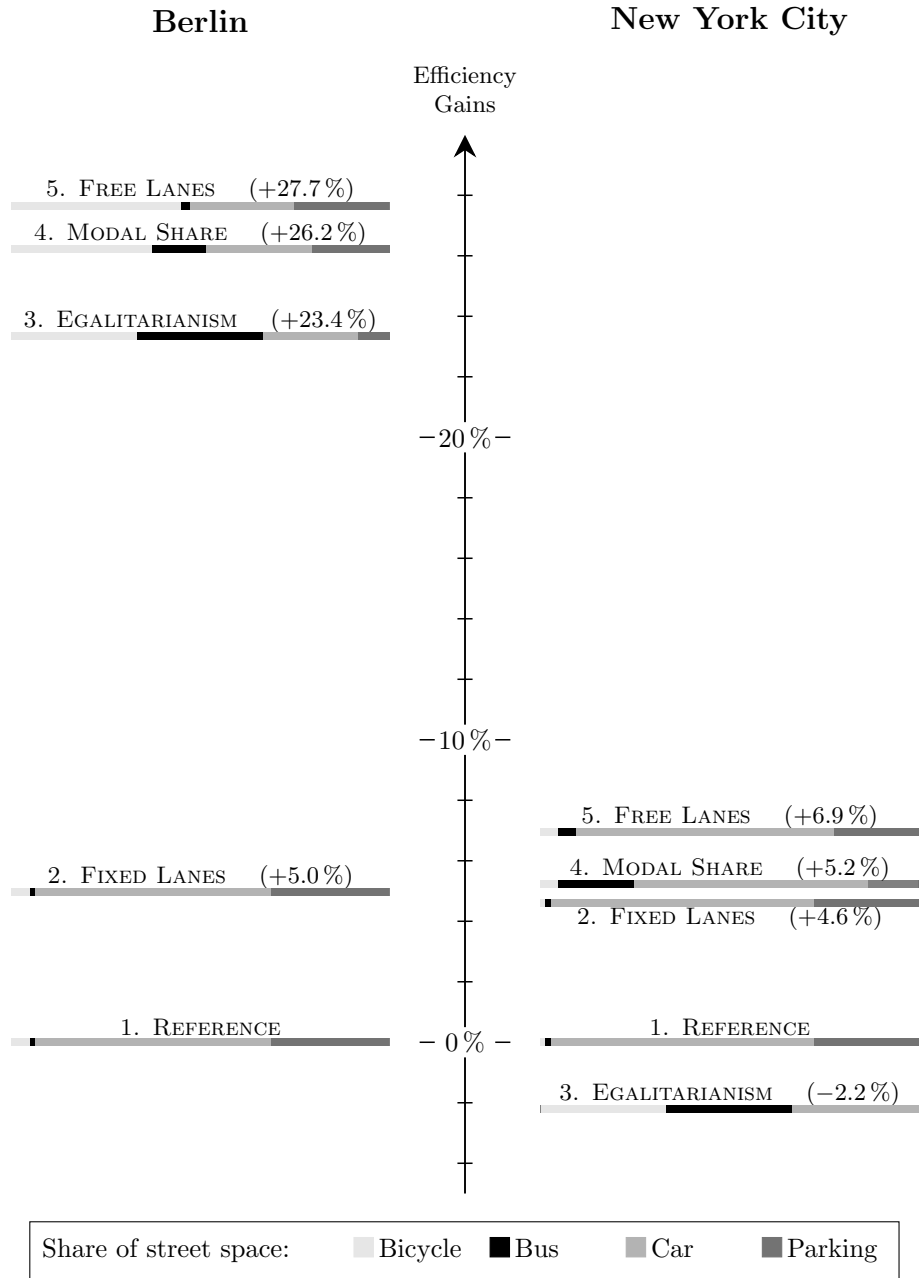


Figure 2: Efficiency gains of main scenarios

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.

Table 1: Main results (Berlin)

Scenario	REFERENCE	FIXED LANES	EGALITARIANISM	MODAL SHARE	FREE LANES
Social welfare	190183.467	199638.719	234609.595	240046.659	242793.930
Efficiency gains w.r.t. REFERENCE		+5.0 %	+23.4 %	+26.2 %	+27.7 %
Consumer surplus	213819.364	213981.130	237337.001	241169.259	242095.787
People	12500	12500	12500	12500	12500
Travelers	11906.277	11902.592	12067.913	12088.789	12093.767
Share of space for bicycles	0.049	0.049	0.333	0.374	0.450
Share of space for buses	0.013	0.013	0.333	0.141	0.022
Share of space for cars	0.626	0.626	0.251	0.281	0.277
Share of space for parking	0.312	0.312	0.082	0.204	0.252
Bus fare (peak)	0.324	0.000	0.000	0.000	0.000
Bus fare (off-peak)	0.324	0.000	0.000	0.000	0.000
Car toll (peak)	0.000	0.716	0.678	0.676	0.672
Car toll (off-peak)	0.000	0.000	0.000	0.000	0.000
Parking fee (on-street)	1.208	1.063	1.726	1.243	1.156
Parking fee (off-street)	0.000	0.000	0.399	0.378	0.447
Bus frequency (peak)	12.000	16.464	25.686	24.259	19.952
Bus frequency (off-peak)	8.000	13.545	22.015	20.825	17.369
Bus size	62.185	72.731	37.360	37.324	43.325
Number of bus stops	3.800	2.945	2.742	2.727	2.746
Share of peak travelers	0.379	0.333	0.461	0.470	0.482
Share of off-peak travelers	0.573	0.619	0.505	0.498	0.486
Share of non-travelers	0.047	0.048	0.035	0.033	0.032
Modal share of car (peak)	0.654	0.496	0.159	0.166	0.156
Modal share of bus (peak)	0.160	0.293	0.169	0.157	0.146
Modal share of bicycle (peak)	0.186	0.212	0.671	0.677	0.698
Modal share of car (off-peak)	0.655	0.617	0.337	0.362	0.357
Modal share of bus (off-peak)	0.095	0.151	0.145	0.139	0.138
Modal share of bike (off-peak)	0.251	0.232	0.518	0.499	0.505
Speed of cars (peak)	17.947	41.088	35.441	38.360	39.412
Speed of buses (peak)	22.706	20.688	28.800	28.920	27.460
Speed of bicycles (peak)	8.379	8.345	17.310	18.177	18.999
Speed of cars (off-peak)	42.426	41.540	35.848	39.033	40.225
Speed of buses (off-peak)	25.833	25.983	31.754	31.853	30.859
Speed of bicycles (off-peak)	11.680	11.675	19.981	19.992	19.997
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000	1.000
Used parking spaces (on-street, minimum)	0.674	0.960	0.960	0.960	0.960
Share of on-street parking (peak, all travelers)	0.095	0.125	0.074	0.172	0.220
Share of on-street parking (off-peak, all travelers)	0.090	0.119	0.070	0.165	0.212
Net revenue of operating transport systems	-20552.954	-12471.661	-2371.658	-976.173	607.081
Parking system: revenue	4221.988	4275.866	6376.674	7327.563	8026.291
Parking system: costs	25772.224	19271.295	8676.896	8451.307	7686.651
Toll system: net revenue	0.000	4362.352	1837.714	1946.808	1867.419
Bus system: revenue	2128.230	0.000	0.000	0.000	0.000
Bus system: costs	1130.948	1838.583	1909.150	1799.238	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 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.

A second important divergence 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.

Despite these differences, 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.

Fixed Lanes 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.

Egalitarianism Street space is now re-allocated and each transport mode receives the same share, resulting in an extreme increase in the space for buses. This allows a strong increase in frequencies in peak and off-peak hours, in turn leading to reduced waiting times at bus stops. Despite this improvement, bus ridership shrinks from

the previous scenario FIXED LANES and bus sizes are reduced to avoid idle capacity.

This rather surprising reduction in bus ridership is due to the strong increase in street space for cyclists. Cycling speed more than doubles in the peak period, and also increases substantially in the off-peak period. This improvement weighs even stronger than that for buses, hence also shifting individuals from bus to cycling. Consequently, the modal share of cycling increases to 67.1 % in peak hours, and 51.8 % in off-peak hours.

On the other hand, egalitarianism substantially reduces the space for cars. Initially, this reduction would increase congestion and slow cars down, but the above-outlined shift to bikes increases speed again. In this case, the former effect is stronger than the latter, so that car speed is modestly reduced in contrast to the previous scenario. Subsequently, the modal share of cars is strongly reduced in both peak and off-peak hours.

Space for on-street parking is also very scarce, which is reflected in the highest on-street parking fee (\$1.72 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 \$0.40 per hour. This would not have been sensible in the previous scenario, because buses and bikes were already severely affected by congestion. An off-street parking fee would then have exacerbated bus and bike congestion by shifting car users to these modes. In this scenario, however, bikes and buses have more space, thus reducing their congestion problems and enabling charging off-street parking fees.

The use of public funds is greatly reduced in this scenario, 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.

Modal Share Each transport mode now receives the share of street space that corresponds to the respective modal share. Compared to the previous scenario EGALITARIANISM, this mainly reduces the space for busses, and increases the space for cars. All characteristics of the bus system remain very similar to the previous scenario, indicating that the same outcome can be achieved by giving buses much less than a third of the available street space.

The inefficiently used bus space is mainly re-allocated to cars. More space for cars relieves congestion and subsequently reduces the negative externality of an additional on-street parking space on car speed. Hence, on-street parking spaces can be increased significantly, because they are less costly to provide and maintain than off-street parking spaces. The increase in the supply of on-street parking spaces and the mitigated externality on car speed then allow reducing the fees for on-street

parking, resulting in a higher utility of traveling by car and greater cost recovery for parking.

Additionally, the space for bikes is slightly increased, thereby leading to a slightly higher cycling speed in peak-hours. Cycling speed in off-peak hours is not significantly affected, as it was already very close to the free-flow speed.

It should be noted that re-allocating street space according to modal shares leads to *new* modal shares, which are then no longer congruent with the *new* street space allocation. Continuing this allocation process until the street space allocation and modal shares converge would result in 22.8 % of street space for cars, 1.6 % for parking, 14.2 % for buses, and 61.4 % for bikes. Social welfare would be 237,358, and thus even lower than after the first iteration outlined above.

Free Lanes Economic efficiency is maximized in this scenario. Despite significant changes in street space allocation, many outcome variables such as modal shares and travel speeds are rather similar to the previous scenario MODAL SHARE. The efficiency gain then results primarily from the reduced costs of operating the entire transportation system. This is mainly due to the increase in on-street parking space, which induces more individuals to park on-street and thus allows reducing the supply of costly off-street parking spaces. In this case, the better cost-recovery of on-street parking spaces exceeds the negative externality on travel speeds.

Bus space is set to 2.2 % of street space, which is a significant reduction from the previous scenario. Nevertheless, efficiently allocating street space 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 significant increase from the REFERENCE scenario (+40.1 pp), and still a notable increase from the previous scenario. 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 %, which is slightly more than in the previous scenario, but still a significant 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 %). While on-street parking has a negative externality on driving speed, this is offset by the much lower construction and maintenance costs compared to off-street parking.

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.⁸ 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 5. 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.

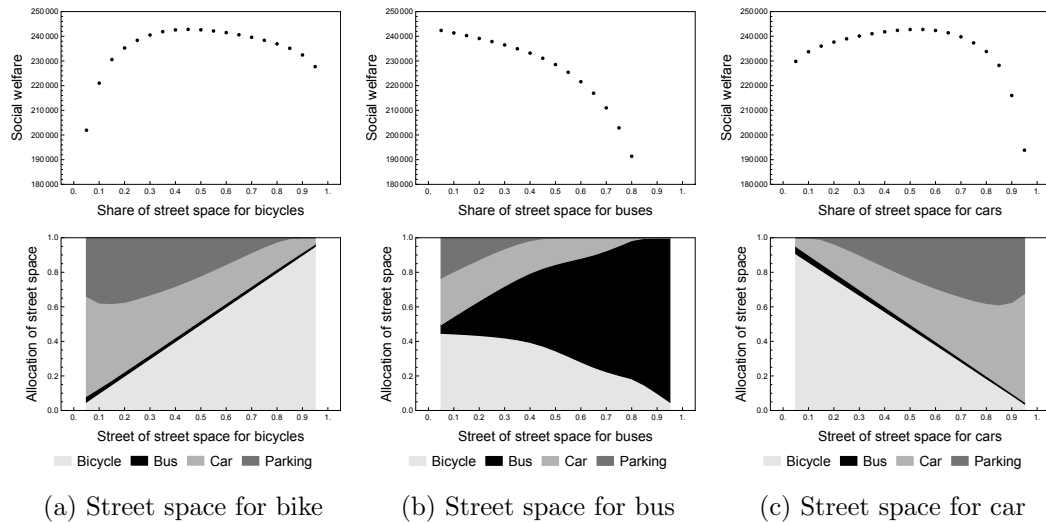


Figure 3: Transport-mode-specific impact of allocated space on economic efficiency (Berlin)

Scenario 5 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 inefficiently allocated to buses. The reductions in welfare become more pronounced the more space is already allocated to buses.

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

⁸To generate these Figures, we use Scenario 5 as a baseline, and gradually constrain the share of street space allocated to a given mode of transport. We begin by allocating 5 % of street space to the given transport mode, and proceed in steps of 5 pp until we reach 95 %.

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 %.

3.4.2 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.⁹ 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

⁹It 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.

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 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).¹⁰

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

¹⁰Monetary values for Stockholm and London were taken from the official web pages of the congestion pricing system, and subsequently converted to 2020 US dollars.

to Barcelona’s *superblock* project.

3.5 Main results for New York City

3.5.1 Analysis of the underlying economic channels of impact

The detailed results for New York City are presented in Table 2. 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.

In general, the underlying channels through which street space re-allocations then impact on social welfare are similar to those in Berlin, so we continue by focusing only on the main differences between the cities. In New York City, allocating street space according to egalitarianism or the modal share does not increase efficiency as much as in Berlin – in fact, egalitarianism decreases efficiency even below the REFERENCE scenario, and allocating street space according to modal shares is barely better than the current street space allocation. 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.¹¹ 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.

Egalitarianism substantially reduces the space for cars, thereby increasing congestion and car travel times. In New York City, car drivers perceive buses and bikes as much worse alternatives, so that they are more likely to stick to traveling by car than switching to buses or bikes. Consequently, more individuals are affected negatively by longer car travel times. When allocating street space according to modal shares, this effect is less pronounced, because the reduction in car space is also smaller. This leads to a slightly higher efficiency than in Scenario 2.¹²

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

¹¹In Section 4.2, we further discuss the role of the alternative-specific constants in our model.

¹²Iteratively allocating street space according to modal shares until both figures converge would result in 66.8 % of street space for cars, 4.1 % for parking, 22.6 % for buses, and 6.4 % for bikes. Social welfare would be 431,255, and thus even lower than after the first iteration.

Table 2: Main results (New York City)

Scenario	REFERENCE	FIXED LANES	EGALITARIANISM	MODAL SHARE	FREE LANES
Social welfare	413495.783	432607.008	404339.768	435065.993	442210.860
Efficiency gains w.r.t. REFERENCE		+4.6 %	-2.2 %	+5.2 %	+6.9 %
Consumer surplus	450259.831	453682.958	392229.343	445944.104	457992.616
People	14800	14800	14800	14800	14800
Travelers	14572.187	14581.722	14427.691	14568.749	14590.688
Share of space for bicycles	0.012	0.012	0.333	0.046	0.046
Share of space for buses	0.017	0.017	0.333	0.203	0.048
Share of space for cars	0.694	0.694	0.333	0.617	0.673
Share of space for parking	0.277	0.277	0.000	0.134	0.233
Bus fare (peak)	0.508	0.000	0.000	0.000	0.000
Bus fare (off-peak)	0.508	0.000	0.000	0.000	0.000
Car toll (peak)	0.000	0.686	0.574	0.807	0.949
Car toll (off-peak)	0.000	0.000	0.000	0.000	0.000
Parking fee (on-street)	3.148	2.958	10.086	3.789	3.013
Parking fee (off-street)	0.000	0.000	1.326	0.255	0.010
Bus frequency (peak)	12.000	23.148	67.725	61.823	48.862
Bus frequency (off-peak)	8.000	19.986	55.909	50.328	41.356
Bus size	49.768	46.480	34.033	23.849	26.392
Number of bus stops	3.900	2.950	2.951	2.848	2.868
Share of peak travelers	0.650	0.630	0.679	0.649	0.635
Share of off-peak travelers	0.335	0.356	0.296	0.335	0.350
Share of non-travelers	0.015	0.015	0.025	0.016	0.014
Modal share of car (peak)	0.831	0.717	0.358	0.585	0.625
Modal share of bus (peak)	0.131	0.243	0.484	0.323	0.289
Modal share of bicycle (peak)	0.039	0.039	0.158	0.092	0.086
Modal share of car (off-peak)	0.888	0.819	0.548	0.759	0.797
Modal share of bus (off-peak)	0.073	0.145	0.369	0.197	0.165
Modal share of bike (off-peak)	0.039	0.036	0.083	0.044	0.038
Speed of cars (peak)	19.769	30.017	23.249	33.330	35.849
Speed of buses (peak)	23.622	23.073	25.223	28.080	27.581
Speed of bicycles (peak)	12.917	13.098	19.999	19.053	19.320
Speed of cars (off-peak)	42.300	43.317	35.232	44.188	43.844
Speed of buses (off-peak)	26.296	27.396	29.470	31.247	30.837
Speed of bicycles (off-peak)	18.846	19.025	20.000	19.997	19.998
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000	1.000
Used parking spaces (on-street, minimum)	0.573	0.701	0.734	0.734	0.782
Share of on-street parking (peak, all travelers)	0.051	0.062	0.000	0.036	0.060
Share of on-street parking (off-peak, all travelers)	0.049	0.059	0.000	0.034	0.057
Net revenue of operating transport systems	-31968.737	-18326.913	10530.804	-9459.227	-13723.267
Parking system: revenue	9196.959	9275.070	29809.855	15166.545	8691.240
Parking system: costs	43200.863	35789.135	18571.763	30617.227	31478.263
Toll system: net revenue	0.000	10311.055	4639.931	10198.505	12520.165
Bus system: revenue	3100.865	0.000	0.000	0.000	0.000
Bus system: costs	1065.699	2123.903	5347.219	4207.050	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.

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.

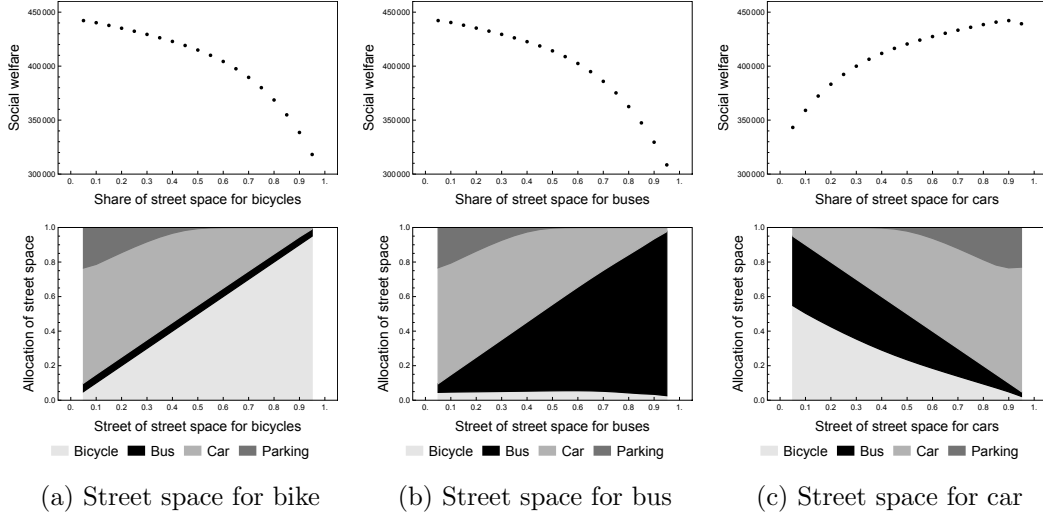


Figure 4: Transport-mode-specific impact of allocated space on economic efficiency (New York City)

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

In Scenario 5, 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 4.2.

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.

3.6 Sensitivity analysis

3.6.1 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 7 and 9 are outlined in Appendix B.1, and detailed results for the scenarios are presented in Tables 4 and 5 in Appendix B.2.

6. **POLITICAL CONSTRAINTS:** First, we test the robustness of Scenario 5 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.
7. **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.
8. **CAPACITY REDUCTION:** Recently, there is intensified discussion on turning “streets for traffic” into “streets for people”. Thus, we model a scenario where 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 repurposed street space has no impact on social welfare. This scenario thus basically corresponds to a reduction in street space capacity of 20 %.
9. **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 5 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) *Free Lanes (With Bike Parking)*

These two scenarios allow us to verify whether the efficiency gains between the original Scenarios 1 and 5 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.

3.6.2 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 5.

A self-financed transportation system is already achieved in the welfare-maximizing Scenario 5 in Berlin. In New York City, however, operational net revenue is 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 5. 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 5. 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 5, 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 5. This additional space helps to mitigate speed reductions from frictions between cars and buses on the same lane.

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.

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 5. 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 5. 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 5, 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 5. In Berlin, the pressure on making cycling relatively more expensive was mitigated by the generally high attractiveness of cycling.

4 Discussion

4.1 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 cyclist 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).

4.2 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 8.

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.

5 Conclusion

We find that street space re-allocations are an effective policy instrument for increasing the efficiency of the transportation system. If the street space allocation is fixed and policy makers can only optimize over traditional policy instruments such as congestion tolls, parking fees, bus fares, and bus frequencies, the attainable efficiency gains are around 5 % in Berlin and in New York City. If policy makers can additionally optimize over the street space allocation, however, efficiency can be improved by 27.7 % and 6.9 %, respectively. 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.

We also find that allocating street space equally across transport modes or according to modal shares *can*, but *need not* lead to greater economic efficiency. In Berlin, these allocation mechanisms lead to a more efficient use of street space, but this is not or only marginally the case in New York City, where people have a greater

preference for driving by car. From an economic perspective, therefore, caution is advised when calling for these rather intuitive, yet simple allocation mechanisms. Instead, 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.

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Appendix

A Data Sources

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 General parameters

Similar to Basso and Silva (2014), we choose a three-lane setting with a road capacity of 3,600 vehicles per hour. This capacity was already reduced by a factor of 0.6 in order to account for traffic lights. The width of each lane is set to 3.5 meters, based on values in the German guidelines on constructing city streets (Forschungsgesellschaft für Straßen- und Verkehrswesen, 2008) and also in line with the guidelines from the National Association of City Transportation Officials in the US. Thus, the considered street is 10.5 meters wide.

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 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.

Table 3: Main parameter values

Parameter	Berlin	New York City
Road capacity [veh/hr]	3,600	3,600
Street width [m]	10.5	10.5
Total travel demand [pax/day]	12,500	14,800
Share Group 1 (public parking)	0.83	0.836
Share Group 2 (private parking)	0.17	0.164
Average trip length [km]	5.9	5.22
Considered hours per day	20	20
Peak duration [hr]	6	11
Off-Peak duration [hr]	14	9
Car occupancy [pax/veh]	1.3	1.51
Car operating costs [\$ / km]	0.46	0.46
Bike operating costs [\$ / km]	0.06	0.06
Parking space area for cars [m ²]	16	16
Parking space area for bike [m ²]	1.6	1.6
Cost per on-street car parking space [\$ / day]	3.43	3.43
Cost per off-street car parking space [\$ / day]	14.88	14.88
Cost per on-street bicycle parking space [\$ / day]	0.08	0.08
Parking garages [garages / km]	2	2
Average parking duration [hr]	6.33	7.09
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]	60	60
Free flow speed, bike [km / h]	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]	2.5	2.5
Constant time a bus spends at the bus stop [seconds]	15	15
Equivalence factor bus ($b_{bus}(k = 75)$)	2.0	2.0
Equivalence factor bike (b_{bike})	0.25	0.25
Walking speed [km / h]	3.9	4.77
Marginal costs of public funds	1.15	1.15
Operational costs of congestion pricing [share of revenue]	0.35	0.35

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).¹⁴ 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 data from Germany’s largest mobility survey “Mobilität in Deutschland” (Nobis and Kuhnimhof, 2018).¹⁵ 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

¹⁴In 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).

¹⁵We 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.

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.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).¹⁶ 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.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 $\eta_{toll} = 0.35$.

A.4 Model calibration

Despite relying heavily on parameter values from the transport literature and city-specific sources, there are still some parameters that we have to calibrate for our model. These are the six period-specific modal constants, the six period-specific marginal utilities of time, the marginal utility of money, three scale parameters, as well as the number of individuals considered.

¹⁶Older 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 pederlecs, 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.

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 VOT_{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).

Moreover, the model is calibrated so that additional elasticities also correspond to values from the 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 Albalade (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 in Guzman et al. (2018), who show that elasticity values below 0.03 can also be realistic.
- The number of individuals considered is set so that Equation 11 results in the observed travel speed for cars.¹⁷

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.¹⁸ All in all, the calibration ensures that the model reflects real-world choice behavior as closely as possible, thereby enhancing the validity of our model results.

A.5 Street space allocation for calibration and reference scenario

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.

¹⁷Apart from the share of car space that is used in Equation 11, the real-world street space allocation does not impact on the calibration.

¹⁸Of 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.

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.

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

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

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

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

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

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

$$B_{parkbike} = \max \left\{ (Y_{Peak,bike} \cdot n_{Peak}^{max} + Y_{Off-peak,bike} \cdot (d_p - n_{Peak}^{max})), \right. \\ \left. (Y_{Off-peak,bike} \cdot n_{Off-peak}^{max} + Y_{Peak,bike} \cdot (d_p - n_{Off-peak}^{max})) \right\}. \quad (29)$$

The parking cost function of Equation 17 changes to

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

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	
	<i>No Congestion Toll</i>	<i>No Subsidies</i>			<i>Reference</i>	<i>Free Lanes</i>
Social welfare	241656.973	242793.930	241808.974	238430.487	183839.652	229322.952
Efficiency gains w.r.t. REFERENCE	+27.1 %	+27.7 %	+27.1 %	+25.4 %		+24.7 %
Consumer surplus	241316.909	242095.787	240380.110	238879.897	210043.451	235995.019
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	–	0.021	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
Share of space for parking cars (in p.p.)					0.207	0.012
Share of space for parking bicycles (in p.p.)					0.105	0.378
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 bicycles (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

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	
	<i>No Congestion Toll</i>	<i>No Subsidies</i>			<i>Reference</i>	<i>Free Lanes</i>
Social welfare	440386.544	441869.695	432644.766	431451.943	400853.599	426693.130
Efficiency gains w.r.t. REFERENCE	+6.5 %	+6.9 %	+4.6 %	+4.3 %		+6.4 %
Consumer surplus	459116.951	441869.694	441554.988	442360.658	439149.586	441035.245
People	14800	14800	14800	14800	14800	14800
Travelers	14591.377	14560.947	14578.813	14561.527	14571.503	14575.607
Share of space for bicycles	0.046	0.051	0.048	0.049	0.012	0.041
Share of space for buses	0.049	0.051	–	0.049	0.017	0.027
Share of space for cars	0.703	0.634	0.743	0.607	0.694	0.736
Share of space for parking	0.202	0.264	0.209	0.095	0.277	0.196
Share of space for parking cars (in p.p.)					0.249	0.129
Share of space for parking bicycles (in p.p.)					0.028	0.067
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	0.000
Car toll (peak)	0.000	1.005	1.304	0.750	0.000	1.202
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	3.579
Parking fee (off-street)	0.462	0.290	0.000	0.302	0.000	0.000
Bus frequency (peak)	49.466	50.033	38.930	50.251	12.000	34.372
Bus frequency (off-peak)	41.161	41.517	23.240	42.229	8.000	23.097
Bus size	25.859	29.326	33.906	29.055	49.904	36.079
Number of bus stops	2.866	2.872	2.373	2.884	3.900	2.409
Share of peak travelers	0.703	0.638	0.615	0.651	0.650	0.616
Share of off-peak travelers	0.283	0.345	0.370	0.332	0.335	0.368
Share of non-travelers	0.014	0.016	0.015	0.016	0.015	0.015
Modal share of car (peak)	0.663	0.574	0.600	0.586	0.830	0.622
Modal share of bus (peak)	0.259	0.327	0.306	0.319	0.131	0.286
Modal share of bicycle (peak)	0.078	0.099	0.095	0.095	0.039	0.091
Modal share of car (off-peak)	0.746	0.763	0.812	0.754	0.887	0.810
Modal share of bus (off-peak)	0.207	0.193	0.151	0.200	0.073	0.152
Modal share of bike (off-peak)	0.047	0.044	0.038	0.046	0.040	0.038
Speed of cars (peak)	28.887	37.011	34.819	32.061	18.346	33.899
Speed of buses (peak)	27.685	26.995	24.648	26.908	12.998	23.757
Speed of bicycles (peak)	19.382	19.272	19.308	19.162	12.905	18.763
Speed of cars (off-peak)	54.471	43.744	39.099	44.032	39.246	38.975
Speed of buses (off-peak)	30.869	30.524	27.195	30.420	22.150	27.011
Speed of bicycles (off-peak)	19.998	19.998	19.998	19.998	18.834	19.996
Used parking spaces (on-street, maximum)	1.000	1.000	1.000	1.000	0.900	0.657
Used parking spaces (on-street, minimum)	0.444	0.806	0.940	0.717	0.516	0.582
Share of on-street parking (peak, all travelers)	0.042	0.073	0.058	0.025	0.046	0.034
Share of on-street parking (off-peak, all travelers)	0.041	0.070	0.056	0.024	0.044	0.033
Net revenue of operating transport systems	-16287.310	0.000	-7748.019	-9485.839	-33300.858	-12471.404
Parking system: revenue	25159.266	19734.713	8060.636	15674.249	8569.177	5731.174
Parking system: costs	37980.812	28318.754	28821.939	30986.344	43400.547	30772.474
Toll system: net revenue	0.000	12244.085	15986.128	9508.951	0.000	15340.417
Bus system: revenue	0.000	0.000	0.000	0.000	3113.623	0.000
Bus system: costs	3465.764	3660.043	2972.844	3682.695	1583.111	2770.522

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.

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