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Ride to the hills, ride to your school: Physical effort and mode choice

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ABSTRACT

Altering the network of public facilities like schools is likely to affect travel choices, in particular route and mode choice. Traveling to school is not only a major contributor to public transport demand in peak periods, but is in many instances also the trip purpose where young people are engaged in bicycling. However, in contrast to public transport, an active travel mode like bicycling needs (substantial) own physical activity as input into the 'production' of a trip. The objective of this paper is to improve our understanding of the substitution between bicycling and public transport in school travel focusing on an underrated determinant in the literature – the personal effort (e.g. energy input in terms of kcal) of students when traveling by bike (or walk). It is shown that a local government aiming at maximizing social welfare when making decisions on the density of public school facilities would be well advised to take this cross effect into account. We use a large unique data set of travel-to-school mode choice in the city of Dresden (Germany). We estimate a series of multivariate extreme value models and derive the elasticity of bike usage and the cross-elasticity of public transport demand with respect to the physical effort. The results reveal that effort elasticity of bike usage is significantly negative, whereas the effort cross-elasticity of public transport demand is significantly positive. In both cases, the responses are highest for school travel distances between 1 and 3 km, but relatively inelastic, meaning that a widespread adoption of pedelecs (or even e-bikes) in school travel could have only limited impacts on peak-period public transport demand.

1. Introduction

Cost-Benefit-Analysis (CBA) in the field of transportation is heavily reliant on travel demand forecasts in various ways. More specifically, the evaluation of the potential benefits associated with the construction of new transport infrastructure (roads, tunnels, bridges, ports, runways, cycling tracks etc.), the introduction of subsidy programs to foster demand for environmentally friendly vehicles, specific transport policies like the launch of road pricing schemes, the tightening of speed limits, enjoining driving bans, or with transport related legislation such as a bicycle helmet law, requires information about changes in e.g. route choice, travel mode choice at the intensive margin and changes in e.g. destination choice or trip demand (making or canceling the trip) at the extensive

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margin.[1] By means of this information, policymakers and researchers are able to calculate the impacts of policy measures in terms of costs and monetized benefits (Small and Verhoef, 2007).

Less known, but not less important, is that even public policy analysis not directly related to transportation issues hinges on travel demand forecasts provided by transport modelers. A prominent example is school network planning and the corresponding (economic) appraisal of school closures, e.g., as a responses to declining school enrollment (Haase and Müller, 2013). A change in the network of public facilities like schools is likely to affect travel choices, in particular route and mode choice (Antunes and Peeters, 2000; Castillo-López and López-Ospina, 2015; Haase et al., 2020). Traveling to school is not only a major contributor to public transport demand at peak periods (e.g. early in the morning), but is in many instances also the trip purpose where young people are engaged in bicycling most frequently for longer distances (Marique et al., 2013; MID, 2008). Note, unlike other countries, in Germany there is no dedicated school bus service. Instead, students use generic transit services but may be eligible for a financial refund. However, in contrast to motorized transport, an active travel mode like bicycling needs own physical activity as input into the 'production' of a trip (Bigazzi and Lindsey, 2019; Brown et al., 2016; Mackett, 2013; Raffler et al., 2019; Rérat, 2019). The importance of public transport and bicycling for school traveling (and the society as a whole, see below) on the one side and the difference in the requirement of physical effort to overcome the friction (distance and altitude) between the place of residence and school location on the other side raise two questions: how does the choice between both travel modes depend on the effort students are forced to put into school travel when bicycling or walking and what are the broader societal consequences of this choice.

Against this background, the objective of this paper is, first, to improve our understanding of the substitution between active modes (bike, for example) and public transport in school travel focusing on an underrated determinant in the literature – the personal effort (e.g. energy input in terms of kcal) of students when walking or cycling,[2] and, second, to highlight the societal welfare implications of a public policy that may induce changes in the physical effort on the commute-to-school.

To shed light on these issues, in the first part of the paper we establish a microeconomics consistent CBA of the public policy 'school closure' and show that our main point of interest – the personal/physical effort students have to make when bicycling – may affect social welfare in various ways through its potential to cause substitution between the travel modes transit and bike. Technically speaking, we show that the wider societal impacts of such a policy crucially depend on the cross-elasticity of public transport demand with respect to the effort put into bicycling. In the second part, we use a large unique data set of travel-to-school mode choice in the city of Dresden (Germany) which we have additionally linked with geodata in order to capture energy intensities of all bike- and walk-related school trips within the data set. We estimate a series of multivariate extreme value models and derive the travel demand elasticity that is in the center of our interest. In deriving this effort elasticity of bicycling, we also make a novel contribution to the empirical literature which provides various kinds of estimates of behavioral responses in the transportation sector.[3]

Even though the travel demand modeling literature is dominated by motorized transport, in particular in recent years a number of studies on cycling choice have been carried out. Research on cycling route choice is mainly concerned with the determination of bicycle infrastructure preferences (e.g. designated cycle track) or preferences for certain route characteristics (e.g. level of crowding, green surroundings, route length, route gradient/slope, number of intersections, intersection control), and how preferences depend on trip type (utilitarian vs. non-utilitarian) and socio-demographic characteristics (gender, age, profession, income etc.).[4] Among the route choice studies that control for slope – which is an essential parameter of our measures of effort – evidence on revealed/stated preference in favor or against routes with positive average road gradients or large fractions with steep terrain is mixed. While cyclists seem to prefer routes with flat terrain for trips with utilitarian purpose, e.g. commuting to work (Bhat et al., 2015; Broach et al., 2012; Casello and Usyukov, 2014; Dill, 2009; Hood et al., 2011), cyclists are suggested to be more in favor of routes located in hillier areas if the trip purpose is more fitness oriented (Bhat et al., 2015; Griffin and Jiao, 2015). Similarly, there has been comprehensive research in terms of cycling choice modeling, indicating a wide range of factors influencing the choice of bike as travel mode.[5] There is even evidence that the hilliness of the geographical area may also be essential for the choice of bike in general and not just for the choice of a certain route given the cycling choice (Parkin et al., 2008). Instead of focusing on the binary choice between bicycling and non-bicycling as travel mode alternatives and using slope as proxy for physical effort, our contribution to this literature is the special attention to school travel, where the substitution between bicycling and public transport is of major importance, explicitly taking into account a students' effort put into bicycling as a potential driver of travel mode choice.

As we will outline in Section 2, the cross-elasticity of public transport demand with respect to physical effort of bicycling is a matter

[1] See, e.g., Anguera (2006), Eliasson (2009), Hirte and Tscharaktschiew (2013), Massiani (2015), Sælensminde (2004), Sieg (2016), Van Benthem (2015), to name only a few.

[2] Boussauw and Witlox (2009) and Marique et al. (2013) also look at the relationship between a travel mode's energy requirement and commuting. However, their view differs from ours as they focus on the (external) energy input of specific travel modes which they assume is zero for non-motorized travel modes such as walk and bike. The study most related to ours is Raffler et al. (2019) which also looks at the internal energy input.

[3] Among many others: the fuel price elasticity of car vehicle kilometer traveled, the fuel price elasticity of fuel demand, the demand for public transport trips with respect to ticket price, the cross fuel price elasticity of public transport demand. See e.g. Brons et al. (2008), Goodwin et al. (2004), Hensher (2008). Wardman et al. (2018) provide a review of inter-modal cross-elasticities.

[4] See Bhat et al. (2015), Broach et al. (2012), Buehler and Dill (2016), Casello and Usyukov (2014), Caulfield et al. (2012), Dill (2009), Griffin and Jiao (2015), Hood et al. (2011), Larsen and El-Geneidy (2011), Menghini et al. (2010), Stinson and Bhat (2003), Vedel et al. (2017), Zimmermann et al. (2017).

[5] See Parkin et al. (2008), Rietveld and Daniel (2004), de Dios Ortuzar et al. (2000), Standen et al. (2019), Orozco-Fontalvo et al. (2018), Larouche et al. (2016), Piatkowski et al. (2015).

of concern. It is shown that a local government aiming at maximizing social welfare when making (CBA-based) decisions on the density of public facilities – schools in our case – would be well advised to take this cross effect into account and we will provide some reasons for it. In Section 3, we estimate the cross-elasticity empirically with the special focus on the derivation of our measures of effort. Our results suggest that higher effort put into bicycling in hilly terrain may cause a significant mode shift toward public transport. The cross-elasticity is positive, but relatively small in magnitude. Finally, Section 4 concludes.

2. Theory

In this section we develop an economic CBA of school closure where a (local) government aims at maximizing social welfare by choice of the school network density. Social welfare is defined as the sum of the utility of the representative household relevant for travel-to-school decisions, government revenue, and the well-being of the rest of society. We derive the marginal social welfare effect of school closure (more precisely a change in school network density) and discuss the various determinants influencing social welfare, where our main concern is the special role of the physical effort on the commute-to-school.

2.1. Model setup

A representative household derives utility from consumption of general goods and services, X, and from the opportunity of children – being subject to compulsory schooling – to travel some (round-trip) distance to school by bike (m_B) and public transport (m_P), respectively.[6] We assume that over the year, on average, both travel modes – bicycle and public transport – are basically available,[7] where $m = m_B + m_P$. From the perspective of the household, m is treated as fixed,[8] but its composition can be changed by choice of m_B, respectively m_P, such that $\partial m/\partial m_B = 1 + \partial m_P/\partial m_B = 0$, i.e. for simplicity we assume that changing the means of transport does not affect school travel distance. Annual aggregate round-trip distance traveled to school within the school district under consideration is denoted by M. It also represents an indicator for the density of the school network. For example, closing schools as policy option of the government in order to save costs makes the overall school network less dense. This causes, on average, the annual distance traveled to school to be longer (implying a larger M) since (at least some) pupils are forced to attend schools that are farther away from home. Individual distances traveled by bike and public transport depend on the density of the school network M and on the potential effort put into bicycling ϕ_B (hereafter referred to as energy intensity) of using the non-motorized travel mode bicycling, thus $m_i = m_i(M, \phi_B(M)), i = B,P$. Changes in the density of the school network can affect a school trip's energy intensity through various channels, e.g., longer travel distances per se, steeper slopes, altitude etc. Whether higher energy intensity of bicycling affects school travel demand by bike, respectively demand for public transport, is our focal point of interest so that, for the time being, we do not make a specific assumption as to the direction of $\partial m_B/\partial \phi_B$, respectively $\partial m_P/\partial \phi_B$.[9]

Following empirical evidence, bicycling is assumed to generate positive health benefits (Mueller et al., 2015),[10] where H_B^I and H_B^S denote individual (such as better general well-being due to the impacts of physical activity) and societal/economic health benefits (e.g. benefits of higher productivity due to a lower level of absenteeism), respectively. Furthermore, both travel modes are assumed to be associated with personal inconveniences, denoted I_B and I_P. For example, adverse weather events may reduce utility when bicycling, whereas crowded buses/trams diminish utility when using public transport. Similarly, traveling to school increases the individual risk of pupils of being involved in a serious accident with injury A_i^I. The personal risk is transport mode specific and we reasonably assume $A_B^I > A_P^I$ due to the serious consequences associated with cycling accidents (e.g. major head injuries; Destatis, 2017; ROSPA, 2017).

Eventually, traveling to school by motorized public transit causes negative externalities E_P (Nieuwenhuijsen and Khreis, 2016), e.g. through higher accident risk of other, more vulnerable, transport users caused by large and heavy vehicles (e.g. pedestrians hit by a bus

[6] Although traveling (distance, trips etc.) is in many cases a derived demand, it is common in the transport economics literature to treat it as an integral part of utility (see, among many others, Parry and Small, 2005, 2009; De Borger and Wuyts, 2011; Tscharaktschiew, 2014, 2015, 2020). Comprehensive rationales for this modeling can be found in Rietveld and van Woudenberg (2003).

[7] We could easily include private transport by car, either driven by parents or by pupils themselves, or walking. This, however, would not add any additional insights to the analyses such that we only focus on traveling by bike as non-motorized travel mode and public transport as the most important motorized travel mode regarding school travel (Müller et al., 2008).

[8] That is, we do not consider voluntary school change. However, note that m can change on account of policy intervention (see below).

[9] Interestingly, some evidence exists with respect to trips not related to school trips. Griffin and Jiao (2015) and Dill (2009) found that bicycling for fitness is positively associated with steep terrain and/or longer distances, whereas utilitarian bicycle trips (in particular commuting to work) avoid steep slopes and seek to minimize the total distance on a given ride.

[10] Physical activity such as cycling is found to be a fundamental way of improving mental and physical health of individuals, thereby leading to reduction in cardiovascular diseases, stroke, cancer, type II diabetes, anxiety and depression, which in the end may increase the productivity of the working force (Andersen et al., 2011, 2018; Cavill et al., 2007; Jarrett et al., 2012; Rabl and De Nazelle, 2012; Rissel and Watkins, 2014). For example, Rojas-Rueda et al. (2011) and de Hartog et al. (2010) found that the health gains from a higher level of cycling far outweigh potential negative impacts such as the increased exposure to local air pollutants. Hendrikson et al. (2010) found that commuters who cycled to and from their places of work had one day less of absenteeism than non-cyclists. Mulley et al. (2013) estimates health economic savings at $1.12 (Australian Dollars) per km of cycling. Deenihan and Caulfield (2014) calculates the health benefits from the construction of a new cycling facility in Ireland. The results suggest that switching the travel mode for commuting to cycling would reduce the mortality rate of commuters as a group by 18%. Pucher et al. (2010) found that areas with more cycling have lower proportions of obese adults. Of course, transit use may have positive impacts on public health as well (see Fasihozaman Langerudi et al., 2014), since transit use of one person may reduce pollution or noise exposure.

or tram), the contribution of vehicles to road congestion,[11] through local air pollution and carbon dioxide emissions of public transit vehicles, noise, and due to passenger crowding (Kraus, 1991; De Palma et al., 2017).[12]

The utility function

$$U = u\left(m_B, m_P, X, H_B^I(m_B), H_B^S(m_B), M, I_B(m_B), I_P(m_P), A_B^I(m_B), A_P^I(m_P), E_P(m_P)\right) \quad (1)$$

is quasi-concave and increasing in arguments m_B,m_P,X,H_B^I,[13] and H_B^S; but decreasing in longer school trips (a smaller number of schools available or a less dense school network) M, transport mode specific inconveniences $I_i(m_i)$ and accident risk $A_i(m_i)$, and negative externalities E_P associated with trips by public transport. Hence, while bike travel distance m_B may contribute positively to utility, aggregate distance to school (a smaller number of schools available) itself reduces utility.

The monetary budget constraint of the household – equating expenditures for school travel activities and general consumption with aggregate income – can be written as follows:

$$C_B + [(\rho - \delta)m_P] + P_X X = Y - G, \quad (2)$$

where C_B denotes the given fixed cost (i.e. independent from distance traveled) of bicycling (e.g. annual capital depreciation, repair costs), $(\rho - \delta)$ is the net price of using public transport per kilometer with ρ as the public transit ticket price per kilometer and δ as the (per km) compensatory payment of the government for traveling to school by public transport. The fixed price of the representative general consumption goods basket is denoted P_X. Aggregate disposable household income, $Y - G$, is composed of the given household income Y (e.g. labor income of parents) and an endogenous lump-sum tax G levied by the government to finance public expenditures.

The government budget constraint

$$\delta m_P + \tau m_P + C(M) = G \quad (3)$$

states that aggregate tax revenue is used for compensatory payments to households for traveling to school by public transit, for subsidies τ allowing the public transit agency to cover its deficit,[14] and for expenditures (per capita) C needed to sustain a certain stock of school buildings. We clearly assume that the government would initiate school closures and condone the resulting longer school travel distances only if this were associated with a decline in the resource cost of maintaining the school building stock, thus $\partial C / \partial M < 0$.

The budget constraint of the (public) transit agency

$$(\rho + \tau)m_P = \xi m_P \quad (4)$$

equates revenue with supply cost, where ξ denotes marginal operating cost of supplying an extra passenger kilometer. With $\rho < \xi$ (fare does not cover operating cost), it follows $\tau > 0$, i.e. public transport is subsidized to cover the deficit. Recall that students in Germany use general public transport because dedicated school bus services do not exist. The former is presumably less prone to change its network as a response to adjustments in school networks so that we refrain from modeling major transit network effects.

2.2. Optimization

The household's optimization program then is to maximize the utility function (1) with respect to choice variables m_B (and thus m_P) and X[15] subject to the monetary budget constraint (2), where societal health benefits of bicycling, H_B^S, transit-related externalities E_P, school resource costs C, the energy intensity of bicycling ϕ_B, as well as government variables (M, G, δ, τ) are neglected and treated as given by the household. Forming the Lagrangian while denoting λ as the Lagrange multiplier of the household's budget constraint (the marginal utility of income) yields the corresponding first-order conditions (FOCs), equating marginal private benefits of an activity (traveling, consumption) with marginal private cost/disutility:

[11] In what follows, we neglect that in the absence of cycle tracks, bicycling could to some extent also contribute to congestion.

[12] When a person boards a bus or a tram, he/she may impose a crowding externality on everyone else on board through increased discomfort for the other travelers. The crowding externality is especially noticeable when vehicles are close to their capacity, i.e. when there are passengers standing (Tirachini et al., 2013).

[13] It is noteworthy that it is not unreasonable to assume that general consumption X is a function of distance traveled by bike m_B and, thus, implicitly a function of effort. Because at private optimum, indirect effects vanish – an immediate consequence of the envelope theorem – we refrain from indicating this potential indirect effect in the utility function.

[14] In most countries around the world, (urban) public transport is subsidized. Fixed costs such as track and rail station maintenance (so this cost is less important in the case of bus), demand-oriented scale economies due to the 'Mohring effect' (average waiting costs of all users decline as service frequency is increased, implying a positive demand externality; Mohring, 1972), and under-priced private car travel are often advanced as rationales (see e.g. Parry and Small, 2009a).

[15] Note that as $\overline{m} = m_B + m_P$, choosing m_B is at the same time an implicit choice with respect to m_P.

$$\frac{1}{\lambda}\left(\underbrace{\frac{\partial u}{\partial m_B}}_{>0}+\underbrace{\frac{\partial u}{\partial H_B^I}\frac{\partial H_B^I}{\partial m_B}}_{>0}+\underbrace{\frac{\partial u}{\partial I_B}\frac{\partial I_B}{\partial m_B}}_{<0}+\underbrace{\frac{\partial u}{\partial A_B^I}\frac{\partial A_B^I}{\partial m_B}}_{<0}\right)=\frac{1}{\lambda}\left(\underbrace{\frac{\partial u}{\partial m_P}}_{>0}+\underbrace{\frac{\partial u}{\partial I_P}\frac{\partial I_P}{\partial m_P}}_{<0}+\underbrace{\frac{1}{\lambda}\frac{\partial u}{\partial A_P^I}\frac{\partial A_P^I}{\partial m_P}}_{<0}-\underbrace{(\rho-\delta)}_{\geqslant 0}\right) \tag{5a}$$

$$\frac{1}{\lambda}\frac{\partial u}{\partial X}=P_X. \tag{5b}$$

Condition (5a) combines the FOCs with respect to m_B and m_P and, thereby, makes clear that the household trades off individual (monetized) net benefits of cycling against those related to using public transport.

The government's optimization program then is to maximize social welfare, i.e. the government maximizes the household's indirect utility function (expressed as a set of parameters $\Omega \equiv \{M, G, \delta, \tau, H_B^S, E_P, C, \phi_B\}$ that are exogenous to or treated as given by the household)

$$V(\Omega)=\max_{m_B,X} u(\cdot)-\lambda(C_B+[(\rho-\delta)m_P]+P_X X-Y+G) \tag{6}$$

by choice of M, where at this stage, changes in public health effects of bicycling, transit-related externalities, school resource costs, the energy intensity of bicycling (effort) and government revenue/expenditure are explicitly taken into account.

Totally differentiating the indirect utility function (6) with respect to M gives the welfare change due to a marginal increase in aggregate travel distance to school induced by school closure (less dense school network):

$$\frac{dV}{dM}=\frac{\partial V}{\partial M}+\frac{\partial V}{\partial G}\frac{dG}{dM}+\frac{\partial V}{\partial \delta}\frac{d\delta}{dM}+\frac{\partial V}{\partial \tau}\frac{d\tau}{dM}+\frac{\partial V}{\partial H_B^S}\frac{dH_B^S}{dM}+\frac{\partial V}{\partial E_P}\frac{dE_P}{dM}+\frac{\partial V}{\partial C}\frac{dC}{dM}+\frac{\partial V}{\partial \phi_B}\frac{d\phi_B}{dM}. \tag{7}$$

Solving the terms in (7) yields the marginal welfare effect (in monetary terms) of school closure (see Appendix A):

$$\frac{1}{\lambda}\frac{dV}{dM}=\underbrace{c_M+v_M}_{\text{non-travel}}+\underbrace{\Gamma^d(M)+\Gamma^{id}(\phi_B)}_{\text{travel}}, \tag{8}$$

where

$$c_M=-\underbrace{\frac{dC}{dM}}_{<0}>0 \tag{9}$$

is the resource cost saving due to school closure,

$$v_M=\frac{1}{\lambda}\frac{\partial V}{\partial M}<0 \tag{10}$$

is the marginal (dis-) utility of school closure,

$$\Gamma^d=-\left(\delta+\tau+e_{m_P}+h_{m_B}^S\right)\frac{\partial m_P}{\partial M} \tag{11}$$

is the direct travel-related net welfare effect of school closure due to a change in travel mode choice (given the effort put into cycling, respectively the energy intensity of bicycling), and

$$\Gamma^{id}=\left[-\left(\delta+\tau+e_{m_P}+h_{m_B}^S\right)\frac{m_P}{\phi_B}\varepsilon_{\phi_B}^{m_P}\right]\frac{d\phi_B}{dM} \tag{12}$$

is the indirect travel-related welfare effect of school closure due to a change in the energy intensity of bicycling.

In (11) and (12)

$$e_{m_P}=-\frac{1}{\lambda}\frac{\partial V}{\partial E_P}\frac{\partial E_P}{\partial m_P}>0 \tag{13}$$

is the marginal external costs of traveling to school by public transit,

$$h_{m_B}^S=\frac{1}{\lambda}\frac{\partial V}{\partial H_B^S}\frac{\partial H_B^S}{\partial m_B}>0 \tag{14}$$

represents the marginal public health benefit associated with bicycling, and

$$\varepsilon_{\phi_B}^{m_P}=\frac{\partial m_P}{\partial \phi_B}\frac{\phi_B}{m_P} \tag{15}$$

is the cross-elasticity of the demand for public transport with respect to the effort put into bicycling.

2.3. Interpretation

As (8) reveals, school closure (causing an increase in aggregate travel distance to school) affects welfare through various channels, where the first and second term refer to effects not related to traveling and the third and fourth term to travel-related effects.

The effects not related to school traveling capture the most intuitive welfare effects of school closure. The first term reflects the fiscal rationale for school closure, the (at first glance) resource cost saving of a less dense school network, c_M. Under declining school enrollment, school closure while pooling pupils in remaining schools may save, e.g., maintenance or energy costs. On the other side, there is a direct effect on the household's subjective well-being, v_M. For example, school closure and associated with it the increase in travel distance to school might compel pupils (or even their parents) to wake up earlier in morning, thereby devouring some time for recreation at night. It might also force pupils to give up their familiar school environment, which could mean to get used to new teachers or schoolmates.[16] But maybe most obviously, pupils might see traveling to school as a boring, time consuming and unproductive activity, irrespective of the travel mode chosen. Further, school closures reduce the choice set cardinality and as such the households consumer surplus is reduced as well. Roughly saying, there are less schools to choose from (less opportunities) and hence it is likely that the variety of the school menu is reduced. In total, because c_M and v_M are likely to run in opposite directions, the net welfare effect of the non-travel-related effect of school closure is ambiguous.

The travel-related effect captures the welfare implications of school closure associated with traveling to school.[17] Let us now start our exposition with Γ^d, referred to as the direct travel-related effect. Subsequently we proceed with the indirect effect, denoted Γ^{id}.

Through changes in travel-to-school mode choice, school closures may have several (direct) welfare effects left unconsidered by individuals. Suppose that $\partial m_P/\partial M > 0$, i.e. the policy (increase in M) raises demand for motorized public transport (at the expense of bicycling). The ignorance of individuals as to the positive public/societal health benefit of bicycling, the marginal external costs associated with public transport (more congestion, higher accident risk of vulnerable road users, more local and global pollution), and the burden to the taxpayers[18] would cause social welfare to decrease.

The most interesting effect occurs with respect to Γ^{id}, capturing our main research question at hand. It shows that a change (either positive or negative) in the effort put into bicycling induced by school closures, i.e. $\partial\phi_B/\partial M \neq 0$, may actually induce indirect impacts on social welfare, provided that mode specific school travel demand is responsive with respect to the effort put into bicycling, i.e. $\varepsilon_{\phi_B}^{m_P} \neq 0$. Inspection of the overall effect reveals that it mirrors Γ^d, but adjusted by the indirect effect of school closures on the effort put into bicycling. The overall term is likely to be negative (welfare reduction) if $\varepsilon_{\phi_B}^{m_P} > 0$.

To sum up, as the theory shows, school closure induced changes in the effort put into bicycling ($\partial\phi_B/\partial M \neq 0$) may cause indirect beneficial or adverse effects on social welfare, but whether this effect is capable to evolve in practice crucially depends on $\varepsilon_{\phi_B}^{m_P}$, i.e. whether a higher effort associated with bicycling induces significant changes in travel mode choice, either away from bike and toward public transport ($\varepsilon_{\phi_B}^{m_P} > 0$) or the other way around ($\varepsilon_{\phi_B}^{m_P} < 0$). Essentially, if $\varepsilon_{\phi_B}^{m_P}$ would to take a non-zero value, a policymaker that disregards the indirect effect Γ^{id} would either under- or overestimate the societal consequences of school network planning. Against this background, in the empirical part we therefore test whether this might be the case, i.e. whether we observe a non-zero – and if so a positive or negative – effort cross-elasticity $\varepsilon_{\phi_B}^{m_P}$, using a large unique data set of travel-to-school mode choice in the city of Dresden (Germany), which we have additionally linked with geodata in order to capture effort of all bike-related school trips within the data set.

3. Empirical analysis

In this section we first briefly discuss the data of our analysis, followed by the econometric model and the interpretation of the results.

3.1. Data

Müller et al. (2008) introduced a large data set on the travel to school mode choices of students in the city of Dresden, Germany (Fig. 6 in the Appendix). The data contains mode choices of more than 4,000 college students, detailed information about the location of the schools and of the students, distance traveled, car availability, age, and gender of the students. Each student is observed two times: once in the summer term and a second time in the winter term. Müller et al. (2020) enhance this data by detailed topographical information. Based on this we compute new explanatory variables *energy* and *altitude variance* which measure the physical effort -

[16] Of course, being forced to get used to new teachers or schoolmates might also be a windfall for some pupils.

[17] Unfortunately, this effect is often not taken into account by public authorities deciding on school network planning and, thus, on school closures (Müller et al., 2009)

[18] The burden is the larger the more the transit agency is forced to increase passenger kilometers (frequency) rather than to increase vehicle occupancy as a response to an increase in demand.

Table 1
Average body weights $\mathcal{W}_n$ with respect to age and gender.

	kg	
Age	Female	Male
9	28.1	28.6
10	31.9	32.0
11	36.9	35.6
12	41.5	39.9
13	45.8	45.3
14	47.6	50.8
15	52.1	56.0
16	53.5	60.8
17	54.4	64.4
18	56.7	66.9
19	57.1	68.9
20	58.0	70.3

Reference: https://www.disabled-world.com/calculators-charts/height-weight-teens.php.

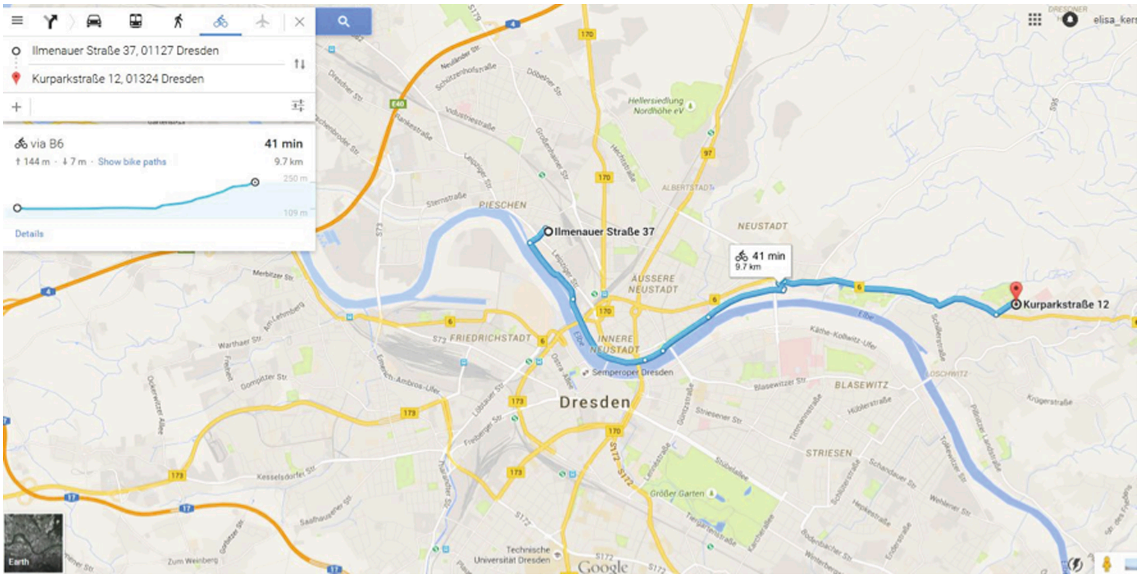

Fig. 1. Example of shortest-path query using Google Maps API.

beside distance - a student spends on the shortest path from home to school (and way back).[19] To compute the energy effort of student n on her school commute we make the following assumptions: student surface: 0.42 m^2 (Hagen, 1966); bike weight: 15 kg; air density 1.25 kg/m^3; gravity: 9.81 m/s and student weight $\mathcal{W}_n$ according to Table 1.

Consider for each student n a set of shortest-paths $\mathcal{P}_n = \{\text{home} - \text{school}, \text{school} - \text{home}\}$. We estimate the average speed v_n^ν of student n with $\nu \in \mathcal{P}_n$ by querying Google Maps API[20] (Fig. 1). Further, the data provides a height profile of the shortest-path from home to school (and back). For each student n we consider sequential sections of the paths denoted as set K_n^ν. Each section $k \in K_n^\nu$ is distinctly characterized by

1. the altitude of k above sea level denoted as $\mathcal{A}_k$, and
2. either positive, negative, or zero slope σ_k, i.e., $\sigma_k > 0$ or $\sigma_k < 0$ or $\sigma_k = 0$.[21]

The length of k is denoted by l_k. Energy intensity [Joule] of student n when traveling by bike (ϕ_B in (7)) is calculated as

[19] Students did not use e-bikes or pedelecs.
[20] https://cloud.google.com/maps-platform/products
[21] Slope is a function of $\mathcal{A}_k$.

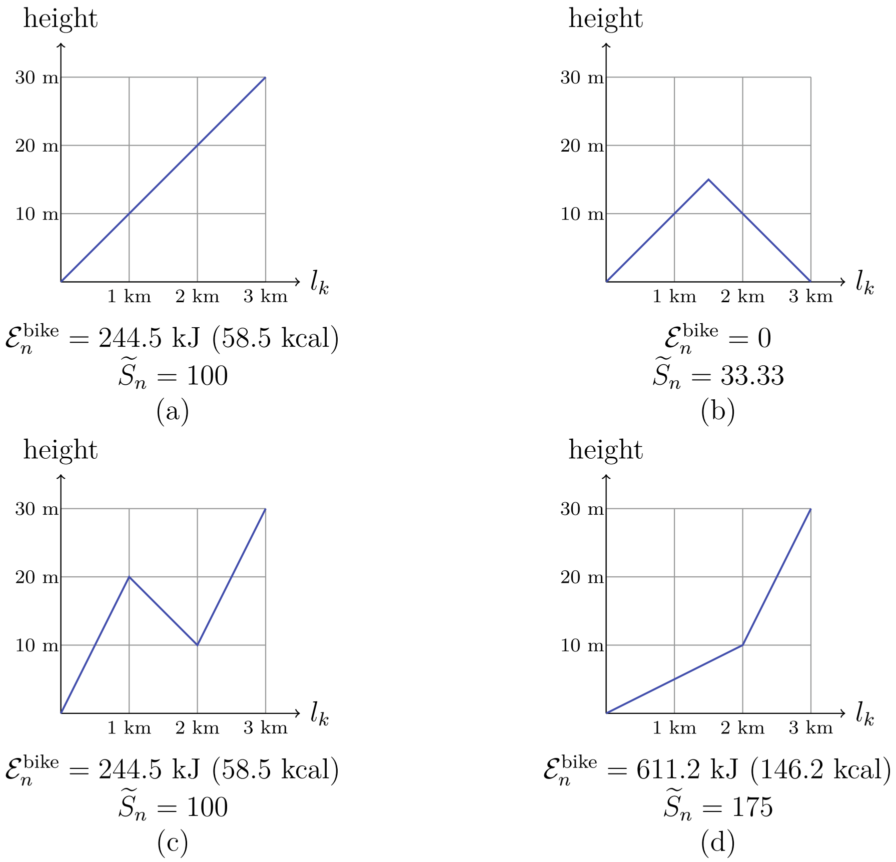

Fig. 2. Topography & effort for physical active means of transport. To show how different height profiles impact our effort measures we consider four simple examples. We consider only home-school trip to simplify the computation. Further let $v_n = 2.8$ m/s and $t_n = 1080$ s, i.e., 18 min of travel time. Each segment k is 1 km long.

$$\phi_B \equiv \mathcal{E}_n^{\text{bike}} = \sum_\nu F_n^\nu \left[\frac{\text{kgm}}{\text{s}^2}\right] \cdot v_n^\nu \left[\frac{\text{m}}{\text{s}}\right] \cdot t_n^\nu[\text{s}] \tag{16}$$

with t_n^ν as bike travel-time (taken from Google Maps) and total force

$$F_n^\nu = c_n \cdot \left(v_n^\nu\right)^2 \sum_{k\in K_n^\nu} \sigma_k. \tag{17}$$

with $c_n = 0.0058 \times 0.5 \times 1.1 \times 1.25 \times 0.42 \times (9.81 \times (\mathcal{W}_n + 15))^2$ is given according to Gressmann (2005) and considers our assumptions above (students weight etc.). We compute the energy intensity for walking accordingly, i.e.,

$$\mathcal{E}_n^{\text{walk}} = 1.5 \cdot \mathcal{W}_n\text{kg} + \mathcal{W}_n\text{kg} \times \left(1.5 \cdot \left(\overline{v}_n^\nu \left[\frac{\text{m}}{\text{s}}\right]\right)^2 + 0.35 \cdot \overline{v}_n^\nu \left[\frac{\text{m}}{\text{s}}\right] \sum_{k\in K_n^\nu} \sigma_k\right) \tag{18}$$

with $\overline{v}_n^\nu$ as the average walking speed taken from Google Maps. For details see Hutchinson (2018). We do not consider the energy effort for the walk to the bus stop, if students choose the bus for their commute to school. All schools in Dresden have a bus stop within close vicinity to the main entrance and as outlined by Müller et al. (2008), the walking distances from students' home to the used bus stop are very short. We assume that the physical effort to get to the bus stop does not effect the mode choice.

Due to the physical definition of total energy the summands in (16) and (18) may be negative and/or positive. This means that a trip with flat slope costs the same energy as a trip with steep positive and a steep negative slope. Therefore, we also consider the variance in altitude as a proxy for the measure of effort:

$$\phi_B \equiv \widetilde{S}_n = \frac{\sum_\nu \sum_{k\in K_n^\nu} \left(\mathcal{A}_k - \overline{\mathcal{A}_n}\right)^2}{\sum_\nu \left|K_n^\nu\right| - 1} \tag{19}$$

Table 2
Descriptive statistics of exogenous variables.

Variable χ_{nir} in (21)	Description	Unit	Mean	S.D.	Min	Max
Same shore	= 1, if student and school are located on the same side of the river	Dummy variable	0.85	0.36	0	1
Female	= 1, if female	Dummy variable	0.56	0.5	0	1
Car availability	= 1, if car is always available	Dummy variable	0.08	0.27	0	1
Winter	= 1, if winter season	Dummy variable	0.5	0.5	0	1
Grade	School grade	Grade	8.73	2.11	5	12
Distance	Distance between school and place of residence	km	3.4	2.66	0.04	17.8
$\widetilde{S}_n$	Variance of differences in altitude (19)	square meter	344.98	846.10	0	6884.65
$\mathcal{E}_n^{\text{bike}}$	Energy spent when cycling (16)	kJ	242.45	379.40	0.13	3,131.95
$\mathcal{E}_n^{\text{walk}}$	Energy spent when walking (18)	kJ	884.52	1,913.26	0.254	25,659.89
	$N = 8{,}556$ # students $\mathcal{N} = 4{,}278$					

with $\overline{\mathcal{A}}_n$ as the mean altitude over all segments k and paths ν of student n. The different results of $\mathcal{E}_n^{\text{bike}}$ and $\widetilde{S}_n$ for a given topography (height profile) are best explained by numerical examples. Fig. 2 implies, the steeper the slope, the larger the energy intensity. However, a negative slope yields a negative energy consumption by construction which may yield a net zero energy effort (panel b). This value is non-distinguishable from a flat ride. However, we would expect that a height profile of (b) is related to a larger effort than a ride on flat terrain. In contrast to $\mathcal{E}_n^{\text{bike}}$ the corresponding variance measure $\widetilde{S}_n$ implies a larger effort than a flat ride ($\widetilde{S}_n = 0$). Obviously, the efforts for (a), (c), and (d) are larger than (b). Moreover, it is reasonable to assume that the effort of (d) is larger than (a). Note, both measures, $\mathcal{E}_n^{\text{bike}}$ and $\widetilde{S}_n$, can not distinguish between the profiles of (a) and (c).

Additionally to the variables of physical effort, we use the explanatory variables introduced by Müller et al. (2008), distance home-school in km, seasonality (winter/summer), and car availability. *Winter* is a dummy variable that takes the value 1, if the trip takes place in the winter term (or with bad weather conditions) and 0 otherwise. *Car availability* is also a dummy variable that takes value 1, if a car is always available to the student (either as a driver or a passenger) and 0 otherwise (this includes that a car might be available only on some days a week). The variables age, gender, and grade were already available in the data set used by Müller et al. (2008) but were not considered there. Variable *age* gives the students age in years, *female* is a dummy variable that takes value 1, if the student is female and 0 otherwise. *Grade* denotes the grade of the student. We consider students enrolled at a German *Gymansium* what can be compared to a college in US. Gymnasium students are aged between 10 and 19 years. The grades are numbered: 5th, 6th, …, 12th grade. The city of Dresden is divided by the river Elbe (Fig. 6 in the Appendix). There are 7 major bridges in total. Of course, traffic pools at the bridges - in particular in peak hours - such that traffic jams are happening. Hence, the utility of using car (and may be public transport as well) on the commute to school is reduced if school and student are located on different sides (shores) of the river Elbe. We consider the dummy variable *same shore* that takes value 1, if student and school are located on the same side of the river. Table 2 displays the descriptive statistics of the variables used in the students' utility function.

Unfortunately, the data does not include two important variables in mode choice studies: travel cost and travel time. Travel cost are of less interest when studying school commute in Germany, because most students use modes other than car. Public transport costs are covered to a large extent by the local authorities (Müller, 2008; Müller, 2011; Müller et al., 2012). However, the lacking of information about travel times is a drawback and cannot be reconciled since current travel-times are very likely to be different to those from 2004. We assume that the effects of travel times are partially captured by distance and same shore.

3.2. Econometric model

Based on Train (2009), we assume that student n chooses the alternative $i = \{\text{walk}, \text{bike}, \text{transit}, \text{car}\}$ which maximizes her utility Θ_{ni}. That is, n chooses i, iff $\Theta_{ni} > \Theta_{nj}\ \forall j$ with $j \neq i$. Utility

$$\Theta_{ni} = \Psi_{ni} + \epsilon_{ni} \tag{20}$$

is decomposed into deterministic utility Ψ_{ni} and stochastic utility ϵ_{ni}. The deterministic part

$$\Psi_{ni} = \sum_r \beta_{ir}\chi_{nir} \tag{21}$$

consists of $r = 1, \ldots, R$ exogenous variables χ_{nir} described in Table 2. Parameters β_{ir} are estimated by maximum likelihood. Since utility (20) is stochastic, we can only make probabilistic statements about the choice of n:

$$\Pi_{ni} = \text{Prob}\left(\Theta_{ni} > \Theta_{nj}\ \forall j,\ j \neq i\right). \tag{22}$$

Π_{ni} is the choice probability that n chooses i. If we assume ϵ_{ni} to be iid extreme value, (22) transforms to the multinomial logit model (MNL):

Table 3
Estimation results of model parameters.

		MNL 1		MNL 2		MNL 3		MNL 4		NL 1		NL 2		CNL	
Variable	Alternative	$\widehat{\beta}$	*t*-stat	$\widehat{\beta}$	*t*-stat	$\widehat{\beta}$	*t*-stat	$\widehat{\beta}$	*t*-stat	$\widehat{\beta}$	*t*-stat	$\widehat{\beta}$	*t*-stat	$\widehat{\beta}$	*t*-stat
Energy: $\mathcal{E}_n^{\text{walk}}, \mathcal{E}_n^{\text{bike}}$	walk, bike			−0.163	−4.89										
Altitude Var.: $\ln(\widetilde{S}_n + 1)$	walk					0.076	2.11	−0.318	−3.27	−0.318	−3.30	−0.247	−2.24	−0.247	−2.36
	bike					−0.177	−8.27	−0.310	−6.68	−0.310	−6.67	−0.221	−3.03	−0.198	−3.34
$\ln(\widetilde{S}_n + 1) \times$ Distance	walk							0.274	4.17	0.273	4.16	0.246	3.57	0.243	3.81
	bike							0.045	3.20	0.045	3.19	0.032	2.32	0.025	1.87
Distance × Winter	walk	2.217	8.82	2.233	8.88	2.411	9.30	2.325	8.72	2.321	6.06	2.225	8.33	2.072	4.31
	bike	−0.019	−0.28	−0.014	−0.20	0.003	0.05	0.024	0.35	0.024	0.29	0.083	1.24	−0.010	−0.07
	transit	0.154	5.25	0.155	5.25	0.155	5.25	0.157	5.28	0.157	5.27	0.180	5.38	0.182	5.74
Distance	walk	−5.668	−21.07	−5.626	−20.92	−5.989	−21.60	−6.722	−21.54	−6.716	−12.13	−6.480	−18.32	−6.267	−8.79
	bike	−0.879	−17.33	−0.851	−16.60	−0.847	−16.42	−1.002	−13.40	−1.003	−12.92	−0.778	−4.87	−0.788	−5.00
	transit	−0.054	−1.54	−0.055	−1.55	−0.054	−1.52	−0.055	−1.54	−0.055	−1.54	−0.099	−2.32	−0.096	−2.39
Grade	walk	0.094	1.99	0.119	2.49	0.098	2.08	0.101	2.11	0.101	2.09	0.084	1.75	0.088	1.78
	bike	0.210	5.00	0.236	5.59	0.208	4.97	0.209	4.97	0.209	4.96	0.166	3.41	0.163	3.68
	transit	0.016	0.41	0.017	0.43	0.015	0.38	0.016	0.41	0.016	0.41	0.028	0.70	0.029	0.73
Same Shore	walk	0.559	1.33	0.646	1.54	0.562	1.31	0.578	1.36	0.577	1.32	0.604	1.43	0.574	1.32
	bike	−0.644	−2.26	−0.584	−2.03	−0.656	−2.28	−0.621	−2.15	−0.621	−2.15	−0.579	−2.14	−0.548	−1.99
	transit	−0.484	−1.89	−0.481	−1.87	−0.477	−1.86	−0.475	−1.85	−0.475	−1.85	−0.466	−1.84	−0.471	−1.86
Car Avail	walk	−4.828	−15.87	−4.825	−15.62	−4.814	−15.77	−4.829	−15.50	−4.828	−15.12	−4.823	−15.69	−4.810	−15.40
	bike	−4.599	−19.56	−4.570	−19.47	−4.548	−19.30	−4.561	−19.31	−4.561	−19.19	−4.671	−20.46	−4.697	−21.74
	transit	−5.341	−28.24	−5.344	−28.22	−5.344	−28.23	−5.344	−28.22	−5.344	−28.22	−5.293	−28.50	−5.289	−28.77
Winter	walk	−3.647	−10.43	−3.695	−10.52	−3.903	−10.92	−3.858	−10.43	−3.855	−8.37	−3.656	−9.89	−3.492	−6.72
	bike	−2.417	−10.16	−2.449	−10.23	−2.527	−10.56	−2.603	−10.74	−2.602	−9.35	−2.390	−9.83	−2.208	−7.61
	transit	−1.142	−6.03	−1.153	−6.04	−1.155	−6.05	−1.162	−6.07	−1.162	−6.06	−1.365	−5.71	−1.375	−6.28
Female	walk	−0.135	−0.65	−0.152	−0.73	−0.158	−0.76	−0.143	−0.68	−0.143	−0.68	−0.086	−0.41	−0.104	−0.49
	bike	−0.774	−4.14	−0.800	−4.28	−0.794	−4.25	−0.790	−4.22	−0.790	−4.22	−0.633	−3.14	−0.627	−3.25
	transit	−0.020	−0.11	−0.016	−0.09	−0.021	−0.12	−0.017	−0.10	−0.017	−0.10	−0.068	−0.37	−0.071	−0.39
ASC	walk	10.813	15.14	11.325	15.56	11.001	15.16	12.017	16.01	12.012	13.99	11.575	14.52	11.378	12.79
	bike	5.585	10.85	5.984	11.48	6.089	11.76	6.502	12.12	6.503	11.98	6.240	11.86	6.307	11.07
	transit	4.680	9.78	4.673	9.75	4.689	9.78	4.679	9.74	4.679	9.74	4.921	9.85	4.886	9.92
	μ_1									1.001	9.12			1.082	4.20
	μ_2											1.412	3.82	1.898	4.91
	α_1													0.473	0.09
	α_2													0.527	0.04
LL(final)			−4510.007		−4493.418		−4445.029		−4429.115		−4429.115		−4427.714		−4424.125
Adj.Rho-sq.			0.6177		0.6191		0.6231		0.6242		0.6241		0.6243		0.6243

$$\Pi_{ni}^{\mathrm{MNL}} = \frac{e^{\mu\Psi_{ni}}}{\sum_j e^{\mu\Psi_{nj}}}. \tag{23}$$

Scale parameter μ is not identified and is normalized to 1. The MNL exhibits the well known independence from irrelevant alternatives property (IIA). The IIA implies that each alternative j is an equal substitute to alternative i. The IIA results from the iid assumptions and implies that there is no correlation between the alternatives in the MNL. If we want to allow for correlation between alternatives we have to relax the iid assumption. Let us assume ϵ_{ni} to follow a multivariate extreme value distribution. Then, (22) transforms to

$$\Pi_{ni}^{\mathrm{NL}}|i \in B_s = \frac{e^{\mu_s\Psi_{ni}}}{\sum_{j\in B_s} e^{\mu_s\Psi_{nj}}} \frac{\left(\sum_{j\in B_s} e^{\mu_s\Psi_{nj}}\right)^{\frac{\mu}{\mu_s}}}{\sum_{t=1}^{S}\left(\sum_{j\in B_t} e^{\mu_t\Psi_{nj}}\right)^{\frac{\mu}{\mu_t}}}, \tag{24}$$

the nested logit model (NL). We partition the choice set into S non-overlapping subsets denoted $B_1, B_2, \ldots, B_S$ and call them nests from hereon. The parameter μ_s is a measure of the degree of independence in unobserved utility among the alternatives in nest s, i.e. we can derive the degree of correlation between alternatives with nest s from μ_s. Parameters μ_s are estimated along with the coefficients β_{ir} by maximum likelihood.

However, the assumption of disjunctive nests may be too restrictive. In contrast, we can estimate the nest membership of each alternative from the data. This yields the so-called cross nested logit (CNL):

$$\Pi_{ni}^{\mathrm{CNL}} = \sum_{s=1}^{S} \frac{\left(\sum_j \alpha_{js}^{\mu_s/\mu} e^{\mu_s\Psi_{nj}}\right)^{\frac{\mu}{\mu_s}}}{\sum_{s'=1}^{S}\left(\sum_j \alpha_{js'}^{\mu_{s'}/\mu} e^{\mu_{s'}\Psi_{nj}}\right)^{\frac{\mu}{\mu_{s'}}}} \frac{\alpha_{is}^{\mu_s/\mu} e^{\mu_s\Psi_{ni}}}{\sum_j \alpha_{js}^{\mu_s/\mu} e^{\mu_s\Psi_{nj}}}. \tag{25}$$

The additional parameters α_{is} are estimated along the other model parameters β_{ir} and μ_s. They denote the fraction of alternative i belonging to nest s. As such the CNL is more flexible than NL and MNL.

3.3. Results

We analyzed several model specifications, both in terms of utility function (21) and nest specification. Our baseline MNL specification (MNL 1 in Table 3) does not contain age or any terrain specific variables (energy and/or altitude variance). All coefficients show the expected signs and all variables impact the mode choice behavior of students significantly. During the winter term students are more likely to choose the car compared to the other three modes. Least attractive in the winter is walking, followed by biking and taking the bus. Of course, car availability increases the probability of going by car compared to walk, bike, and transit. Distance reduces the utility of walking more than bike or public transport. In particular, there is no statistically significant difference between the impact of distance using the car or public transport. These results are in line with those presented in Müller et al. (2008). We also employ some of the variables introduced by Müller et al. (2020). In line with their results, female students are less likely to go by bike, while gender hardly influences the choice of walk or transit over choosing car. This finding may reveal that female students are more risk averse and they may consider biking as riskier than the other means of transportation. Age appears to be strongly correlated with grade, while using grade instead of age yields a better model fit. Our estimates provide some evidence that older students (higher grade) are more likely to bike. Considering biking to be riskier than the other modes, this finding seems reasonable. Older students are assumed to be more responsible on their commute to school. On top of Müller et al. (2008) and Müller et al. (2020) we here introduce several new variables. If both, student and school, are located on the same side of the river (same shore $= 1$), then we expect that commuting to school by car is more attractive compared to other commuting modes (negative signs). This hypothesis can only be confirmed for the bike mode. The effects for transit and walk are statistically not significant different from zero. Roughly speaking, students are more likely to go by bike if the shortest path to school contains a bridge and as they expect lower travel times than going by car (and being caught in traffic jam on a bridge). The interaction of the distance and the winter variables enables us to identify season-specific distance sensitivities. Compared to car,

- the utility of walk declines per km by
  - 5.7 in the summer and
  - 3.5 in the winter
- the utility of bike declines per km by
  - 0.88 in the summer and
  - 0.9 in the winter, while
- the utility of bus declines per km by
  - 0.05 in the summer and

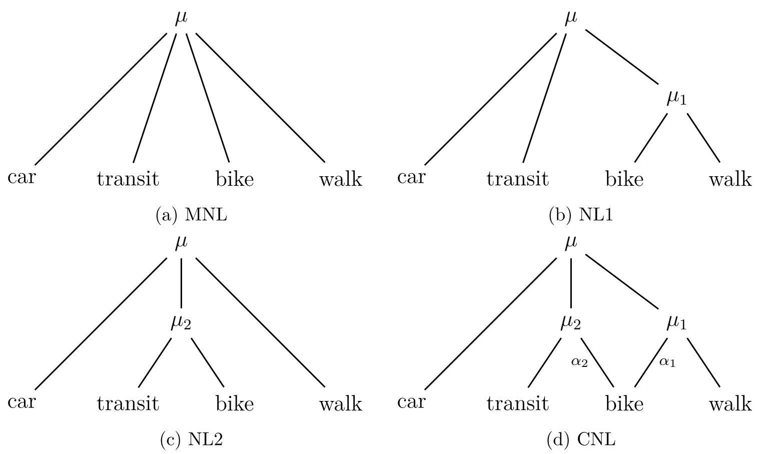

Fig. 3. Nesting structures.

– increases by 0.1 in the winter.

These findings show that students are willing to commute longer distances in the winter by foot compared to the summer. One rationale for this might be, that biking in the winter is more risky and therefore students who bike in the summer may switch to walk (short distances up to 2–3 km) or bus (longer distances of more than 3 km) in the winter (Müller et al., 2008).

Of most interest here are the measures related to the terrain: *energy* and *altitude variance*. MNL 2 in Table 3 considers our energy variables (16) and (18) in a generic specification using a log-transformation. The sign is as expected and the effect shows that the utility of bike and walk declines in the log of 1 kJ by 0.163 units. The effect is statistically significant different from zero and the likelihood ratio test statistic of 33.18 shows that both models (MNL 1 and MNL 2) are statistically significant different from each other. Together, this provides strong evidence, that energy effort while walking or biking impacts the mode choice behavior of students. MNL 3 considers the altitude variance measure (19) in an alternative-specific specification using a log-transformation. A Horowitz-test statistic of 30.9 indicates to reject the hypothesis that MNL 2 is the true model compared to MNL 3. For the bike mode we find the expected negative effect of $\widetilde{S}_n$ in MNL 3. Surprisingly, the effect of $\widetilde{S}_n$ is statistically significant and positive for walking, i.e., the larger $\widetilde{S}_n$ the larger the utility of walking. One rationale for this counter-intuitive finding may be a correlation between distance and $\widetilde{S}_n$: on average we may assume that the longer the trip distance, the more likely it is that we find a larger *altitude variance* compared to a short trip. Of course, if the trip is about 0.8 km, it is quite unlikely to observe large differences in the altitudes (except for some rare occasions). Therefore, we consider in MNL 4 an interaction of distance and $\widetilde{S}_n$, to disentangle such a relationship. Here, the main effects of the altitude variance measure $\widetilde{S}_n$ are negative for both, walk and bike, as expected. The interaction effect indicates that the longer a trip is, the larger is the effect of $\widetilde{S}_n$. However, up to a distance of 1.2 km, the effect of $\widetilde{S}_n$ is negative for walking (nearly 7 km for cycling). About 80% of all walk trips (students who chose walking) are shorter than 1.2 km (99% bike trips are shorter than 6 km). So for most (nearly all) walk (bike) trips the effect of $\widetilde{S}_n$ is negative. The finding reveals that the same variance in altitude $\widetilde{S}_n$ is more negatively evaluated on a short distance trip compared to a trip with longer distance. This is reasonable, since a given $\widetilde{S}_n$ comes along steeper slopes with shorter distances. A likelihood ratio test between MNL 3 and MNL 4 of 31.84 indicates that MNL 4 is superior. Therefore, we continue with the specification of MNL 4 in our analysis.

Since we are interested in the substitution between bike and public transport, we analyze potential correlation between these two alternatives. Therefore, we consider the nesting structures shown in Fig. 3.[22] For NL1 we assume an intuitive correlation between walk and bike (non-motorized, short to medium distances, individual modes etc). So μ_1 represents the nest for *non-motorized modes* (Fig. 3b). By NL2 we account for the fact that there may be some unobserved factors influencing both, the choice of bike and transit. As we learned from the season-specific distance effects, there may be also some unobserved similarities between bike and transit at medium distances (expected travel times, for instance). So μ_2 represents a nest of *environmentally friendly and fast modes*(Fig. 3c). Finally, the bike alternative may be correlated to both, walk and transit, but to different degrees. Therefore, we consider the cross-nesting structure in Fig. 3d. Here, we consider both nests as above while α_1 and α_2 measure the relative nest assignment of the bike alternative. For all three models the nest coefficients are statistically significant different from 1, indicating that the iid assumption of the MNL does not hold. Comparing NL1 and NL2, model NL2 is to be preferred because of (i) a slightly better model fit and (ii) a clearer similarity measure: $\mu_1 < \mu_2$ and μ_1 is very close to 1, indicating a weak correlation between walk and bike. The CNL does not show a reasonable superiority over NL2. The CNL yields a slightly better model fit due to a higher degree of freedom. The nest assignment coefficients, α_1

[22] We also tested various other nesting structures (car, transit, for instance). The ones presented here, are the only ones that are in line with utility maximizing theory.

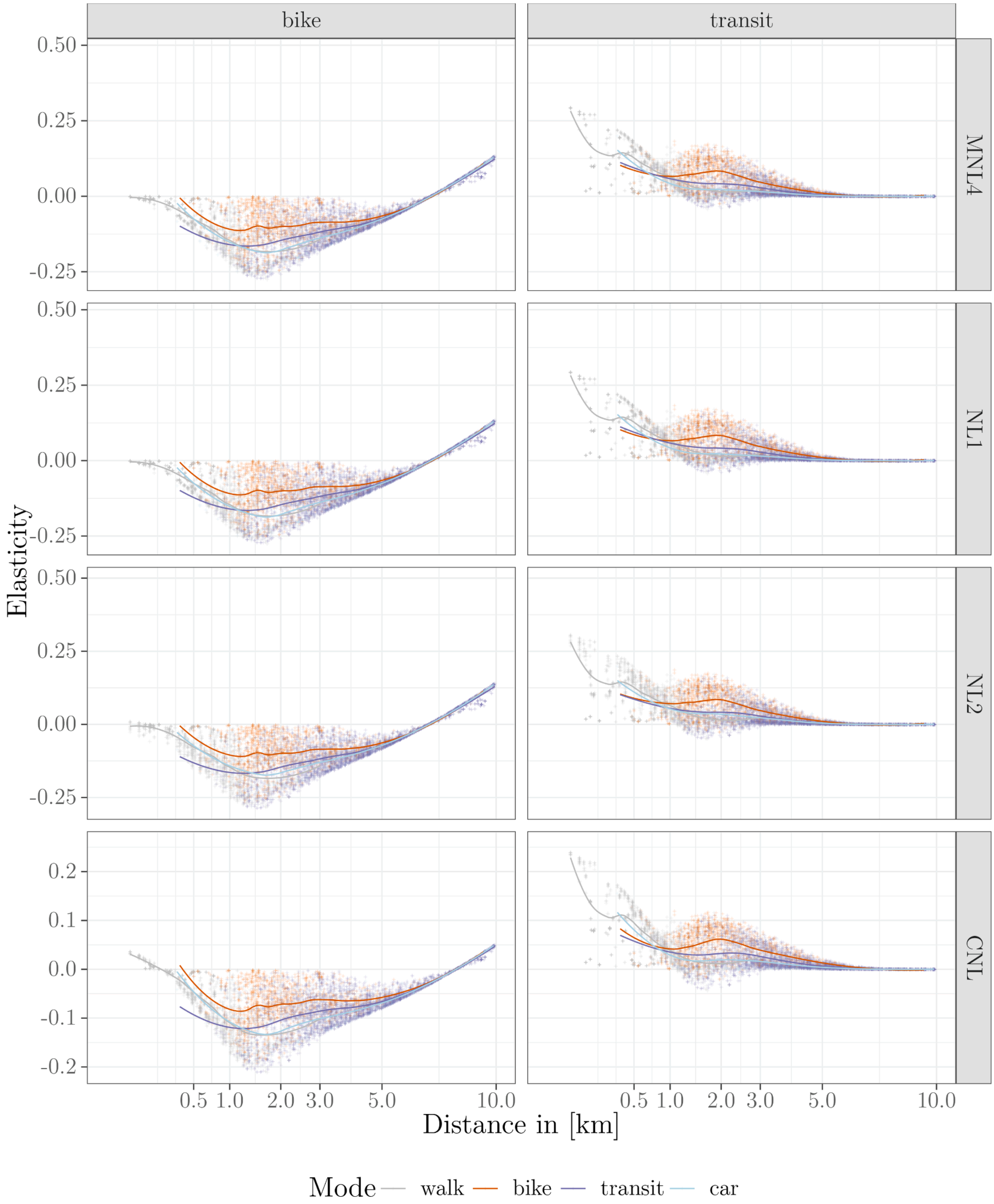

Fig. 4. Elasticity of bike usage and cross-elasticity of public transit demand with respect to effort (variance in altitude $\widetilde{S}_n$)). The plot shows the relative change in choice probabilities (bike and transit) due to a 1% increase in $\widetilde{S}_n$ for our sample. Each observation is characterized by its actual mode choice and distance to school.

and α_2, are not statistically significant different from zero. However, the nest specification of CNL (Fig. 3d) is quite reasonable from a theoretical point of view.

As mentioned before, we are mainly interested in the cross elasticities $\varepsilon^{m_P}_{\phi_B}$ (15) indicating the change of public transit choice probabilities due to a one percentage change in the physical effort when using bike (in what follows wo focus altitude variance $\widetilde{S}_n$ as

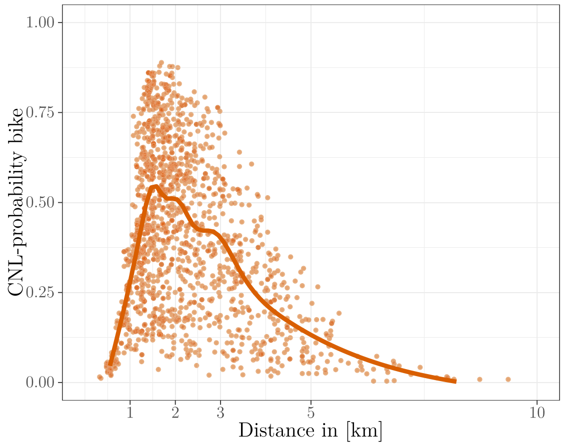

Fig. 5. Bike choice probabilities. The plot shows the predicted CNL choice probabilities for observations who have actually chosen bike with respect to the actual distance to school.

Table 4
Selection of transport elasticities.

Type of elasticity	Value	Study
Elasticity of gasoline demand w.r.t. gasoline price	−0.1/ −0.3[1]	Havranek et al. (2012)
Elasticity of fuel demand w.r.t. fuel price	−0.25/ −0.77[1]	Graham and Glaister (2004)
Elasticity of vehicle miles traveled w.r.t. gasoline price	−0.22[2]	Gillingham (2014)
Elasticity of public transport demand w.r.t. transit fare	−0.39	Hensher (2008)
Elasticity of public transport demand w.r.t. in-vehicle time	−0.55	Hensher (2008)
Elasticity of bicycling demand w.r.t. effort (energy)	−0.13[3]	**This study**
Elasticity of bicycling demand w.r.t. effort (altitude variance)	−0.08[4]	**This study**
Cross-elasticity of car travel demand w.r.t. air fare	+ 0.04	Wardman et al. (2018)
Cross-elasticity of public transport demand w.r.t. fuel price	+ 0.34	Goodwin (1992)
Cross-elasticity of walk w.r.t. fuel price	+ 0.11	Wardman et al. (2018)
Cross-elasticity of non-motorized travel w.r.t. fuel price	+ 0.13/ + 0.01[5]	Litman (2004)
Cross-elasticity of public transport demand w.r.t. effort (energy)	+ 0.03[3]	**This study**
Cross-elasticity of public transport demand w.r.t. effort (altitude variance)	+ 0.04[4]	**This study**

Note: [1] short-term/long-term, [2] medium term, [3] based on MNL2, [4] based on CNL, [5] all travel/only education

energy measure). Fig. 4 shows that the elasticities for bike are negative while the cross elasticities for transit are positive, both as expected. However, there are some exceptions which are artifacts. When the predicted choice probabilities of bike or transit are extremely small, then even small changes may yield unexpected outcome just due to numerical issues. For instance, the positive elasticities for the bike alternative for distances larger than 7 km are due to the extremely small bike choice probabilities for distances larger than 5 km (see Fig. 5). The negative cross-elasticities of transit for some observations in the range between 1 km and 3 km distance are for the same reason.

Overall we see that demand is rather inelastic with respect to effort (altitude variance $\widetilde{S}_n$ and same is true for the energy variables $\mathcal{E}_n^{\text{bike}}$ and $\mathcal{E}_n^{\text{walk}}$ not shown here). The most elastic demand is found for distances smaller than 3 km which is the average commuting distance (Table 2). One rationale for low (cross-) elasticities in our analysis is that commute-to-school mode choice and the school choice are strongly dependent. While travel times, distance, physical effort may mainly impact the mode choice, the choice of a given school is affected by many more variables such as school profile, quality, job location etc (Müller et al., 2012). Hence, these factors may also (indirectly) influence the students mode choice, reducing the demand elasticity of physical effort on their commute to school.

4. Conclusions

We present a cost-benefit analysis for the public policy of school network consolidation and highlight the special role of the physical effort while cycling in inducing welfare effects of such a policy. The intuition is as follows: closing schools – e.g. due to a decline in enrollment – causes higher average travel distances for students. Obviously, this is likely to induce a modal shift from short travel distance modes like walking and bicycling to modes more appropriate for longer travel distances like car or public transport. However,

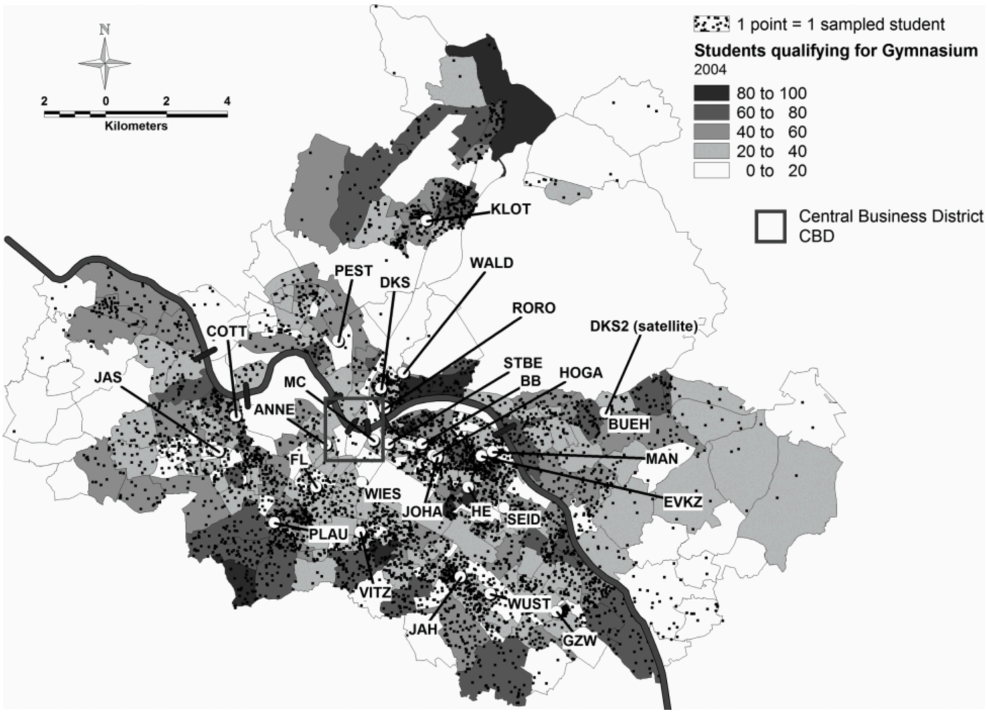

Fig. 6. School locations, student numbers, and sampled students in 2004.

even if the average travel distance to school in the network were the same after a school closure, a change in travel mode choice – in particular away from bike – could be the result in the case that the public policy causes school commutes to take place in hillier terrain on average. The reason for this effect is the physical energy intensity of an active travel mode like bicycling. By means of a stylized CBA we show that such cross effects are highly relevant from a social welfare perspective and we conceptualize one such cross effect through the elasticity of public transport demand with respect to the physical effort put into bicycling.

We then estimate this elasticity using a unique data set of travel-to-school mode choice behavior in Dresden, Germany. Our findings confirm the findings by Müller et al. (2008) and Müller et al. (2020). On top of their results we find that if on the commute-to-school students do not cross the river Elbe this increases the probability of choosing car. This is reasonable, since bridges are notorious jammed by car traffic (increasing the travel times). Our interaction variable Distance-Winter provides some evidence that walk substitutes bike in the winter for short trips and public transport substitutes bike in the winter for long commuting distances. Most importantly, we find statistically significant negative effects of physical effort (energy and altitude variation) on active means of transport (bike, walk), and a significantly positive effort cross-elasticity of public transport demand. In both cases, the responses are highest for school travel distances between 1 and 3 km (the dominating distance for bike travel) but relatively inelastic. Our estimated elasticities are in line with the literature showing that cross-elasticities in transportation are usually rather small (see Table 4). For school travel, our estimates are at the bottom end of the range.

Our findings shed new light on issues beyond the school network consolidation policy. When account is taken of the adverse impacts of motorized transport modes in comparison to active travel modes like walk and bike, any policy affecting the effort put into bicycling may have implications for human health and may exacerbate problems like urban traffic congestion, local and global pollution, noise, crowding in public transport etc. Interestingly, our finding of a positive, but small in magnitude, effort cross-elasticity of public transport demand implicitly suggests that a widespread adoption of pedelecs (or even e-bikes) in school travel[23] could have only limited impact on peak-period public transport demand and so, e.g., on the external cost of crowding in public transit.

An exciting avenue for further research is to test whether our findings do also hold for other locations and/or larger regions. The advancement of our approach toward more general policies in terms of urban sprawl would be another exciting path to follow.

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[23] See Bourne et al. (2020) for a review of the impact of e-cycling on travel behavior in general.

Appendix A. Marginal welfare effect of school closure

The total differential of the household's indirect utility function, as indicated by (7), is (assuming no corner solution, i.e. (5a) holds at private optimum)

$$\frac{dV}{dM}=\frac{\partial V}{\partial M}+\frac{\partial V}{\partial G}\frac{dG}{dM}+\frac{\partial V}{\partial \delta}\frac{d\delta}{dM}+\frac{\partial V}{\partial \tau}\frac{d\tau}{dM}+\frac{\partial V}{\partial H_B^S}\frac{dH_B^S}{dM}+\frac{\partial V}{\partial E_P}\frac{dE_P}{dM}+\frac{\partial V}{\partial C}\frac{dC}{dM}+\frac{\partial V}{\partial \phi_B}\frac{d\phi_B}{dM} \tag{A.1}$$

Assuming that the government is not interested in adjusting compensatory payments for school travel or subsidies to the transit agency in order to balance its budget, using lump-sum taxes as funding instrument instead, replacing term $\partial V/\partial G$ and taking into account that there is no direct effect of ϕ_B[24] and C on V, we get

$$\frac{dV}{dM}=\frac{\partial V}{\partial M}-\lambda\frac{dG}{dM}+\frac{\partial V}{\partial \delta}\frac{d\delta}{dM}+\frac{\partial V}{\partial \tau}\frac{d\tau}{dM}+\frac{\partial V}{\partial H_B^S}\frac{dH_B^S}{dM}+\frac{\partial V}{\partial E_P}\frac{dE_P}{dM} \tag{A.2}$$

Dividing both sides by λ, the marginal utility of income, gives us the welfare change in monetary terms

$$\frac{1}{\lambda}\frac{dV}{dM}=\frac{1}{\lambda}\frac{\partial V}{\partial M}-\frac{dG}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial \delta}\frac{d\delta}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial \tau}\frac{d\tau}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial H_B^S}\frac{dH_B^S}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial E_P}\frac{dE_P}{dM} \tag{A.3}$$

Next we totally differentiate the government budget constraint (3). Assuming that $d\delta/dM = d\tau/dM = 0$ yields

$$\frac{dG}{dM}=\frac{\partial G}{\partial M}+\frac{\partial G}{\partial m_P}\frac{dm_P}{dM} \tag{A.4}$$

which gives us

$$\frac{dG}{dM}=\frac{\partial C}{\partial M}+(\delta+\tau)\frac{dm_P}{dM}+(\delta+\tau)\frac{\partial m_P}{\partial \phi_B}\frac{d\phi_B}{dM} \tag{A.5}$$

Plugging (A.5) into (A.3), gives us

$$\frac{1}{\lambda}\frac{dV}{dM}=\frac{1}{\lambda}\frac{\partial V}{\partial M}-\frac{\partial C}{\partial M}-(\delta+\tau)\frac{dm_P}{dM}-(\delta+\tau)\frac{\partial m_P}{\partial \phi_B}\frac{d\phi_B}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial H_B^S}\frac{dH_B^S}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial E_P}\frac{dE_P}{dM} \tag{A.6}$$

Next we decompose $\frac{dH_B^S}{dM}$ and $\frac{dE_P}{dM}$ to obtain

$$\frac{1}{\lambda}\frac{dV}{dM}=\frac{1}{\lambda}\frac{\partial V}{\partial M}-\frac{\partial C}{\partial M}-(\delta+\tau)\frac{dm_P}{dM}-(\delta+\tau)\frac{\partial m_P}{\partial \phi_B}\frac{d\phi_B}{dM}+\frac{1}{\lambda}\frac{\partial V}{\partial H_B^S}\frac{\partial H_B^S}{\partial m_B}\left(\frac{dm_B}{dM}+\frac{\partial m_B}{\partial \phi_B}\frac{d\phi_B}{dM}\right)+\frac{1}{\lambda}\frac{\partial V}{\partial E_P}\frac{\partial E_P}{\partial m_P}\left(\frac{dm_P}{dM}+\frac{\partial m_P}{\partial \phi_B}\frac{d\phi_B}{dM}\right) \tag{A.7}$$

Rearranging and keeping in mind that per assumption each change in bike usage is captured by an equivalent change in the demand for public transport ($\partial m_B = -\partial m_P$ and vice versa) gives

$$\frac{1}{\lambda}\frac{dV}{dM}=\frac{1}{\lambda}\frac{\partial V}{\partial M}-\frac{\partial C}{\partial M}-\left((\delta+\tau)+\frac{1}{\lambda}\frac{\partial V}{\partial H_B^S}\frac{\partial H_B^S}{\partial m_B}-\frac{1}{\lambda}\frac{\partial V}{\partial E_P}\frac{\partial E_P}{\partial m_P}\right)\frac{dm_P}{dM}-\left((\delta+\tau)+\frac{1}{\lambda}\frac{\partial V}{\partial H_B^S}\frac{\partial H_B^S}{\partial m_B}-\frac{1}{\lambda}\frac{\partial V}{\partial E_P}\frac{\partial E_P}{\partial m_P}\right)\frac{\partial m_P}{\partial \phi_B}\frac{d\phi_B}{dM} \tag{A.8}$$

Using the definitions in (9)–(14), multiplying $\frac{\partial m_P}{\partial \phi_B}$ by $\frac{\phi_B}{m_P}\frac{m_P}{\phi_B}$, and then using the definition in (15), we eventually arrive at (8).

References

Andersen, L.B., Riiser, A., Rutter, H., Goenka, S., Nordengen, S., Solbraa, A.K., 2018. Trends in cycling and cycle related injuries and a calculation of prevented morbidity and mortality. Journal of Transport & Health 9, 217–225.

Andersen, L.B., Wedderkopp, N., Kristensen, P., Moller, N.C., Froberg, K., Cooper, A.R., 2011. Cycling to school and cardiovascular risk factors: a longitudinal study. J. Phys. Activity Health 8, 1025–1033.

Anguera, R., 2006. The Channel Tunnel–an ex post economic evaluation. Transp. Res. Part A: Policy Pract. 40, 291–315.

Antunes, A., Peeters, D., 2000. A dynamic optimization model for school network planning. Socio-Econ. Plan. Sci. 34, 101–120.

Bhat, C.R., Dubey, S.K., Nagel, K., 2015. Introducing non-normality of latent psychological constructs in choice modeling with an application to bicyclist route choice. Transp. Res. Part B: Methodol. 78, 341–363.

Bigazzi, A., Lindsey, R., 2019. A utility-based bicycle speed choice model with time and energy factors. Transportation 46, 995–1009.

[24] Recall that health impacts of bicycling are included in H_B. Hence, $\partial V/\partial \phi_B$ can be interpreted as the joy ($\partial V/\partial \phi_B > 0$) or the dislike ($\partial V/\partial \phi_B < 0$) derived from more effort students are forced to put into bicycling. We simply assume that both cancel each other out, yielding a zero net effect.

Bourne, J.E., Cooper, A.R., Kelly, P., Kinnear, F.J., England, C., Leary, S., Page, A., 2020. The impact of e-cycling on travel behaviour: A scoping review. J. Transp. Health 19, 100910.
Boussauw, K., Witlox, F., 2009. Introducing a commute-energy performance index for Flanders. Transp. Res. Part A: Policy Pract. 43, 580–591.
Broach, J., Dill, J., Gliebe, J., 2012. Where do cyclists ride? A route choice model developed with revealed preference GPS data. Transp. Res. Part A: Policy Pract. 46, 1730–1740.
Brons, M., Nijkamp, P., Pels, E., Rietveld, P., 2008. A meta-analysis of the price elasticity of gasoline demand. A SUR approach. Energy Econ. 30, 2105–2122.
Brown, B.B., Tharp, D., Tribby, C.P., Smith, K.R., Miller, H.J., Werner, C.M., 2016. Changes in bicycling over time associated with a new bike lane: relations with kilocalories energy expenditure and body mass index. J. Transp. Health 3, 357–365.
Buehler, R., Dill, J., 2016. Bikeway networks: A review of effects on cycling. Transp. Rev. 36, 9–27.
Casello, J.M., Usyukov, V., 2014. Modeling cyclists' route choice based on GPS data. Transp. Res. Rec. 2430, 155–161.
Castillo-López, I., López-Ospina, H.A., 2015. School location and capacity modification considering the existence of externalities in students school choice. Comput. Ind. Eng. 80, 284–294.
Cavill, N., Kahlmeier, S., Rutter, H., Racioppi, F., Oja, P., 2007. Economic Assessment of Transport Infrastructure and Policy. World Health Organis.
Caulfield, B., Brick, E., McCarthy, O.T., 2012. Determining bicycle infrastructure preferences–A case study of Dublin. Transp. Res. Part D: Transp. Environ. 17, 413–417.
De Borger, B., Wuyts, B., 2011. The tax treatment of company cars, commuting and optimal congestion taxes. Transp. Res. Part B: Methodol. 45, 1527–1544.
Deenihan, G., Caulfield, B., 2014. Estimating the health economic benefits of cycling. J. Transp. Health 1, 141–149.
de Dios Ortuzar, J., Iacobelli, A., Valeze, C., 2000. Estimating demand for a cycle-way network. Transp. Res. Part A: Policy Pract. 34, 353–373.
de Hartog, J., Boogard, H., Nijland, H., Hoek, G., 2010. Do the health benefits outweigh the risk. Environ. Health Perspect. 118, 1109–1116.
De Palma, A., Lindsey, R., Monchambert, G., 2017. The economics of crowding in rail transit. J. Urban Econ. 101, 106–122.
Destatis, 2017. Kraftrad- und Fahrradunfälle im Straßenverkehr.
Dill, J., 2009. Bicycling for transportation and health: the role of infrastructure. J. Public Health Policy 30, S95–S110.
Eliasson, J., 2009. A cost-benefit analysis of the Stockholm congestion charging system. Transp. Res. Part A: Policy Pract. 43, 468–480.
Fasihozaman Langerudi, M., Mohammadian, A., Sriraj, P.S., 2014. Health and transportation: Small scale area association. J. Transp. Health 2, 127–134.
Gillingham, K., 2014. Identifying the elasticity of driving: evidence from a gasoline price shock in California. Reg. Sci. Urban Econ. 47, 13–24.
Goodwin, P.B., 1992. A review of new demand elasticities with special reference to short and long run effects of price changes. J. Transp. Econ. Policy 26, 155–169.
Goodwin, P., Dargay, J., Hanly, M., 2004. Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transp. Rev. 24, 275–292.
Graham, D.J., Glaister, S., 2004. Road traffic demand elasticity estimates: a review. Transp. Rev. 24, 261–274.
Gressmann, M., 2005. Fahrradphysik und Biomechanik. Technik, Formeln, Gesetze. Klasing, Bielefeld.
Griffin, G.P., Jiao, J., 2015. Where does bicycling for health happen? Analysing volunteered geographic information through place and plexus. J. Transp. Health 2, 238–247.
Haase, K., Müller, S., 2013. Management of school locations allowing for free school choice. Omega Int. J. Manage. Sci. 41 (5), 847â€"855.
Haase, K., Knörr, L., Krohn, R., Müller, S., Wagner, M., 2020. Facility location in the public sector, in: Laporte, G. et al.: Location Science, second ed., pp. 745–764.
Hagen, N., 1966. Growth and development of schoolchildren. Report on longitudinal studies in Germany. Deutsche Medizinische Wochenschrift, 91, 1490â€"1497.
Havranek, T., Irsova, Z., Janda, K., 2012. Demand for gasoline is more price-inelastic than commonly thought. Energy Econ. 34, 201–207.
Hendrikson, I., Simons, M., Garre, F., Hildebrant, V., 2010. The association between commuter cycling and sickness absence. Prevent. Med. 51, 132–135.
Hensher, D.A., 2008. Assessing systematic sources of variation in public transport elasticities: some comparative warnings. Transp. Res. Part A: Policy Pract. 42, 1031–1042.
Hirte, G., Tscharaktschiew, S., 2013. The optimal subsidy on electric vehicles in German metropolitan areas: A spatial general equilibrium analysis. Energy Econ. 40, 515–528.
Hood, J., Sall, E., Charlton, B., 2011. A GPS-based bicycle route choice model for San Francisco, California. Transp. Lett. 3, 63–75.
Hutchinson, A., 2018. Endure: Mind, Body, and the Curiously Elastic Limits of Human Performance. Harper Collins, New York.
Jarrett, J., Woodcock, J., Griffiths, U.K., Chalabi, Z., Edwards, P., Roberts, I., Haines, A., 2012. Effect of increasing active travel in urban England and Wales on costs to the National Health Service. Lancet 379, 2198–2205.
Kraus, M., 1991. Discomfort externalities and marginal cost transit fares. J. Urban Econ. 29, 249–259.
Larouche, R., Stone, M., Buliung, R.N., Faulkner, G., 2016. I'd rather bike to school!: Profiling children who would prefer to cycle to school. J. Transp. Health 3, 377–385.
Larsen, J., El-Geneidy, A., 2011. A travel behavior analysis of urban cycling facilities in Montréal, Canada. Transp. Res. Part D: Transp. Environ. 16, 172–177.
Litman, T., 2004. Transit price elasticities and cross-elasticities. J. Public Transp. 7, 37–58.
Mackett, R.L., 2013. Children's travel behaviour and its health implications. Transp. Policy 26, 66–72.
Marique, A.F., Dujardin, S., Teller, J., Reiter, S., 2013. School commuting: the relationship between energy consumption and urban form. J. Transp. Geogr. 26, 1–11.
Massiani, J., 2015. Cost-Benefit Analysis of policies for the development of electric vehicles in Germany: Methods and results. Transp. Policy 38, 19–26.
Menghini, G., Carrasco, N., Schüssler, N., Axhausen, K.W., 2010. Route choice of cyclists in Zurich. Transp. Res. Part A: Policy Pract. 44, 754–765.
MID, 2008. Rückenwind für das Fahrrad? Aktuelle Ergebnisse zur Fahrradnutzung.
Mohring, H., 1972. Optimization and scale economies in urban bus transportation. Am. Econ. Rev. 62, 591–604.
Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., De Nazelle, A., Dons, E., Gerike, R., Götschi, T., Int Panis, L., Kahlmeier, S., Nieuwenhuijsen, M., 2015. Health impact assessment of active transportation: a systematic review. Prev. Med. 76, 103–114.
Mulley, C., Tyson, R., McCue, P., Rissel, C., Munro, C., 2013. Valuing active travel: including the health benefits of sustainable transport in transport appraisal frameworks. Res. Transp. Bus. Manage. 7, 27–34.
Müller, S., Mejia-Dorantes, L., Kersten, E., 2020. Analysis of active school transportation in hilly urban environments: A case study of Dresden. J. Transp. Geogr. 88, 102872.
Müller, S., Haase, K., Kless, S., 2009. A multiperiod school location planning approach with free school choice. Environ. Plan. A 41, 2929–2945.
Müller, S., Tscharaktschiew, S., Haase, K., 2008. Travel-to-school mode choice modelling and patterns of school choice in urban areas. J. Transp. Geogr. 16, 342–357.
Müller, S., 2008. Dynamic school network planning in urban areas: A multi-period, cost-minimizing location planning approach with respect to flexible substitution patterns of facilities. LIT Verlag.
Müller, S., Haase, K., Seidel, F., 2012. Exposing Unobserved Spatial Similarity: Evidence from German School Choice Data. Geograph. Anal. 44 (1), 65–86.
Müller, S., 2011. Assessment of school closures in urban areas by simple accessibility measures. Erdkunde 65 (4), 401–414.
Nieuwenhuijsen, M.J., Khreis, H., 2016. Car free cities: pathway to healthy urban living. Environ. Int. 94, 251–262.
Orozco-Fontalvo, M., Arévalo-Támara, A., Guerrero-Barbosa, T., Gutiérrez-Torres, M., 2018. Bicycle choice modeling: A study of university trips in a small Colombian city. J. Transp. Health 9, 264–274.
Parry, I.W.H., Small, K.A., 2005. Does Britain or the United States have the right gasoline tax? Am. Econ. Rev. 95, 1276–1289.
Parry, I.W.H., Small, K.A., 2009. Should urban transit subsidies be reduced? Am. Econ. Rev. 99, 700–724.
Piatkowski, D.P., Krizek, K.J., Handy, S.L., 2015. Accounting for the short term substitution effects of walking and cycling in sustainable transportation. Travel Behav. Soc. 2, 32–41.
Parkin, J., Wardman, M., Page, M., 2008. Estimation of the determinants of bicycle mode share for the journey to work using census data. Transportation 35, 93–109.
Pucher, J., Buehler, R., Bassett, D.R., Dannenberg, A.L., 2010. Walking and cycling to health: a comparative analysis of city, state, and international data. Am. J. Public Health 100, 1986–1992.
Rabl, A., De Nazelle, A., 2012. Benefits of shift from car to active transport. Transp. Policy 19, 121–131.

Raffler, C., Brezina, T., Emberger, G., 2019. Cycling investment expedience: Energy expenditure based Cost-Path Analysis of national census bicycle commuting data. Transp. Res. Part A: Policy Pract. 121, 360–373.
Rérat, P., 2019. Cycling to work: Meanings and experiences of a sustainable practice. Transp. Res. Part A: Policy Pract. 123, 91–104.
Rietveld, P., Daniel, V., 2004. Determinants of bicycle use: do municipal policies matter? Transp. Res. Part A: Policy Pract. 38, 531–550.
Rietveld, P., van Woudenberg, S., 2003. The utility of travelling when destinations are heterogeneous. How much better is the next destination as one travels further? J. Geogr. Syst. 5, 207–222.
Rissel, C., Watkins, G., 2014. Impact on cycling behavior and weight loss of a national cycling skills program (AustCycle) in Australia 2010–2013. J. Transp. Health 1, 134–140.
Rojas-Rueda, D., de Nazelle, A., Taino, M., Nieuwenhuijsen, M., 2011. The health risks and benefits of cycling in urban environments compared with car use: health impact assessment study. BMJ 343, d4521.
ROSPA, 2017. Road Safety Factsheet (Cycling Accidents); Royal Society for the Prevention of Accidents.
Sælensminde, K., 2004. Cost-benefit analyses of walking and cycling track networks taking into account insecurity, health effects and external costs of motorized traffic. Transp. Res. Part A: Policy Pract. 38, 593–606.
Sieg, G., 2016. Costs and benefits of a bicycle helmet law for Germany. Transportation 43, 935–949.
Small, K.A., Verhoef, E.T., 2007. The Economics of Urban Transportation. Routledge.
Standen, C., Greaves, S., Collins, A.T., Crane, M., Rissel, C., 2019. The value of slow travel: Economic appraisal of cycling projects using the logsum measure of consumer surplus. Transp. Res. Part A: Policy Pract. 123, 255–268.
Stinson, M.A., Bhat, C.R., 2003. An analysis of commuter bicyclist route choice using a stated preference survey. Transp. Res. Rec. 1828, 107–115.
Train, K., 2009. Discrete choice methods with simulation, second ed. Cambridge University Press.
Tirachini, A., Hensher, D.A., Rose, J.M., 2013. Crowding in public transport systems: effects on users, operation and implications for the estimation of demand. Transp. Res. Part A: Policy Pract. 53, 36–52.
Tscharaktschiew, S., 2014. Shedding light on the appropriateness of the (high) gasoline tax level in Germany. Econ. Transp. 3, 189–210.
Tscharaktschiew, S., 2015. How much should gasoline be taxed when electric vehicles conquer the market? An analysis of the mismatch between efficient and existing gasoline taxes under emerging electric mobility. Transp. Res. Part D: Transp. Environ. 39, 89–113.
Tscharaktschiew, S., 2020. Why are highway speed limits really justified? An equilibrium speed choice analysis. Transp. Res. Part B: Methodol. 138, 317–351.
Van Benthem, A., 2015. What is the optimal speed limit on freeways? J. Public Econ. 124, 44–62.
Vedel, S.E., Jacobsen, J.B., Skov-Petersen, H., 2017. Bicyclists' preferences for route characteristics and crowding in Copenhagen–A choice experiment study of commuters. Transp. Res. Part A: Policy Pract. 100, 53–64.
Wardman, M., Toner, J., Fearnley, N., Flügel, S., Killi, M., 2018. Review and meta-analysis of inter-modal cross-elasticity evidence. Transp. Res. Part A: Policy Pract. 118, 662–681.
Zimmermann, M., Mai, T., Frejinger, E., 2017. Bike route choice modeling using GPS data without choice sets of paths. Transp. Res. Part C: Emerg. Technol. 75, 183–196.