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Valuation of public investment to support bicycling

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Abstract

In this paper we develop a framework to value public investments with the purpose of increasing bicycling that explicitly accounts internal costs of bicycling, which are typically neglected in current established approaches that value bicycle spending by means of gross health benefits alone, as are inframarginal benefits to existing cyclists. By monetizing internal costs independent of health benefits, we can assess the degree of internalization of private benefits and/or the internalization of external benefits such as environmental improvements due to altruistic preferences by cyclists. Our framework further conceptualizes the complementarity between "hard" (investments in infrastructure) and "soft" measures (informational campaigns) in bicycle policy. Finally, we propose an empirical method for identifying internal costs using a latent variable approach and apply it to eight Swiss cities. Our results imply that Swiss cyclists internalize more than mortality-based benefits. However, because data for some important bicycle mode choice determinants are not available, our results cannot inform policy directly at the current stage. Instead, the contributions of our paper are the development of an economically consistent framework to value public bicycle investments and the identification of crucial data needs for the development of comprehensive assessments informing bicycle policy decisions.

JEL H43, H76; Q51; R41, R42.

Keywords: Cost-benefit analysis, bicycle, valuation, latent variable, MIMIC

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1. Introduction

Transport agencies in many large cities in industrialized countries, and many regional and federal governments, have offices responsible for designing and carrying out bicycle-friendly policies, usually in coordination with other planning activities such as road construction or public transportation. The role of government to design and finance bicycle policies can be justified by the public-good characteristic of bicycle infrastructure and the substantial fixed costs, but also by net beneficial effects associated with bicycling compared to other modes of transportation, such as a reduction in mortality and morbidity due to increased physical activity, reduction of congestion, and reduction in air pollution (Woodcock et al., 2009). Public interventions to increase the level of bicycling have often been successful, implying that policy has an important role when it comes to bicycling as a mode of transportation (Pucher et al., 2010). Although public funds allocated to bicycle policies rarely exceed a few percent of the total transportation budget, studies quantifying benefits indicate excellent benefit-cost—ratios for cycling interventions (Cavill et al., 2009; Gotschi, 2011; Krizek et al., 2007; Wang et al., 2005).

However, economic decision criteria about bicycle-related investments are not well developed. Progress has been made in terms of identifying the determinants of bicycle mode choice, in assessing effectiveness of policy and infrastructure measures, and in the valuation of particular costs and benefits of bicycling, but these different strands of research have not been integrated in a framework suitable for an economically consistent cost-benefit analysis. This paper takes a first step to fill this gap.

Our main contribution is the development of a conceptual as well as an empirical framework to value bicycle-related policies[1] that explicitly accounts for the internal costs of bicycling. Many of the relevant costs and benefits associated with bicycling are intangible, such as disutility from physical effort, inconvenience, fear of accidents, competition for crowded road space etc. Considering the well-documented and significant health benefits from exercise associated with bicycling, we argue that if it were not for such intangible net costs, the bicycle mode share for short trips would be much higher than current levels in most countries.

Since intangible costs are not directly observable we rely on a latent variable approach, drawing on results from the transportation mode choice literature to select indicator variables for internal costs. Existing valuations of bicycle spending abstract from internal costs and implicitly assume that the pre-intervention level of bicycling is given exogenously. Relative to this benchmark, our framework leads to smaller net benefits for the additional bicycle-km (the increase in bicycling due to the investment), but to additional benefits for inframarginal bicycle-km (bicycling taking place already before the investment), which are not considered in existing valuations. The net difference between our and existing approaches is ambiguous and depends on the context, but in general our model leads to higher benefits at higher levels of bicycling.

As a second contribution, our model allows for an assessment of the degree of internalization of health benefits or time savings. This is of interest because many existing analyses of cycling imply health benefits of a magnitude which does not appear to be reflected in consumers' choices. Along with internal costs, incomplete internalization of health benefits could be part of an explanation for these seemingly "too low" levels of bicycling. It is also possible that consumers consider some of the external effects of bicycling such as savings to the health care

[1] We refer to bicycle policy in the broadest sense, including physical infrastructure but also any institutional and urban planning changes that affect the level of bicycling.

system or a reduction in air pollution (if bicycle-km substitute motorized transportation).[2] Estimating the degree of internalization of health effects or other benefits requires an independent monetization of internal costs. In the current paper we do this via money savings from bicycling relative to public transportation, but alternative methods (e.g. savings relative to motorized traffic, or stated preference surveys) could be used as well.

Our framework further allows to conceptualize one of the most pressing questions in promotion of bicycling, that of interactive effects, or the optimal mix of so called “hard” and “soft” measures. “Hard measures” (e.g. infrastructure) are aimed at reducing internal costs of bicycling. Certain “soft measures” (informational and educational campaigns highlighting benefits of bicycling) enable people to internalize them in their decision making. Hard and soft measures are both considered vital ingredients to an effective mix of measures to promote bicycling (Pucher et al., 2010), but to date there is no modeling approach available to quantify their individual and synergistic effects, leaving it to policy makers’ best guesses to strike the optimal balance.

We apply our model to bicycling in eight Swiss cities using data from the Swiss Microcensus. Our parameters are statistically significant and (mostly) have the expected sign, but due to data and other limitations our results are sensitive to the inclusion of particular variables. The main contribution of our paper is therefore conceptual. An application of the model to a richer data context would be a fruitful avenue of future research.

The next section introduces our model and contrasts it to existing approaches from the literature. Section 3 introduces the data, and Section 4 contains our econometric specification and presents our empirical results. Section 5 concludes.

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[2] Neoclassical economic theory holds that consumers do not consider external effects, but recent research in behavioral and experimental economics implies that this may not be the case in the presence of commitment problems, pro-social preferences or reasons related to self-image (see e.g. Bernheim and Rangel, (2007) or Benabou and Tirole, (2006)

2. Valuation of bicycle policies

A key feature of any economic model is that people choose their actions according to their preferences, conditionally on the set of available information. For bicycling, this means that riders choose the level of bicycling that is optimal for them by weighing the internal costs and benefits of bicycling against the existing alternatives. In the following we describe the most important gross costs and benefits, and then turn to the issue of internal vs. external net costs.

2.1 Gross costs and benefits of bicycling

Bicycling is associated with a number of positive and some negative effects, and a literature has developed on the subject with the aim of defining, quantifying and sometimes monetizing various costs and benefits. In terms of magnitude, the most important effects are a.) decreased mortality and morbidity as a result of physical activity, b.) increased injury risk as a result of exposure to traffic environments, and c.) increased mortality and morbidity due to exposure to air pollutants while riding in traffic (de Hartog et al., 2010; de Nazelle et al., 2011; Rojas-Rueda et al., 2011; Woodcock et al., 2009).

With an assumption about substitution between bicycling and other means of transportation based on empirical findings of substitution (Thakuriah et al., 2012), additional effects include d.) reduced air pollution, noise and congestion, e.) lower demand for parking spaces, f.) less wear and tear on roads, g.) time gain/loss during trips, or substituting for exercising in a gym, and h.) intangible effects such as "livability" (Dumbaugh, 2005; Ellison and Greaves, 2011; Litman, 2004). With the exception of time savings, the substitution effects are borne not only by bicyclists but the population as a whole.

This list is not meant to be exhaustive; its purpose is to illustrate the diversity of impacts, the quantification and monetization of which requires contributions from various disciplines such as epidemiology, physiology, urban planning, and last but not least economics.[3] The literature on (health) impact assessment of cycling has made progress along many of these lines of research by improving the quality of individual pieces along causal pathways and reducing the number of simplifying assumptions necessary to account for the lack of data and effect estimates, which remains a pervasive problem in this area of research.[4]

Existing "gross health benefit" (GHB hereafter) valuations compute average benefits per unit of bicycling and apply them to observed or projected increases in bicycling (e.g. Gotschi, 2011; Saelensminde, 2004). However, most of these benefits accrue to bicyclists and should therefore (at least partly) be internalized in people's decision to bicycle when they trade off costs and benefits. Equating such internal health benefits with net benefits, as is often done, amounts to double-counting, as pointed out by Borjesson and Eliasson (2012). Whether internalization of health benefits is complete is a different question that we address separately below; the point is that the (implicit) assumption of zero internalization is most likely not correct. Separating between internal and external benefits is crucial for the valuation of bicycle spending, as well as for projecting the likely increase in bicycling as a result of bicycle promotion measures.

2.2 Internal costs of bicycling

Abstracting from leisure trips that serve no purpose of transportation, getting from A to B conveys disutility to people in the form of money, time, and other costs. If there were only positive health benefits (net of accident risks and increased exposure to air pollution), bicycling

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[3] Epidemiological studies are needed to estimate dose-response functions between physical activity and air pollution and the most relevant diseases, ideally by age, gender and activity types. Physiologists convert distance traveled by bicycle into exercise units, ideally by intensity (Ainsworth et al., 2000) Surveys are required to get an idea about the likely composition of the additional ridership. Finally, values of risk reduction derived from economic analyses, commonly referred to as the Value of a Statistical Life (VSL), are used to compute the benefits from reduced mortality, and sometimes this is further refined to take into account disability- or quality-adjusted life years.

[4] See, e.g. de Geus et al., 2008; de Hartog et al., 2010; de Nazelle et al., 2011; Gotschi, 2011; Int Panis et al., 2010; Rojas-Rueda et al., 2011; Woodcock et al., 2009).

would be the dominant choice of transportation for all trips below a certain distance and at moderate levels of accident risk.[5] However, the bicycle mode share in Swiss cities is around 5%, with few reaching more than 10% for all trip lengths (Federal Statistical Office, 2007, 2012).

There is a large literature devoted to identifying the determinants of transportation mode choices in general, including bicycling. We reference key publications for selected determinants below and refer to various additional studies for further evidence.[6]

We separate the determinants that have been empirically identified to affect the propensity to bicycle into the following groups:

a.) Route characteristic which can potentially be influenced by city planners. Characteristics shown to influence the amount of bicycling include the presence of bicycle lanes/paths; the lane width, the volume and speed of motorized traffic; competition for space between drivers and cyclists; the number of stops, traffic lights or other obstacles; the number of intersections and their characteristics, accident risk; and qualitative aspects about bike lanes such as continuity and connectivity or the presence of on-street parking. This category may also include trip end facilities such as locking stations or the presence of showers at work (Dill, 2009; Lusk et al., 2011; Berrigan et al., 2010).

b.) External factors about the route that are treated as exogenous by planning authorities, at least in the short or medium term. Such factors include weather (temperature and precipitation), hilliness, city size, cultural and neighborhood characteristics including land use, and prices of alternative modes of transportation.

[5] Dutch cities and Copenhagen prove that there is no "law of nature" capping bicycle mode share anywhere close to what is observed in most cities without long history of systematic bicycle investments.

[6] See e.g. Buehler and Pucher, 2012; Caulfield et al., 2012; Elston, 2002; Harris et al., 2011; Heinen and Handy, 2012; Hunt and Abraham, 2007; Kirner Providelo and Sanches, 2011; Menghini et al., 2009; Parkin et al., 2008; Plaut, 2005; Rietveld and Daniel, 2004; Sener et al., 2009; Smith, 1991; Troped et al., 2001; Vandenbulcke, 2011; Wardman et al., 2007; Xing et al., 2010.

c.) Personal characteristics of actual and potential (i.e. marginal) bicyclists, such as age, race, gender, education, car ownership, aversion to driving, perception of bicycle-friendliness of the traffic environment or environmental preferences (Heinen and Handy, 2012).

d.) Internal costs and benefits. Here we include items that affect the utility from bicycling directly, such as psychological costs due to effort or fear of accidents, conflict with drivers, inconvenience factors such as perspiration or problems with dress code etc, but also costs from time loss relative to other modes of transport (time gains would be benefits). Some mode choice studies explicitly consider this type of cost, whereas in the majority internal costs are implicit.[7] Smith (1991) finds that psychological costs of bicycling are a significant predictor of bicycle mode choice. Similarly, Rietveld and Daniel (2004) report "generalized costs" as a significant predictor variable, in which they include measures such as costs of effort or fear of accidents, and Hunt and Abraham find that bicyclists choose routes that are least "onerous". Menghini et al. (2010) conclude that trip length is the dominant factor for route choice, which is consistent with high time costs and/or costs of physical exertion.[8]

In our empirical model, we rely on some these mode choice determinants to control for the overall level of bicycling in a city, as well as to proxy for the internal costs of bicycling.

2.3 The social value of bicycle spending

The effect of including internal costs of bicycling on the valuation of bicycle spending can be profound. Figure 1 illustrates. On the horizontal axis we measure bicycle-km per capita in a

[7] For example, it is not necessarily the presence of a bike path per se that increases the propensity to bike, but the lowering of the perceived risk, and of interactions with motorized vehicles due to the physical separation from traffic. The same is true for other mode choice determinants.

[8] This study is based on GPS data of actual routes, which are compared to constructed non-chosen alternative routes. The main result is that Zurich bicyclists are willing to make only slight detours in order to improve along another dimension (such as the presence of a bike trail or fewer stops), implying large time and effort costs of bicycling.

population (Q), ordered by the internal net marginal cost associated with them.[9] The MC curve contains all marginal (net) costs per km that vary over the amount of bicycling, allowing for the possibility of negative net marginal costs associated with the "lowest-hanging" fruit. At higher Q, marginal costs of bicycling increase because an increasing share of trips take place during inclement weather, over hilly terrain, or are carried out by people with a stronger aversion against exercise or risk. Naturally, the MC curve need not be linear; we focus on the linear case due to tractability, and also because of a lack of information about the shape of the "true" MC curve.

The marginal benefits curve MB_p reflects the internal or private health benefit per additional bicycle-km that is assumed to be constant for all bicycle-km.[10] The initial level of bicycling is given by Q_0; beyond this point, the internal costs of an additional bicycle-km are larger than the internal benefits, and vice versa.

In addition to internal costs and benefits, there also exist external (net) benefits, such as health care cost savings that accrue to the entire population in the form of lower insurance premia and/or taxes (these positive externalities are an important justification for government spending aimed at increasing bicycling). According to standard economic theory, consumers exclude all external effects but fully consider all internal effects, but there is evidence that some people choose to cycle out of environmental concern (Eriksson and Forward, 2011), meaning that perhaps not all externalities are ignored. We return to this issue below.

If bicycling itself could be subsidized, we could achieve the social optimum Q_0^{opt} by placing a Pigovian subsidy equal to marginal external benefits on every bicycle-km travelled. However, a

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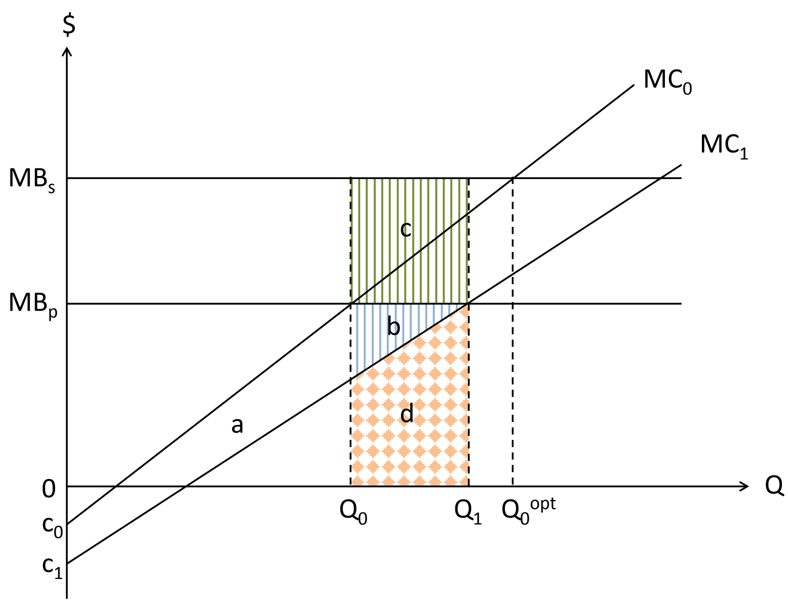
[9] The assumption that internal costs vary across bicycle-km is essential for our analysis and can be justified by heterogeneous preferences across people, as well as spatial heterogeneity of route characteristics and of exogenous factors. Ordering bicycle-km by internal cost leads to an increasing MC curve by construction.

[10] This assumption confers no loss of generality since we can simply place any benefits (e.g. time savings) that depend on Q negatively into the MC cost function, thus ensuring that the MB_p curve is constant in Q.

per-km subsidy of bicycling is currently not feasible in practice. In order to increase the level of bicycling without a direct subsidy, the government can carry out policies that increase the "bicycle-friendliness" of a city by reducing the internal costs associated with bicycling from MC_0 to MC_1, leading to an increase in bicycle-km to the new equilibrium Q_1. Examples include the expansion of bicycle infrastructure, driver education programs to raise awareness about sharing the street, rule changes such as a reduction in the speed limits for motorized traffic or subsidies for firms to install showers and locker rooms for their staff.

Figure 1: Costs and benefits from bicycling



The social value from bicycle spending that changes MC_0 to MC_1 is the sum of internal net benefits associated with the increase in Q (area *b* in the figure), the corresponding external benefits (area *c*), plus the benefit increase for inframarginal bicycle-km (area *a*). In a cost-benefit application, a bicycle-related public investment would be warranted if the costs required to shift the MC curve are less than the discounted stream of annual benefits *a+b+c*.

In contrast, benefits computed by the GHB approach would consist of internal gross benefits (area *b+d*) plus external benefits (area *c*). Which approach yields higher benefits is ambiguous ex ante and depends on the relative magnitude of inframarginal benefits *a* and internal costs *d*.

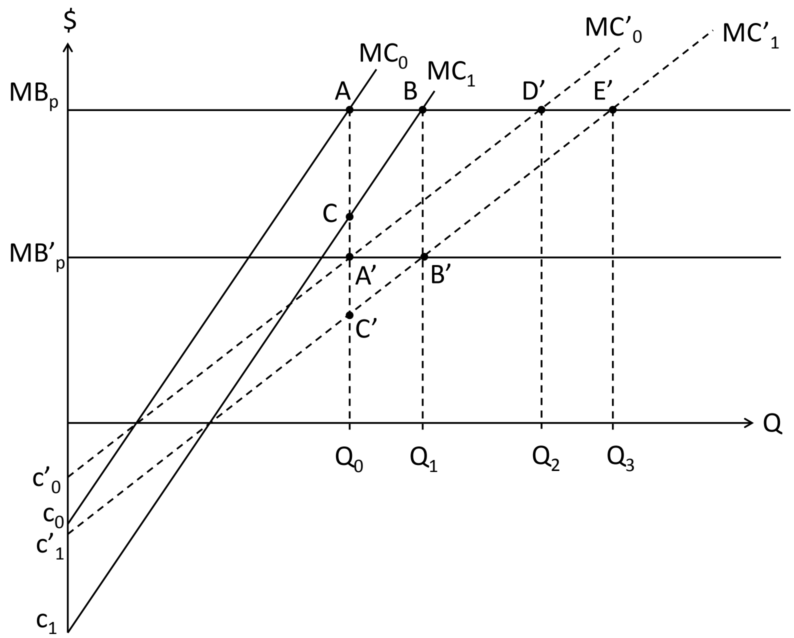
2.4 Incomplete internalization of benefits

Bicyclists may not fully internalize health benefits, either due to information costs or issues related to commitment. For example, many people exercise less than they themselves deem optimal in the long run (Bernheim and Rangel, 2007). On the other hand, it is also possible that bicyclists have altruistic preferences and therefore internalize benefits that are technically external to them, such as a reduction in greenhouse gas emissions.

Suppose that bicyclists (on average) only internalize $MB_p' < MB_p$ and refer to Figure 2, where we abstract from external benefits since they are counted equally under both approaches. The social value of the investment computed with the GHB approach is given by rectangle Q_0ABQ_1. Applying our choice-based approach under the (wrong) assumption that consumers fully internalize health benefits would results in the computation of the marginal cost curve MC_0. The projected level of bicycling after investing in bicycle-friendly policies is Q_1, with resulting net benefits of c_1c_0AB. However, if bicyclists internalize health benefits only partially and we are able to identify the internal marginal costs curve given by MC_0', the projected benefits for the same increase in bicycling is c_1'c_0'A'B' plus the rectangle of "quasi-externalities" AA'BB'.

Conversely, it is also possible that consumers internalize most or all of the internal benefits, plus some of the (true) externalities, leading to a situation where $MB_p' > MB_p$. In this case, GHB plus valuation of the externalities yields relatively larger benefits than our approach, because consumers incur internal costs beyond those associated with purely internal benefits.

Figure 2: Incomplete internalization of benefits



2.5 Policy implications: Soft vs. hard measures of bicycle policy

Besides "hard measures" such as investments in bicycle infrastructure, but there is also scope for "soft measures" such as information campaigns that aim to raise awareness about the full health benefits from exercise that accrues to bicyclists. In practice, effective promotion of bicycling requires a broad mixture of measures, including infrastructure improvements as well as informational and educational campaigns (Krizek et al., 2009; Pucher et al., 2010). How to optimize allocation of funds between these various measures may be among the most challenging research questions regarding the advancement of bicycling.

Suppose that the initial equilibrium is characterized by Q_0 in Figure 2, and that people internalize $MB'_p < MB_p$. Reducing internal costs by spending on infrastructure leads to a new equilibrium at

Q_1. However, the government could instead engage in an information campaign about the health benefits associated with bicycling. Assuming that this campaign is 100% successful in the sense that it causes people to exactly internalize the private benefits from bicycling, the new equilibrium will be at Q_2 (note that Q_2 could be to the right or the left of Q_1, depending on the degree of internalization and the shift in the cost curve).

If the government decides to invest both in infrastructure and an information campaign, it could achieve an equilibrium level of bicycling at Q_3 (which is unambiguously greater than either Q_1 or Q_2). More generally, any level of bicycling between Q_0 and Q_3 could be achieved by a mix of hard and soft policy instruments, with the maximally achievable net benefit given by the sum of inframarginal benefits c_1c_0AB, plus the net benefits from the additional bicycle-km given by ACD (plus the benefits from "true" externalities, ignored in the figure). Depending on the relative costs of both approaches, the policy maker would then choose the optimal policy mix, characterized by the highest social benefits for a given overall investment cost.

3. An econometric model of bicycling

In the following, we set up a theoretical model of bicycling that fits the situation depicted in Figures 1-2, and propose an econometric specification to estimate it.

3.1 Theoretical model

Let Q_{it} be the level of bicycling in city *i* at time *t*,[11] and μ_{it} the marginal internal costs associated with Q_{it}. Marginal costs not only depend on the level of bicycling, but also on all relevant mode choice determinants discussed in the previous subsection, which we combine in the vector X_{it}. We express internal costs as

[11] The model could of course also be developed in a cross-sectional or in a pure time-series context, but we introduce a double subscript since we will make use of panel data in our empirical analysis.

$$\mu_{it} = f(Q_{it}, X_{it}) + g(X_{it}) \tag{1}$$

The function $f(\cdot)$ translates the level of bicycling into internal costs, with $\partial f / \partial Q_{it} > 0$, whereas $g(X_{it})$ controls for features that determine the level of bicycling (route, city and personal characteristics). For a given level of bicycling Q_{it}, the internal marginal cost of bicycling will be lower in cities with better amenities for bicycling, all else equal. The translation between the level of bicycling and associated internal costs may further depend on X_{it}.

If consumers fully internalize internal benefits and do not consider externalities, they will equate internal marginal costs with private marginal benefits:

$$\mu_{it} = MB_{p,it} \tag{2}$$

Making the assumption of full internalization allows us to substitute (2) into (1) and thus eliminate internal marginal costs, which are unobservable. We could then quantify $MB_{p,it}$ using estimates for gross health benefits, specify a functional form for the functions $f(\cdot)$ and $g(\cdot)$, and estimate the corresponding parameters. However, this approach is not feasible if health benefit estimates per km of bicycling do not significantly differ across observations.

If we are interested in assessing the degree of internalization of internal and external costs, we need to estimate internal costs independently of internal benefits. Specifically, we express internal costs as a function of observable variables combined in a vector Y_{it}:

$$\mu_{it} = h(Y_{it}) \tag{3}$$

The natural choice for Y_{it} are relevant mode determinants that the marginal bicyclist is likely exposed to. To illustrate, suppose that $x_{it}^{k} \in X_{it}$ refers to the hilliness of a city, expressed as average elevation gain per trip from all modes combined. The corresponding instrument for internal marginal costs Y_{it} would then be the average elevation gain from trips carried out by bicyclists, or a distribution measure such as the 90th percentile.[12] The underlying assumption of this choice is that the elevation gain of the marginal bicyclists is higher if the average elevation gain is higher, all else equal.[13] An alternative would be to use psychological cost determinants based on stated preferences as considered in Smith (1991), Rietveld and Daniel (2004) or Hunt and Abraham (2007).

In addition to mode choice variables applied to bicyclists, Y_{it} can include measures of mode substitution possibilities. For example, marginally increasing the level of bicycling in a city where many short trips are carried out by car or public transportation should be associated with a lower increment of internal costs, compared to increasing bicycling in a city where no such "cheap" substitution possibilities exist.

There are two major empirical problems with estimating the marginal cost function: First, internal costs are not observable, which requires the application of a latent variable framework if we want to address the degree of internalization of internal and external benefits. Estimates from latent variable approaches are indirect and therefore tend to be imprecise and sometimes also

[12] In this one-dimensional example, the measure at the margin would be the maximum altitude (i.e. the steepest trip), however, since there are numerous factors determining the marginal cost at the same time the true exposure at the margin remains unknown. For practical reasons the mean or the 90th percentile can be used as proxies to reflect the distribution across cities of exposures at the margin.

[13] Since $h(Y_{it})$ is a multi-dimensional function, this assumption is somewhat stringent. For example, the marginal bicycle-km could take place in the rain on a crowded but completely flat road. One approach would be to create an index of marginal costs that depends on all known mode choice determinants, including personal characteristics of actual and potential riders, but such an index would have to rely on the same type of variables that we employ. We therefore chose the instrumental variable over the index approach.

sensitive to the model specification. Second and equally important, the data situation concerning bicycling in general is poor. Our modeling framework therefore serves two main purposes: We propose an empirical method to estimating the value of bicycle spending that is consistent with economic theory, and we show what type of data would be required to make our approach more policy-relevant.

3.2 A latent variable approach

Since the dependent variable has to be observable, we start by reverting (1):

$$Q_{it} = \psi(\mu_{it}, X_{it}) + \kappa(X_{it}) \tag{4}$$

with $\partial\psi / \partial\mu_{it} > 0$. The level of bicycling is a function of internal costs, with the effect possibly being influenced by mode choice variables, and of mode choice variables themselves. A linearized formulation of (4) is a model known as "Multiple Indicators and Multiple Causes" (MIMIC) originally developed by Hauser and Goldberger (1971), as well as restricted versions. We estimate the following system of equations:

$$Q_{it} = b_i + b_t + (\varphi + X_{it}\lambda)\cdot\mu_{it} + X_{it}\beta + e_{it} \tag{5}$$

$$\mu_{it} = Y_{it}\gamma + u_{it} \tag{6}$$

Comparing this system to the model (1)-(3) makes it clear that $f(Q_{it}, X_{it}) = Q_{it} / (\varphi + X_{it}\lambda)$, $g(X_{it}) = -X_{it}\beta / (\varphi + X_{it}\lambda)$, and $h(Y_{it}) = Y_{it}\gamma$. The vectors of observed variables X_{it} and Y_{it} have dimensions $(1\,x\,k)$ and $(1\,x\,m)$, respectively, with corresponding parameter vectors β and λ of dimension $(k\,x\,1)$, and γ of dimension $(m\,x\,1)$.

Intuitively, we express the level of bicycling in city *i* at time *t* as a function of the internal costs associated with an additional bicycle-km, while controlling for observable mode choice characteristics collected in X_{it}. These variables explain the "general" level of bicycling (e.g., we expect a greater number of bicycle-km in a flat city than in a hilly one), whereas the latent variable explains how "high up the marginal cost curve" bicycling takes place: If the level of bicycling differs across two cities that are identical otherwise, marginally increasing bicycling is associated with greater internal costs in the city where bicycle mode share is already higher. The city- and time-specific constants b_i and b_t proxy for unobserved characteristics that influence the level of bicycling. Unobserved characteristics that vary over both time and space end up in the error term $e_{it} \sim N(0, \sigma_Q^2)$. The system can be estimated by maximum likelihood.

There are two natural restrictions that can be imposed on (5-6). First, the full MIMIC model assumes that the proxy variables are measured imprecisely, which results in an additional error term $u_{it} \sim N(0, \sigma_\mu^2)$. This can improve precision of the estimate but also may be a cause for unobserved variable bias. If instead no error is allowed, the MIMIC model reduces to the "parametrically-weighted covariates" model (Yamaguchi, 2002).

Second, the marginal effect of a variable $y_{it}^m \in Y_{it}$ on Q_{it} (via μ_{it}) may vary over all or a subset of mode choice characteristics:[14]

$$\frac{\partial Q_{it}}{\partial y_{it}^m} = \gamma_m \cdot (\varphi + X_{it}\lambda) \tag{7}$$

[14] Technically speaking, the effect is of course reversed: A high level of bicycling is associated with high marginal costs, not the other way around. We had to invert the relationship in order to estimate it.

The modulating effect $X_{it}\lambda$ has the interpretation of an interaction term. Consider the marginal effect of $x_{it}^{k} \in X_{it}$ on the dependent variable:

$$\frac{\partial Q_{it}}{\partial x_{it}^{k}} = \beta_k + \lambda_k \cdot \mu_{it} \tag{8}$$

Variable x_{it}^{k} affects the dependent variable directly through β_k, but also indirectly via the latent variable μ_{it}. If the relationship between μ_{it} on Q_{it} is constant such that $\lambda_k = 0 \; \forall \; k$, estimating (5)-(6) is equivalent to the estimation of "Sheaf coefficients" (Heise, 1972).

3.3 Identification

In order to identify φ, λ and γ, we have to set the origin, direction and unit of the latent variable. The definition of the origin is implicit in (6), namely the exclusion of a constant in the MC function, such that $\mu_{it} = 0$ if all variables in Y_{it} are zero. This restriction is necessary because an additional constant in the MC function could not be individually identified, because it appears only as a product with other parameters.

The direction of the latent variable has to be specified because a positive μ_{it} is equivalent to a negative μ_{it}, with the sign of φ and λ switched. The most natural way in our context is to specify internal marginal costs to be positive.

The default to specify the unit of μ_{it} is to set its standard deviation to 1, which is sufficient to determine the relative size of areas *a* and *d* in Figure 1. The absolute magnitude of μ_{it} is required for policy decisions and can be derived from (2) by multiplying the parameter vector $\hat{\gamma}$

by $MB_{p,it} / \hat{\mu}_{it}$. This is equivalent to assuming that cyclists fully internalize internal benefits, and do not consider any external benefits.

If we are interested in the degree of internalization, we need to identify the unit of μ_{it} independent of internal benefits. For example, if internal (net) costs of bicycling another km include money savings due to substituting away from driving or public transportation, we could define the unit of μ_{it} by setting the parameter on money savings y_{it}^{m} to $\gamma_m = -1$ (the sign must be negative because these are internal benefits, i.e. negative costs). This yields an estimate of internal marginal costs that is independent of $MB_{p,it}$. We can now estimate

$$\hat{\mu}_{it} = \delta MB_{p,it} + \theta E_{it} + \varepsilon_{it} \tag{9}$$

where E_{it} refers to external benefits (computed outside the model, using techniques outlined in Section 2.1), $\delta, \theta \in [0,1]$ capture the extent to which internal and external benefits are internalized, and ε_{it} is a random error. With fully informed and rational consumers, neoclassical economic theory implies that $\delta = 1$ and $\theta = 0$, which can be the basis of one-sided significance tests against the alternative that cyclists do not fully internalize health effects $\delta < 1$, and that they internalize some of the external benefits ($\theta > 0$). Again, this approach is not feasible if the empirical estimates of internal benefits and externalities do not vary across observations.

3.4 The value of bicycle spending

We now turn to the computation of the areas in Figures 1 and 2. Area *c* has to be computed outside of our model by specifically focusing on external effects of bicycling such as the share of cost decreases in the health care system that accrues to non-riders, environmental benefits etc. This is beyond the scope of this paper, and we will focus on the relative sizes of areas *a*, *b* and *d*.

To do this, we first estimate (5)-(6) subject to the identification restrictions outlined in the previous subsection and use the parameter estimates to compute expected bicycle-km $\hat{Q}_{it}$. We then invert the relationship and express expected marginal costs as a function of expected bicycle-km, observed explanatory variables and estimated parameters (detailed calculation in appendix). The social value of bicycle spending in city *i* using our choice-based approach and suppressing subscripts for convenience is[15]

$$a+b=Q_0\frac{\Delta_0 MC+\Delta_Q MC}{2}+\frac{\Delta Q\cdot\Delta_Q MC}{2} \tag{10}$$

where ΔQ is the difference in bicycle-km that results from the proposed policy, and $\Delta_0 MC$ and $\Delta_Q MC$ refer to the vertical difference between the old and new marginal cost function at $Q=0$ and at Q_0, respectively. The difference between our approach and GHB is determined by the relative sizes of areas *a* and *d* (derivation in appendix):

$$D\equiv a-d=\Delta Q\cdot\left(\alpha_1\frac{\Delta Q}{2}+\alpha_1 Q_0-MB^p\right)+Q_0^2\frac{(\alpha_1-\alpha_0)}{2} \tag{11}$$

If the investment leads to a parallel shift of the MC curve such that $\alpha_1=\alpha_0$ (which will be the case if the mode determinants targeted by the policy are not modulator variables affecting the relationship between internal cost and bicycle-km), the second term in (11) cancels. Taking partial derivatives yields (derivation in Appendix)

[15] Since a nonlinear function of a variable's expectation is not the same as the expectation of a nonlinear function of the variable, we compute areas a, b and d for all city/year combinations and then take averages in our application.

$$\frac{\partial D}{\partial Q_0} = \Delta_0 MC > 0\,; \qquad \frac{\partial D}{\partial MB^p} = -\Delta Q < 0\,;$$
$$\frac{\partial D}{\partial \alpha_1} = \frac{(\Delta Q + Q_0)^2}{2} > 0\,; \qquad \frac{\partial D}{\partial (\Delta Q)} = -c_1 \tag{12}$$

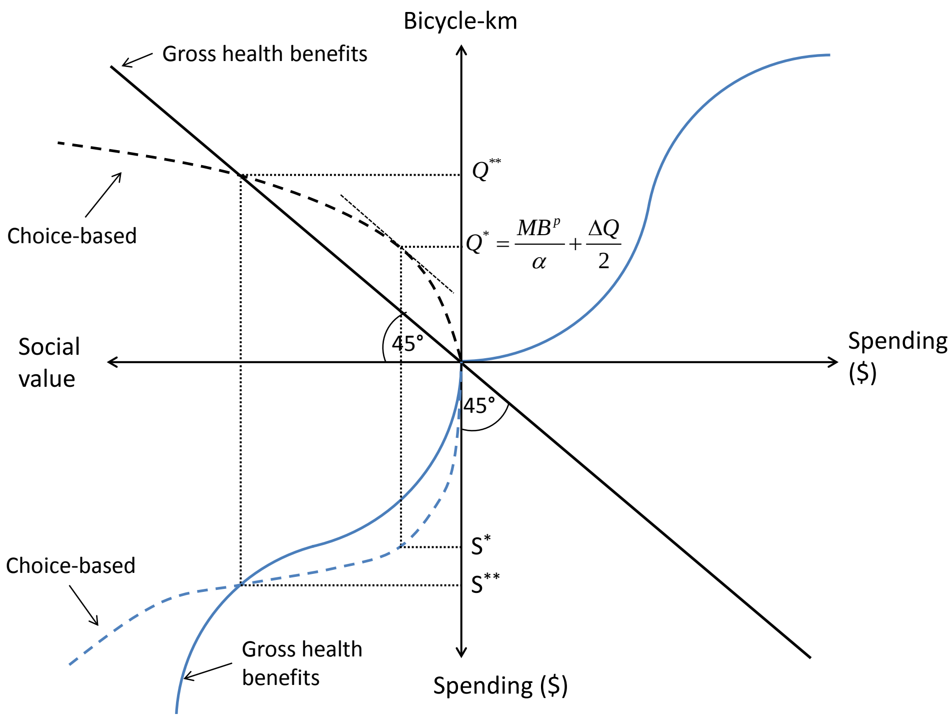
In order, these results imply that the valuation of bicycle investments using our choice-based approach, relative to that computed using GHB, 1.) increases with the bicycle mode share before the investment (because this implies higher inframarginal benefits); 2.) decreases with the degree of internalization of health benefits (because more costs are internalized and thus have to be subtracted from benefits); 3.) increases with the slope of the new MC function (holding Q_0, ΔQ and MB^p constant, a steeper MC function requires a larger downward shift, thus increasing inframarginal benefits); and 4.) increases with the amount of additional bicycling if the new intercept is negative, and vice versa (a higher ΔQ increases both *a* and *d*; the effect on the former is larger if the "cheapest" bicycle-km are associated with negative costs).[16]

There is evidence implying that the relationship between bicycle spending and the resulting increase in bicycling may be S-shaped, due to fixed costs and network effects (Levinson et al., 2003). Combining this with an approximately linear valuation of bicycle-km that results from the GHB approach (Lee and Skerrett, 2001) implies an S-shaped relationship between bicycle spending and social benefits as well. Our approach affects this relationship, as it subtracts internal costs from additional bicycle-km, but adds benefits to inframarginal km. At high levels of bicycling, the latter term dominates and results in less flattening out of the spending/benefit relationship relative to GHB, whereas the opposite occurs at low mode shares.

[16] To provide some intuition on this last point, suppose that we shift the horizontal axis in Fig. 1 upwards. This decreases area *d*, while leaving area *a* unaffected.

Figure 3 illustrates, using the example of a parallel shift in the MC function. The upper right quadrant shows the relationship between investment and bicycle-km. The upper left quadrant translates bicycle-km to social value. This translation is approximately linear using the GHB approach (solid line; we chose the units of social value per bicycle-km such that the slope is -1). This leads to a relationship between spending and social value as shown by the solid line in the lower left quadrant that is the mirror image of the spending/km relationship.

Figure 3: Spending, bicycle-km and social value



The relationship between bicycle-km and social value as computed by our approach is represented by the dashed line. Compared to GHB, our approach leads to a lower social value per additional bicycle-km at cycling levels below $Q^{*}=MB^{p}/\alpha+\Delta Q/2$ (setting the first term in eq. 11 to zero and solving for Q_0), and higher above, meaning that the slope of the km/value relationship is flatter below, and steeper above this threshold. At sufficiently high levels of bicycling, the total social value from bicycling is higher when measured using our approach, relative to GHB. In terms of the spending/social value relationship, our approach implies lower social value per dollar of spending below S^* than GHB and vice versa, leading to higher welfare after an aggregate spending level of S^{**}.

4. Application

In the following we describe our data and the employed variables, and present the results from an empirical application of our model to eight Swiss cities.

4.1 Data

We use data from the Swiss national travel survey (Federal Statistical Office, 2007, 2012), a large population based survey conducted approximately every five years. For methodological comparability we restrict our analysis to data from the surveys from 1994, 2000, 2005 and 2010. As part of the computer assisted telephone interview (CATI) subjects are asked to provide information on one day of travel, tracking their mobility stage by stage. Travel mode, distance, duration, trip purpose and additional variables are captured for each stage. Earlier surveys (1994 and 2000) captured start and endpoints of stages by address only, more recent surveys recorded geo-coordinates using mapping software to assist CATI. Numerous additional variables are available at the levels of trip, travel day (e.g. weather), subject (e.g. public transport pass or car ownership), and household (e.g. number of vehicles available, including bikes).

We used Mapquest's address search feature and GIS software to identify direct routes between start and endpoints, which we overlaid with topographic data to derive elevation gains for each trip stage. We extracted the number of fatal and severe accidents from annually published accident statistics.

We compiled data for the 10 largest cities in Switzerland. We included all trips that originated or ended within the limits of our sample cities. Because Lausanne and Lugano had very few observed bicycle trips, we limited our analysis to Zurich, Bern, Basel, Geneva, St. Gallen, Luzern, Biel and Winterthur, which gives us a total of 32 observations.

4.2 Variables

We use annual bicycle-km per capita as our dependent variable, which requires multiplying the values from the Swiss Microcensus by 365. We work with annual rather than daily numbers because the computation of health benefits presumes sustained long term behavior (see below).

Determinants of city-level cycling

As explanatory variables we use mode choice characteristics identified by the literature, and which we can observe. For example, we do not have data on chosen routes and route characteristics, which others have used successfully to identify important mode choice determinants. (Dill and Gliebe, 2008; Menghini et al., 2009; Winters and Teschke, 2010) More generally, we believe that the most important missing information is the extent and quality of the bicycle network.

We control the observed level of bicycling using the following variables (for X_{it} in eq. 5):

Hilliness: Average elevation gain of all trips (m/km). In hillier cities we expect fewer bicycle-km per capita, all else equal.

City dispersion: Average distance of all trips. The relationship between city dispersion and bicycle-km is nonlinear. Starting from low dispersion, increasing distances will presumably lead to more bicycle-km, but when increasing dispersion further there will be a point where very few trips are carried out by bicycle, thus reducing the number of bicycle-km.

Average precipitation: Number of days per year with >2 mm precipitation (Meteoswiss, 2012). We expect less bicycling in rainy cities, all else equal.

Accident risk for bicyclists, computed as the number of accidents involving bicyclists that lead to fatalities or severe injuries per million bicycle-km (source: Swiss Federal Roads Office, ASTRA). We expect a higher bicycle mode share and therefore more bicycle-km in safer cities, all else equal.

Price for public transportation (CHF per km) faced by the population as a whole, computed as the price for a day pass within a city, divided by the average daily km travelled by public transportation within the day pass zone, and adjusted for the fraction of the population that have transportation passes.[17] We accessed the price of day passes over time from the city transportation offices of each city. Since bicycling and public transportation are substitutes at least for short trips, we expect a positive relationship between this variable and bicycle-km.

Bicycle environment proxy: Survey responses from a large convenience sample of bicyclists (N=5800 across our cities) to the statement "I like riding a bicycle in this city". Available answers ranged from 1 (completely disagree) to 6 (fully agree). (Pro Velo Switzerland, 2010)

Dummy for large cities, equal to one for Zurich, Basel, Bern and Geneva and zero otherwise. These cities are more urban and have a more developed public transportation network (including tramways) than the other cities in the sample.

Time dummies to identify the survey years 1994, 2000, 2005 and 2010 (reference category).

[17] Because we are interested in the marginal rather than average cost, we set the marginal price per km of public transportation to zero for people with a transportation pass, and to 75% of the full price for people with "half-fare card" (the name comes from the fact that it reduces long-distance fares by 50%; however, the typical price for city-tickets is about 75% of the full price).

Indicator variables for internal costs of bicycling

As indicators for internal costs (the variables collected in Y_{it} in eq. 6), we use variables that we observe in bicyclists only, not the population at large. We use the following variables:

Bicycle trips in rain: Distance in km traveled by bicycle on days with >2mm precipitation. We interpret a larger value as an indicator for higher marginal costs to increase cycling compared to a city where still most cycling occurs on sunny days.

Steepness: Average elevation gain of bicycle trips (m/km).

Mode shift potential: 10th percentile of trip distances carried out by car or public transport. Higher values (longer motorized trip distances) indicating higher MC for shifting some of these (short) trips to bicycling.

Trip length: Average distance of bicycle trips (km).

Bicycle mode share: Proportion of all transportation stages carried out by bicycle.

Cost savings (CHF per km) that accrue when replacing 1 km using public transportation with the bicycle. We compute this as the price for a day pass divided by the average daily km travelled by bicycle and adjusted for the fraction of annual or monthly passes owned by public transportation users.

We expect all but the last of these indicator variables to be positively correlated with internal costs. Since price savings from bicycling are negative costs, we expect a negative relationship. The reason to include this variable here (rather than on the benefits side) is that we rely on it to identify the magnitude of the coefficients in eq. (6) and thus to monetize internal costs.

Table 1 contains summary statistics of all used variables.

4.3 Computation of gross benefits

We calculate gross health benefits using the World Health Organisation's Health Economic Assessment Tool (HEAT) for cycling (Rutter et al., 2013; WHO, 2008). The tool uses a relative risk estimate for all-cause mortality from a large Danish cohort study (Andersen et al., 2000) to estimate avoided number of deaths from a certain level of observed cycling. We then monetize the reduction in mortality using the value of a statistical life of $7.4 Mio (2006 dollars) used by the US Environmental Protection Agency, which is equivalent to CHF 9.33 Mio (2010 francs). We derive an average estimate for increasing the level of cycling by one km per capita per year in our cities of CHF 0.50.

Table 1: Summary statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
(N=32)					
Av. bike-km	km*year/cap	252.56	139.55	39.08	778.41
Hilliness (all modes)	m/km	13.65	4.35	6.72	19.37
Dispersion (all modes)	km	29.19	7.06	17.12	47.71
Rain days	days/year	160.03	17.72	111.00	192.00
Accident risk	fatal & severe acc. per mio bike-km	0.72	0.39	0.12	1.54
Cost of public transport (all)	CHF/km	0.68	0.33	0.26	1.98
Subj. quality of bicycle environment	answers from 1 (very bad) to 6 (very good)	4.31	0.57	3.63	5.39
Large city	0/1	0.50	0.51	0	1
Bicycle-km in rain	km	1.30	1.57	0	5.49
Elevation gain (bicycle)	m/km	12.24	5.49	3.78	24.77
Mode shift potential (10th p. of car & PT trips)	km	0.93	0.13	0.71	1.22
Trip length (bicycle)	km	3.92	1.56	1.93	10.67
Bicycle mode share	%	6.43	2.82	1.59	11.53
Cost savings (switch from PT to bicycle)	CHF/km	0.34	0.14	0.15	0.61

4.4 Estimation

We estimate (5)-(6) by maximum likelihood in Stata, using code developed by Buis (2007). Table 2 shows the estimation results. Model 1 is the most inclusive specification where we included all mode choice determinants that seemed most important to us and for which we had data, whereas Model 2 is a more restricted version where we removed some variables that were statistically insignificant (dispersion and bicycle environment) and/or did not have the expected sign (rain days). For each model, we estimated a "Sheaf coefficients" specification where $\lambda = 0$ in eq. (5) such that the relationship between internal costs and bicycle-km is constant and given by φ (the models labeled 1a and 2a), as well as a version that allows the relationship between bicycle-km and internal costs to vary over the "hilliness" variable (models 1b and 2b). We were not able to further generalize this "parametrically-weighted covariates" model to the MIMIC model with our data, because the estimation did not converge when an additional error term was included.

The relationship between internal costs and bicycle-km is positive, consistent with our theory. The coefficients on the variables that explain the city-level of bicycling (main equation) are quite sensitive to the model specification. Among the variables that are significant in all specifications are the "general" price for public transportation and the "large city" dummy, whereas accident risk is only significant in the more restricted model 2. Hilliness is significant when it is also used as a modulator variable, but not otherwise. Furthermore, the level of bicycling seems to be increasing over time, as the time dummies are mostly negative (2010 is the reference category).

As for the indicator variables for internal costs, the amount of bicycling in rainy weather, the distance of the most likely replacement trips and the bicycle mode share are positive and statistically significant (although sometimes at $p<0.1$) in all models, whereas elevation gain ("steepness") and distance traveled by bicycle are significant only in some specifications. Price savings from bicycling relative to using public transportation are always statistically significant and negative, as expected. We re-scaled all coefficients in the MC equation such that the coefficient on money savings per km is identically equal to minus one.[18]

Table 2: Regression results (dep. Variable: Bicycle-km per capita and year)

	Model 1a		Model 1b		Model 2a		Model 2b	
	Coef	p	Coef	p	Coef	p	Coef	p
Main equation								
Hilliness	12.34	0.361	-58.70	0.001	10.09	0.339	-33.28	0.015
Dispersion	-5.19	0.260	-2.76	0.316				
Raindays	1.76	0.514	4.27	0.025				
Accident risk	-119.51	0.191	-77.88	0.204	-175.40	0.021	-161.89	0.002
PTprice_all	247.93	0.032	214.23	0.001	215.05	0.021	158.44	0.011
bike_environment	-59.52	0.540	-63.89	0.294				
d_94	-92.44	0.220	-118.46	0.011	-61.83	0.325	-67.93	0.109
d_00	-88.33	0.205	-99.04	0.016	-81.74	0.221	-97.02	0.029
d_05	-47.75	0.524	11.17	0.825	-73.44	0.202	-61.56	0.115
Large	187.62	0.020	187.23	<0.001	160.65	0.020	145.14	0.001
Const.	-677.03	0.217	-261.76	0.381	-449.41	0.088	110.47	0.383
lambda								
Const. (φ)	446.032	0.001	2.248	0.551	340.838	<0.001	14.193	0.700
Hilliness (λ_1)			28.953	<0.001			25.581	<0.001
MC equation								
Rain_bike	0.099	0.008	0.111	<0.001	0.116	0.003	0.113	<0.001
Steepness	0.007	0.703	0.017	0.112	0.005	0.829	0.007	0.523
Replace_trips	1.022	0.022	1.218	<0.001	0.978	0.066	1.104	0.001
Trip_length	0.059	0.203	0.056	0.025	0.056	0.268	0.042	0.097
Bike_mode	0.104	<0.001	0.126	<0.001	0.082	0.001	0.085	<0.001
PTprice_savings	-1.000	0.018	-1.000	0.001	-1.000	0.053	-1.000	0.003

[18] We report a t-statistic because we estimated the equation under the standard identification condition that the standard deviation of the constrained equation be one, which yields a regular estimate including standard errors for the cost savings variable. Scaling the point estimate and the associated standard error does not affect the t-statistic.

The sign on hilliness as a modulator variable may be counter-intuitive. We expected the relationship between bicycling (the slope α of the MC function in Fig. 1) to be higher for hilly cities. Since α is the inverse of the lambda function, a positive λ_1 indicates a *lower* slope for hilly cities. A possible explanation could be that in hilly cities, the general level of bicycling is lower, such that a larger "reserve" of non-cyclists exists that could start to bicycle at relatively low costs (recall that the coefficient on the indicator variable "steepness" is insignificant, implying that this is not a major source of disutility in our sample).

Based on these parameter estimates we can now compute costs and benefits associated with an increase in bicycling as discussed in Figures 1 and 2. Table 3 shows costs and benefits associated with an increase in bicycling that would result from a public investment reducing accident risk by 25% (since accident risk is not a modulator variable, a decrease in accident risk implies a parallel shift of the MC curve). These calculations are based on the parameter estimates from model 2b, which is our preferred specification (the corresponding average numbers for the other models are shown in Table A.1 in the appendix).

The increase in safety leads to an expected increase in average bicycling of about 29 km per capita and year. Multiplied by the health benefits from a reduction in mortality as computed by the HEAT tool (and the corresponding city populations), this yields an average benefit of CHF 1.9 mio using the GHB approach. This number corresponds to the sum of areas *b* and *d* in Fig. 1.

Using our choice-based approach and identifying internal costs by means of health benefits computed by HEAT, we compute benefits that are less than half of those based on GHB (areas *a*+*b* in Fig. 1). As shown in the theory section, this result depends on the baseline level of bicycling. If we base the calculation on the minimum and maximum levels of bicycling in our sample (corresponding to 39 resp. 778 km per year) rather than the mean, we obtain health benefits of CHF 0.21 million and CHF 2.59 million, respectively. Increasing the baseline level of bicycling increases the benefits computed with the choice-based approach relative to GHB, because it leads to higher inframarginal benefits but has no effect on costs and benefits associated with the additional bicycle-km.

Table 3: Costs and benefits of bicycling from reducing accident risk by 25%

	Mean	st.dev.	
HEAT benefits (CHF/km)	0.50	0.17	
MB'_p (CHF/km)	1.63	0.34	
ΔQ (km/cap-year)	28.99	15.65	
Baseline level of bicycling (km per cap. and year)	Q_0=253	Q_0=39	Q_0=778
Areas in Figs. 1 & 2 (mean values, mio CHF per city)			
Fig. 1, area *a*	0.82	0.13	2.51
Fig. 1, area *b*	0.08	0.08	0.08
Fig. 1, area *d*	1.82	1.82	1.82
Fig. 2, area c_0ACc_1	2.66	0.41	8.21
Fig. 2, area ABC	0.28	0.28	0.28
Benefits (mean values, mio CHF per city & year)			
GHB based on HEAT	1.90	1.90	1.90
Choice-based, identification of MC through HEAT	0.89	0.21	2.59
Choice-based, identification of MC through cost savings	2.94	0.69	8.48

When identifying the magnitude of internal costs by means of cost savings from bicycling relative to using public transportation, the implied benefits exceed those computed by HEAT. Even though our results are generally sensitive to the model specification, this qualitative result obtains in all models presented here.[19] In order to map the resulting benefits to the areas marked in Figure 2, we need to switch MB'_p and MB_p. The benefits based on our approach are now area c_0ABc_1, which is the sum of c_0ACc_1 (inframarginal benefits) and ABC (net benefits associated

[19] In fact, we were not able to find an economically meaningful specification that yielded internalized benefits below those computed by HEAT.

with the additional bicycle-km), whereas the benefits based on HEAT are given by $Q_0A'B'Q_1$. Not surprisingly, the former exceeds the latter, but this is not due to the method of benefits computation per se (i.e. internal vs. external and inframarginal vs. marginal costs and benefits), but because HEAT benefits are based on $MB_p < MB'_p$.

There are two explanations which can apply separately or jointly. First, it is possible that consumers have altruistic preferences and internalize external benefits such as environmental improvements (Eriksson and Forward, 2011) or a decrease in overall health costs. Second, total internal benefits may exceed mortality-based benefits, which is the sole bases for the HEAT numbers. If bicyclists also value decreased morbidity and generally improved physical fitness, true internal health benefits may exceed CHF 0.5/km perhaps by enough to explain our results, especially when considering the standard errors of our estimates.

Interestingly, the value of a statistical life (VSL) used for these computations is typically based on mortality risk reductions only. As for internal benefits of bicycling, it is possible that people value changes in risk-relevant parameters by more than only their impact on mortality. VSL estimates based on hedonic wage regressions have been shown to be sensitive to the inclusion of non-fatal risk (Black et al., 2003; Hintermann et al., 2010).[20] Taking our results at face value and making the neoclassical assumption of full internalization of internal benefits coupled with no internalization of externalities, they would imply that the morbidity-adjusted value of risk is about 3 times larger than that based solely on mortality.

Naturally, our capability to accurately model the complex relationships between determinants and resulting bicycle behavior, given the limited quality of the underlying data, may serve as an explanation. Since we are unable to control for some of the main determinants of bicycling (e.g.

[20] While many hedonic wage studies include nonfatal risk in the regressions, its role is to control for wage-effects based on nonfatal risk. However, the VSL is computed solely based on the coefficient for fatal risk.

the quality and extent of a bicycle lane network for the main equation and route-specific characteristics for the MC equation) we would like to emphasize that our results have to be viewed with great caution and cannot be used to inform policy.

5. Conclusions

The proposed framework for valuation of bicycle investments adds an economic perspective to a relatively young field of research, which to date has been studied primarily by health and transport scientists. In particular, it expands the valuation beyond simple gross benefits calculations, as provided by WHO's popular HEAT tool and others. Our framework explicitly considers internal costs to cyclists, thus allowing for the calculation of net benefits, which may explain the often startling – and economically implausible – contrasts between large gross benefits and surprisingly low levels of cycling. An optimal bicycle policy will maximize social benefits. For a cost-benefit application of bicycle-related spending, the present value of annual net benefits has to exceed the public investment.

By monetizing internal costs independently (i.e. via public transportation costs) from the benefits (based on mortality reductions), the degree of internalization of benefits can be estimated (more exactly, the net of internalizing internal benefits plus internalizing some externalities). This is interesting in its own right, as it gives an indication about information costs and/or the presence of altruistic preferences in bicyclists. Independent monetization further allows for conceptualizing (quantifying) two key elements of a typical bicycle policies mix. The magnitude of IMC indicates the extent to which predominantly "hard measures" – mainly infrastructure improvements – are needed to lower internal costs. The degree of internalization on the other hand indicates the potential of certain "soft measures" – educational campaigns that inform people about the benefits of cycling and lead them to internalize these.

Finally, the framework considers inframarginal benefits, an improvement over traditional approaches that ignore benefits to existing cycling/cyclists, even though the same measures leading to new cycling often improve conditions for existing cycling too. Our analysis shows that the higher the level of cycling is, the more relevant inframarginal benefits become. Our framework is therefore preferable over gross benefits approaches in particular when valuing investments over long assessment periods, which is appropriate given the often slow uptake of usage, the long infrastructure lifetime and the significant non-linearities from network-effects.

A robust quantitative estimation of our framework is not yet possible, given the limited data available to us, as well as others. The presented framework hence also serves as a rationale and guidance for future investments in data collection efforts. While the travel survey data available to us are quite rich and considered state of the art, they nonetheless are limited in their capability to predict bicycle behavior. Based on existing literature and our expertise on the topic we identify the main gaps in information relevant for internal costs at the level of routes, namely network characteristics such as connectivity and route attributes such as objective and perceived safety and infrastructure types. Besides richer data sets, progress in research on determinants of cycling (including those with great spatial resolution), is needed to advance towards a quantitative implementation of our framework.

Appendix

Computing slopes and intercepts in Fig. 1 using regression estimates

Estimating (5)-(6) and taking expectations gives

$$\hat{Q}_{0it} = \hat{b}_i + \hat{b}_t + X_{it}\hat{\beta} + \left[\hat{\varphi} + X_{it}\hat{\lambda}\right] \cdot Y_{it}\hat{\gamma} \tag{A.1}$$

where we added a zero-subscript to indicate the benchmark (i.e. pre-investment) situation. Substituting $MC_{it} = Y_{it}\hat{\gamma}$ and inverting (A.1) leads to

$$MC_{0it} = \hat{c}_{0it} + \hat{\alpha}_{0it}\hat{Q}_{0it} \tag{A.2}$$

$$\text{with} \quad \hat{\alpha}_{0it} = \frac{1}{\hat{\varphi} + X_{it}\hat{\lambda}} \tag{A.2}$$

$$\hat{c}_{0it} = -\hat{\alpha}_{0it}(\hat{b}_i + \hat{b}_t + X_{it}\hat{\beta}) \tag{A.3}$$

Suppose that bicycle spending shifts the marginal cost function by changing the mode choice determinant $x_{it}^k \in X_{it}$ (for example accident risk). The new MC function becomes

$$MC_{1it} = \hat{c}_{1it} + \hat{\alpha}_{1it}\hat{Q}_{1it} \tag{A.5}$$

$$\text{with} \quad \hat{\alpha}_{1it} = \frac{1}{\hat{\varphi} + X_{it}\hat{\lambda} + \Delta x_{it}^k \hat{\lambda}_k} \tag{A.6}$$

$$\hat{c}_{1it} = -\hat{\alpha}_{1it}(\hat{b}_i + \hat{b}_t + X_{it}\hat{\beta} + \Delta x_{it}^k \hat{\beta}_k) \tag{A.7}$$

$$\hat{Q}_{1it} = \hat{Q}_{0it} + \Delta x_{it}^k \left(\hat{\beta}_k + \hat{\lambda}_k \hat{\mu}_{it}\right) \tag{A.8}$$

If x_{it}^k is not a modulator variable such that $\lambda_k = 0$, the slope will remain unchanged at $\hat{\alpha}_{0it}$, whereas the intercept is adjusted by $-\hat{\alpha}_{0it}\Delta x_{it}^k \hat{\beta}_k$.

Derivation of equations (11) and (12)

Suppressing subscripts and setting $MC = MB_p$, the areas in Figure 1 are given by

$$
\begin{aligned}
b &= (\Delta_Q MC \cdot \Delta Q)/2 \\
d &= \Delta Q \cdot MB_p - (\Delta_Q MC \cdot \Delta Q)/2 \\
a &= Q_0 \cdot \left(\Delta_0 MC + \Delta_Q MC \right)/2
\end{aligned}
\tag{A.9}
$$

with $\Delta Q = Q_1 - Q_0$. If consumers internalize private health benefits only partially, or if they internalize some of the external benefits, MB_p is replaced by MB_p' in Fig. 2, but all else remains the same. We now subtract *a* from *d* while making the following substitutions:

$$
\begin{aligned}
\Delta_0 MC &= c_0 - c_1 \\
&= MB_p - \alpha_0 Q_0 - (MB_p - \alpha_1 Q_1) \\
&= Q_0(\alpha_1 - \alpha_0) + \alpha_1 \Delta Q
\end{aligned}
\tag{A.10}
$$

$$
\begin{aligned}
\Delta_Q MC &= c_0 + \alpha_0 Q_0 - (c_1 + \alpha_1 Q_0) \\
&= c_0 - c_1 - Q_0(\alpha_1 - \alpha_0) \\
&= \alpha_1 \Delta Q
\end{aligned}
\tag{A.11}
$$

Using these substitutions, we get

$$
\begin{aligned}
D \equiv a - d &= Q_0 \frac{Q_0(\alpha_1 - \alpha_0) + 2\alpha_1 \Delta Q}{2} - \Delta Q \cdot MB_p + \alpha_1 \frac{(\Delta Q)^2}{2} \\
&= \Delta Q \cdot \left(\alpha_1 \frac{\Delta Q}{2} + \alpha_1 Q_0^2 - MB_p \right) + Q_0^2 \frac{(\alpha_1 - \alpha_0)}{2}
\end{aligned}
\tag{11}
$$

The partial derivatives of (10) w.r.t. MB_p, α_0 and α_1 are straightforward. Using (A.2) and (A.10), the partial w.r.t. Q_0 and ΔQ are

$$
\begin{aligned}
\frac{\partial D}{\partial Q_0} &= \alpha_1 \Delta Q + Q_0(\alpha_1 - \alpha_0) \\
&= \alpha_1 Q_1 - \alpha_0 Q_0 = (MB_p - c_1) - (MB_p - c_0) \\
&= (c_0 - c_1) = \Delta_0 MC
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial D}{\partial(\Delta Q)} &= \alpha_1 \Delta Q + \alpha_1 Q_0 - MB_p \\
&= \alpha_1 \cdot Q_1 - MB_p = -c_1
\end{aligned}
$$

Table A.1: Benefits from reducing accident risk by 25%, all models

	Model 1a		Model 1b		Model 2a		Model 2b	
	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Parameters								
HEAT benefits (CHF/km)	0.503	0.168	0.503	0.168	0.503	0.168	0.503	0.168
MB'_p (CHF/km)	1.722	0.369	2.167	0.424	1.518	0.335	1.633	0.341
ΔQ (km/cap-year)	0.930	0.502	0.494	0.267	31.407	16.961	28.987	15.654
Benefits from reducing acc. risk by 25% (mio CHF per city and year)								
GHB based on HEAT (areas *b+d* in Fig. 1)	0.061	0.050	0.032	0.027	2.057	1.703	1.899	1.572
Choice-based, MC identified through HEAT (areas *a+b* in Fig. 1)	0.017	0.013	0.010	0.009	0.922	0.665	0.894	0.807
Choice-based, MC identified through cost savings (area c_0ABc_1 in Fig. 2)	0.060	0.051	0.042	0.037	2.916	2.293	2.939	2.545

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