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Promoting active transportation: A comparative assessment of paths and prices

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**Promoting Active Transportation:
A Comparative Assessment
of Paths and Prices**

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Darja Mihailova and Colin Vance*

Promoting Active Transportation: A Comparative Assessment of Paths and Prices

Abstract

The time people spend traveling has far reaching implications for their health and for environmental outcomes. Urban planning paradigms – such as that of the “15-minute city” – have consequently endeavoured to bring key services and amenities to residents within a walkable or cycleable 15-20-minute distance. These efforts notwithstanding, the policy levers that influence travel-related time allocation remain poorly understood. Drawing on a panel of household travel data from Germany covering 2005 to 2020, the present study analyses the role of two such levers – bicycle/pedestrian paths and fuel prices – as determinants of time allocation across modes. We start with a descriptive analysis that identifies a stable average travel time expenditure ranging between 65 – 70 minutes for women and 75 – 80 minutes for men until 2020, when it dropped precipitously as COVID-19 spread. We subsequently estimate fractional response models to identify the influence of the policy variables on time expenditures across motorized, nonmotorized, and public transit modes. We complete the analysis by feeding the model estimates into the World Health Organization’s on-line Health and Economic Assessment Tool (HEAT) to quantify the health and environmental impacts of the planned expansion of the bike path network in the city of Munich, comparing this with the impact of Germany’s recently introduced carbon tax on fuel. Both measures yield substantial benefits, with the implementation of the tax yielding a considerably higher benefit/cost ratio owing to its lower cost of implementation.

JEL-Codes: D61, R23, R48

Keywords: Mode choice; time allocation; bicycle/pedestrian paths; fuel prices;
Health Economic Assessment Tool

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1 Introduction

The formulation of policies that balance accessibility with environmentally benign travel modes is among the more pressing challenges confronting urban planners. This challenge is particularly evident in Europe, where greenhouse gas emissions from transportation are on the rise, increasing by almost 30% since 1990 (European Commission, 2020). Beyond its climate impacts, the European Environmental Agency identifies transport as one of the main sectors contributing to emissions of local air pollutants. Exposure to fine particulate matter, as generated from starting and operating a vehicle (Drozd et al., 2016; Frondel et al., 2021), was estimated to cause about 417,000 premature deaths in Europe in 2018 (EEA, 2020).

Over the past three decades, European countries have introduced a variety of demand-side measures to curb the transportation sector's growing environmental footprint, most recently embodied in the EU's Smart and Sustainable Mobility Strategy (COM/2020/789 final). One such collection of measures, collectively referred to as *nature-based solutions* (NbS), aim to integrate ecosystem services and infrastructure in urban planning and thereby mitigate anthropogenic stressors such as air and noise pollution. NbS are complemented by other planning paradigms, such as that of the "15-minute city," which places time as its focal point, the objective being to encourage lifestyles that are physically active and low-emissions by situating urban infrastructure and amenities such that people can walk or cycle to any given activity within a time frame of 15-20 minutes (Allam et al., 2022).

Achieving these objectives raises the question of what policy measures can be availed to influence people's travel time expenditure toward more active and less polluting modes of travel. One line of inquiry focuses on the relationship between urban form, physical activity (PA), and health and happiness. Physically active transportation, in particular, has been shown to improve air quality and reduce various health impairments, including cardiovascular disease and diabetes (Woodcock et al., 2011; Maizlish et al., 2013; Stevenson et al., 2016), while

outdoor PA contributes to mental well-being ([Thompson Coon et al., 2011](#); [Lahart et al., 2019](#); [Remme et al., 2021](#)). As documented in a systematic review by [Woodcock et al. \(2011\)](#), several studies have quantified a dose-response relationship between the time spent in non-vigorous physical activity and improved health, highlighting the potential for urban planners to positively influence air quality and health through land-use planning that encourages nonmotorized modes ([Stevenson et al., 2016](#)). Many such initiatives explicitly position NbS as a source of betterment, recognizing the relationship between experiencing nature and being mentally and physically healthier. Fully exploiting this potential, however, is currently hampered by limited understanding of how people's mobility behavior responds to variables over which policy-makers have leverage, such as transport infrastructure and fuel costs, and then connecting these responses to health impacts and environmental outcomes.

The present paper takes up this issue by drawing on household survey data from Germany to model the determinants of travel time expenditures across modes. Time is an important outcome in policy assessments of urban planning because of its direct relevance for many dimensions of welfare. In this study, we are particularly interested in quantifying the effect of two regionally-measured policy variables: the coverage of bicycle/pedestrian paths and the fuel price. Employing a theoretical framework adopted from [Bhat and Misra \(1999\)](#), the relation of these variables to time allocation is framed as a utility maximization problem, from which an empirical counterpart in the form of a fractional response model is derived. We estimate the model using individual-level travel diary information from the German Mobility Panel (MOP by the German acronym), identifying the effect of the explanatory variables on time spent across several categories: at home, at an out-of-home destination, and traveling, with the latter distinguished by mode. This set-up allows us to gauge how changes in each of these categories – expressed in minutes – connects to health and environmental outcomes by an integrative assessment that joins the econometric estimates with the World Health Organization's (WHO) Health Economic Assessment Tool ([Kahlmeier et al., 2020](#))

(referred to as HEAT).

Our work thereby builds on several studies – comprehensively reviewed by [Litman \(2024\)](#) – that find that improved walking and biking conditions are positively associated with nonmotorized transport and transit use, and negatively associated with car use ([Buehler and Pucher, 2012](#); [Guo and Gandavarapu, 2010](#); [Yang et al., 2021](#)). The question of causality is an issue that looms large in such research, particularly as regards the likely endogeneity of location choice: To the extent that people choose where to live based on their transportation preferences, studies that aim to estimate the effect of landscape features such as infrastructure face the challenge of disentangling causation from correlation. Various identification strategies have been employed to address this challenge, including comparative analyses ([Pucher and Buehler, 2006](#)), instrumental variables ([Holian, 2020](#); [Vance and Hedel, 2008](#)), and sample selection models ([Kayser, 2000](#); [Frondel and Vance, 2017](#)). [Cao et al. \(2009\)](#) undertake a systematic review of such studies and conclude that most find a statistically significant relationship between measures of urban form and travel behavior, usually measured with respect to individual modes. Focusing specifically on cycling, [Mölenberg et al. \(2019\)](#) review studies that strive to causally infer the impacts of infrastructural interventions, and likewise conclude that the majority finds statistically significant effects. In the present study, we employ an instrumental variable via the control function method to address the potential endogeneity of our measure of bicycle/pedestrian paths. Following [Duranton and Turner \(2018\)](#), the instrument is derived from subterranean measures of the earth’s surface, the expectation being that this is correlated with transport infrastructure but not with travel decisions.

Among our key results, we find a stable average travel time expenditure ranging between 65 – 70 minutes for women and 75 – 80 minutes for men until 2020, when it dropped precipitously as COVID-19 hit. This stability notwithstanding, we find substantial scope for policy to influence time allocation across travel modes, identifying positive effects of both paths and fuel prices in increasing time spent using nonmotorized travel. We complete the analysis by feeding the econo-

metric estimates into HEAT to quantify the health and environmental impacts of the city of Munich’s planned expansion of the bicycle/pedestrian path network, and compare this with a price-based measure that, following Germany’s Climate Action Programme 2030, currently levies a carbon tax of 10 cents per liter of fuel. We find that both measures yield positive net benefits, but that the carbon tax has a much higher benefit-cost ratio, driven largely by the relatively low administrative costs of its implementation.

2 Data and Analytical Approach

2.1 Data

The main data source draws from the 2005-2020 waves of the German Mobility Panel (MOP, 2024), a representative multi-year travel survey financed by the German Federal Ministry of Transport and Digital Infrastructure and administered by the Karlsruher Institut für Technologie. All members of participating households are surveyed daily for a period of one week over a maximum of three years in the autumn. After three years, they exit the panel and are replaced by a new cohort of households. We eliminate households who reported taking a vacation during the survey period and we exclude trips taken by plane. Also, respondents under 18 are excluded. The resulting estimation sample comprises 15,199 respondents from 9,761 households. 6,315 respondents participate in one survey year, 4,715 in two, and 4,169 in all three, yielding 28,252 observations in total. To correct for the non-independence of repeat observations over multiple time points in the data, the regression disturbance terms are clustered at the level of the individual, so that the estimates of the standard errors are robust to this survey design feature.¹

During the survey, respondents keep a travel diary that records the details

¹We also ran the analysis on randomly selected subsets of the data that covered the entire period and ensured that no person appeared more than once in the estimation sample, which revealed the regression coefficients to be robust. The code for producing these and all other results presented in the paper can be obtained from the corresponding author. The data can be obtained from the Clearingstelle Verkehr at the German Aerospace Center (<https://daten.clearingstelle-verkehr.de/192/>).

of each trip, including the departure and arrival time, the mode used, the trip purpose, and the distance traveled. Based on these entries, we calculate the time spent traveling by mode, as well as the time spent at home and at an out-of-home destination for all 1440 minutes of the day, from which we calculate the respective shares over the course of a 7-day week. These shares are presented in the top panel of [Table 1](#), along with a suite of socioeconomic and demographic control variables in the lower panel. The variables *home* and *away* measure the share of time spent at home or at an out-of-home destination,² while *motorized*, *nonmotorized*, and *transit* measure the share of time spent traveling by mode. Specifically, motorized transport is by car or motorcycle, nonmotorized is by foot or bike, and transit is by any mode of public transportation.

Table 1: Descriptive statistics

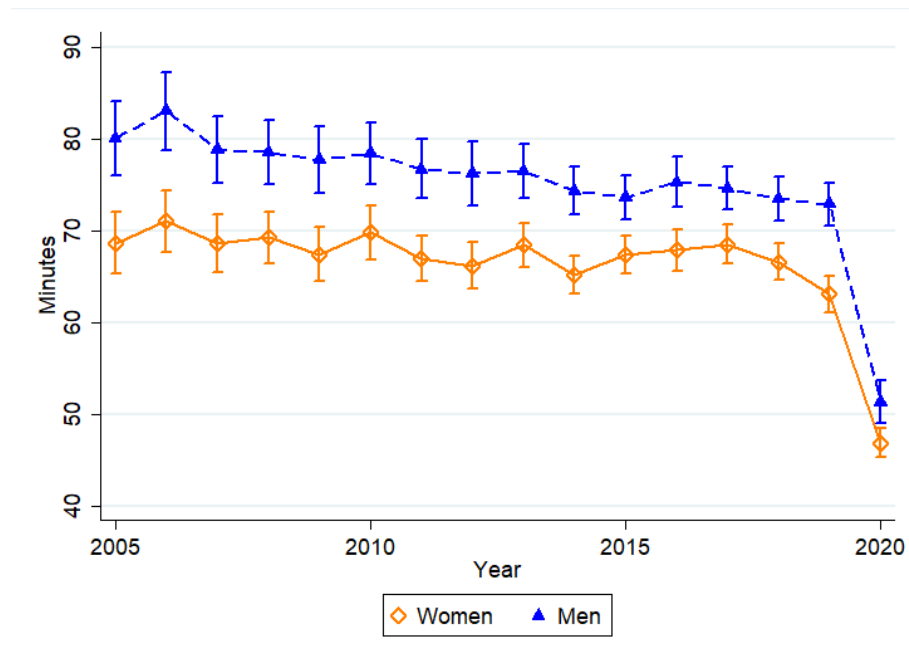
Variable	Description	Mean	St. Dev
Home	Share of minutes spent at home	0.766	0.126
Away	Share of minutes spent at an out-of-home destination	0.186	0.113
Nonmotorized	Share of minutes spent on bicycle or walking	0.010	0.014
Motorized	Share of minutes spent in cars or motorcycle	0.030	0.025
Transit	Share of minutes spent in public transit	0.009	0.020
Path density	Density of bike paths in residential zone	0.783	0.937
Fuel price	Retail fuel price (10 cents/liter)	13.071	1.522
Female	1 = Female	0.514	0.500
Posths	1 = Has post high school degree	0.482	0.500
Full-time	1 = Respondent is full-time employed	0.366	0.482
Part-time	1 = Respondent is part-time employed	0.166	0.372
Age 66	1 = Respondent is 66 or older	0.276	0.447
Cars	Number of cars in household	1.381	0.868
Low income	1 = Household in lowest 25% of income distribution	0.250	0.433
Number employed	Number of employed in household	1.069	0.908
Young kids	1 = kids younger than 9 in household	0.097	0.296
Porous	Share of highly porous subsurface in residential zone	0.382	0.312

[Figure 1](#) plots the point estimates and 95% confidence intervals of the daily average time spent traveling with any mode between 2005 and 2020, distinguished by gender. Three features stand out. First, consistent with the hypothesis of a con-

²The category *away* includes trips such as *Rundgänge*, which are walks or cycling trips that begin and end at home with no intermediate stop, i.e. walks, jogs and cycling tours.

stant travel-time budget – whereby people across locations and time have been observed to travel "70 minutes plus or minus ten" per day (Ahmed and Stopher, 2014), the time spent on daily travel has remained remarkably stable over the years through 2019, a possible reflection of a physic limit on the amount of time people are willing to travel (Metz, 2008). Second, with an average of 77 minutes per day, men spend about 8 more minutes traveling than women, a difference that is statistically significant at the 5% level. Last, the effects of the COVID-19 pandemic in 2020 are clearly visible. Both women and men decreased travel by about 21 minutes.

Figure 1: Daily minutes of travel by women and men



The two key explanatory variables of interest are the *fuel price* and *path density*. The *fuel price* is obtained in a separate survey of the MOP carried out yearly in the spring. Over a 6 week period, respondents record the price paid for fuel – whether diesel or petrol – with each visit to the gas station. We use this data to calculate the average fuel price by year and county recorded in the data, resulting in a panel of regional diesel and petrol prices spanning 2005-2020. Households owning an electric car, which comprise less than 1% of the sample, are not included in the analysis. Using a household identifier, we merge the fuel prices with the travel data recorded in the fall survey, assigning the petrol price if the

household's car stock is exclusively petrol and the diesel price if the household has at least one diesel car.³ Households not owning a car, about 13% of the sample, are assigned the petrol price.⁴

The measure of *path density* is derived from shapefiles obtained from Open Street Map (OSM, 2017) and merged with the MOP data using the open-source software QGIS. This merge was facilitated by using indicators recorded in the MOP for the 3-digit zip code and the county in which the household resides. The average size of a 3-digit zip code is 532 square kilometers, while the average size of a county is 814 square kilometers. To achieve a higher spatial resolution, we intersected two shapefiles of the zip code and county boundaries and used the polygons created by this intersection to identify the household's location. This process created a layer having a total of 1413 polygons across Germany, with an average size of 253 square kilometers. Drawing on the data from OSM, we then calculated the length in kilometers of bicycle/pedestrian paths per square kilometer of the polygon, depicted in Figure 2, which also shows the location of Munich covered in the case study below.

Along with the variables listed in the bottom panel of Table 1, the specification is completed by *state X year* interactions, which serve to control for time-varying influences spanning Germany's 16 states over the 16-year coverage of the data.

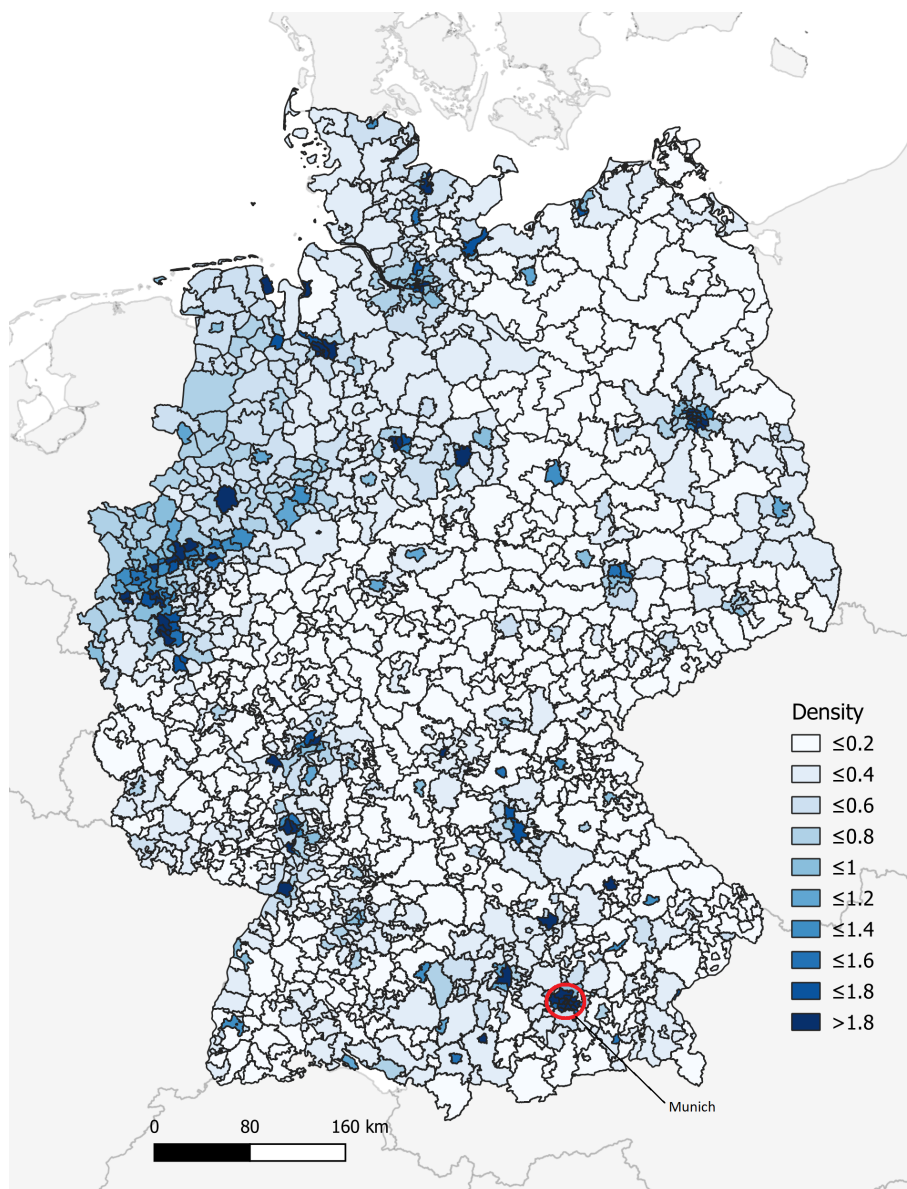
2.2 Theoretical and econometric model

The decision of how to temporally space one's daily activities is a resource allocation problem, one that is subject to the constraint of a 24-hour day. Adopting a simple theoretical framework developed by Bhat and Misra (1999) to study discretionary time allocation, we formalize this decision as one of allocating the hours of the day between the time spent at home, the time spent at an out-of-

³To account for the changes in the price level between the spring, when the fuel price data is recorded, and preceding fall, when the travel data is recorded, we apply a weight constructed from a time-series of monthly fuel prices published by the fuel company Aral (2023). The price series is additionally deflated using a consumer price index for Germany obtained from Destatis (2023a).

⁴Members of these households may still engage in some amount of driving using a borrowed car or one obtained through carsharing.

Figure 2: Bike/pedestrian path density per square kilometer



home destination, and the time spent traveling by motorized, non-motorized, and public transit modes to maximize utility. This yields five categories of activities, indexed by j . Letting f_j be the continuous share of time allocated to category j , the utility function is assumed to take a logarithmic form written as:

$$U_j = \alpha_j \ln(f_j), \alpha_j > 0 \quad (1)$$

where α_j is a category-specific preference term. The functional form of Equation 1 is consistent with the assumption that increases in the time allocated to category j increase utility at a decreasing rate. Two additional assumptions are made, the first being that utility is additive, equal to the sum of the utilities from the five individual categories. The second is that α_j can be written as $e^{\beta_j x}$, where x is a vector of exogenous variables and β_j is a vector of parameter estimates associated with category j . Given these assumptions, the optimization problem is:

$$\begin{aligned} \text{Maximize:} \quad & U(f_1, f_2, f_3, f_4, f_5) = \sum_{j=1}^5 e^{\beta_j' x} \\ \text{subject to} \quad & \sum_{j=1}^5 f_j = 1, f_j > 0, j = 1, 2, 3, 4, 5. \end{aligned} \quad (2)$$

The corresponding Lagrangian function \mathcal{L} is expressed as:

$$\mathcal{L} = \sum_{j=1}^5 e^{\beta_j' x} \ln(f_j) + \lambda \left(1 - \sum_{j=1}^5 f_j \right) \quad (3)$$

Taking the partial derivatives of the above function with respect to the shares f_j and the multiplier λ obtains the first-order conditions, comprising six equations with six unknowns. Solving this system yields the optimum fractional allocation of time to each category:

$$f_j^* = \frac{e^{\beta_j' x}}{\sum_{h=1}^5 e^{\beta_h' x}}, \quad (4)$$

The shares in Equation 4 add to one and are therefore interrelated; when one share increases, at least one other necessarily decreases. The multinomial link function can be used to create a quasi-likelihood model that allows for this cor-

relation. Following [Mullahy \(2015\)](#), the model is estimated by maximizing the log likelihood of a regular multinomial logit model using the shares as dependent variables. We estimate the model with Stata 14.0 using the *fmlogit* package authored by [Buis \(2023\)](#).

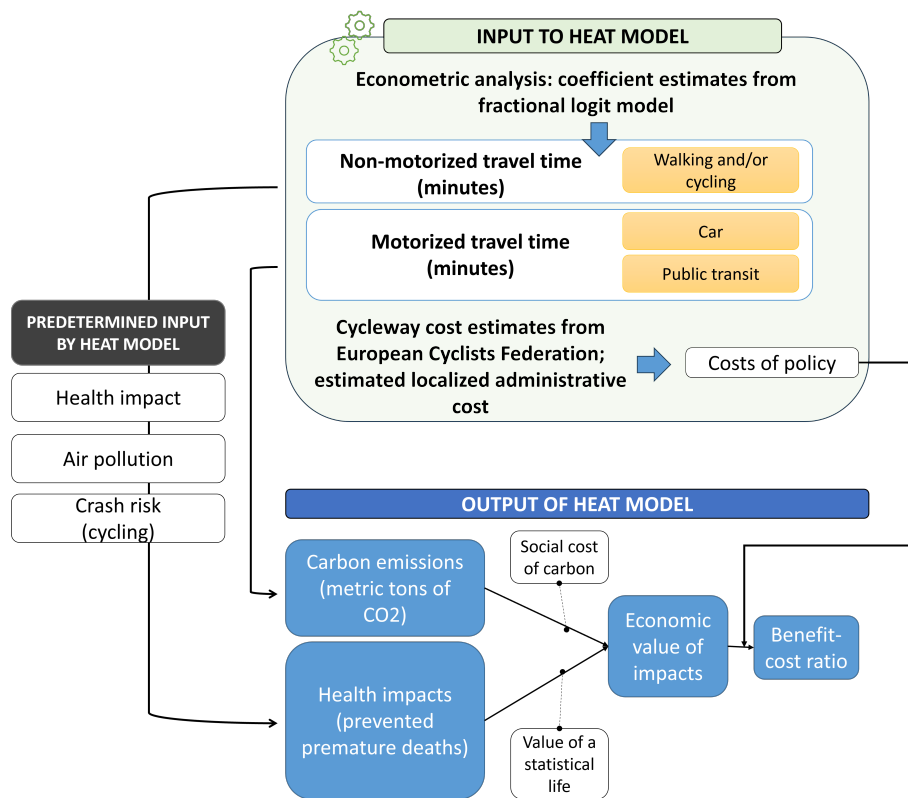
Among the explanatory variables included in vector x , *path density* is a potentially endogenous measure given that people may settle near such infrastructure based on their preference for (or aversion to) nonmotorized (motorized) transport. To mitigate bias, we avail of an instrumental variable that is argued to be correlated with path density but, conditional on the other covariates, uncorrelated with the outcome variable. Borrowing from [Duranton and Turner's \(2018\)](#) analysis of the effect of land use on car-dependency in the US, the instrument measures variation in the composition of the subterranean aquifer. Data to construct the instrument is taken from Germany's Federal Institute for Geosciences and Natural Resources ([BGR, 2023](#)), which publishes a shapefile that maps the subterranean surface in four categories according to the degree of porosity. We use this data to calculate the share of the household's polygon of residence in the highest category ("highly porous"), denoting the instrument as *porous*. Given that bicycle/pedestrian paths are typically paved in urban areas, and urban areas are predicted by the location of aquifers, we expect a positive correlation between *porous* and *path density*, an expectation that is empirically verified below.

Owing to the nonlinearity of the fractional response model, estimation proceeds in two stages using the control function method. Stage one runs an OLS regression of the endogeneous explanatory variable, *path density*, on all the exogenous variables, z , from which the residuals, v are obtained. Stage two runs the fractional response model on *path density*, z and v . The coefficient on v serves as a heteroskedasticity-robust Hausman test of the null hypothesis of exogeneity; if statistically significant, exogeneity is rejected ([Wooldridge, 2015](#)). The standard errors are adjusted for the two-step estimation using bootstrapping, with 200 replications.

2.3 Interface with HEAT

The estimates from the econometric model quantify the effects of the explanatory variables on changes in time allocation, expressed in minutes. These changes are entered in HEAT, which uses city-specific background data to calculate the associated impacts on premature mortality and CO₂ emissions. Figure 3 provides an overview of HEAT and its link with the econometric model. The key user-provided inputs are the changes in time spent with nonmotorized, motorized, and public transport from a policy intervention, such as the expansion of the bicycle path network, and the associated costs.⁵

Figure 3: Econometric/HEAT interface



HEAT's calculation of changes in premature mortality recognizes that walking and cycling confer a protective benefit through improved fitness but also expose people to health-impairing air pollution. Based on a meta-analysis of the epidemiological literature, HEAT consolidates these effects and assigns relative risk (RR) factors. The RR assigned to biking (walking) is 0.90 (0.89), meaning that cy-

⁵Other inputs, which are optional, include whether the transportation is in traffic or away from traffic and the uptake period.

clists (pedestrians) are 10% (11%) less likely to die from all causes combined than a population of non-cyclists (non-pedestrians). These figures are then scaled by the local volume of the respective mode and the exposure using data measured at either the country or city level, depending on the scale of the intervention analyzed. A separate category for crash risk is assigned to cyclists based on the local incidence of cycling and of fatal crashes. From these inputs, the health impacts in terms of prevented premature deaths is calculated. HEAT further allows monetizing these impacts with country-specific measures of the value of a statistical life (VSL) based on a comprehensive review of VSL studies by the OECD (2012). The VSL for Germany is \$4,308,000.

HEAT calculates changes in carbon emissions by assessing user-inputted modal shifts from motorized travel and/or public transit to walking and/or cycling (or vice versa) under the alternative policy scenarios. These changes in travel activity are converted into saved carbon emissions by considering country-specific operational emissions and energy supply emissions. The former includes background values on fuel splits, vehicle fleet composition, and ambient temperature, among other factors, while the latter includes background values on well-to-tank emissions for various transport fuels. The calculation also includes vehicle life-cycle emissions that considers embedded carbon emission factors for materials and energy used in vehicle manufacturing. To monetize the changes in emissions for Germany, HEAT assigns a social cost of carbon (SCC) that varies by year over the time horizon of the analysis. In the present application, this value averages \$182 per metric ton of CO_2 , slightly higher than the \$180 figure used by the German Environmental Agency (Löffler, 2021) and slightly lower than the preferred value of \$185 forwarded by Rennert et al. (2022).

3 Results

Table 2 presents the main coefficient estimates from two fractional response models, the latter distinguished by the application of the control function method to instrument for *path density*. We explored two specifications for the modeling of

path density, one in which we enter the variable linearly and one in which we additionally include its square to allow for a nonlinear effect. Following [Wooldridge \(2015\)](#), we also include the square of the residual. This latter specification recognizes the possibility that the expansion of bike paths has a diminishing effect with increased coverage. Having found the coefficients of *path density* and its square to be jointly statistically significant across the *Nonmotorized* and *Transit* categories, we focus on this quadratic specification in the discussion that follows.

The full set of model estimates, including those using the linear specification of *path density* and those from the first-stage model, are presented in the appendix. As expected, the first-stage model documents a positive and statistically significant association between *path density* and *porous* ([Table A.1](#)). The F-statistic of the model is 6228, far exceeding the threshold of 10 below which weak instruments may be of concern ([Staiger and Stock, 1997](#)).

Noting that *Home* is the base category, the pattern of estimates in [Table 2](#) comports with intuition. Based on the estimates from Model I, increases in bike path density are associated with higher time shares spent in the *Away*, *Nonmotorized*, and *Transit* categories. In all three cases, the magnitude of the effect diminishes as path density increases. A negative association is seen between path density and motorized transportation, though with no evidence of a nonlinear effect. Fuel prices likewise have a negative and statistically significant effect on motorized transportation, contrasted by a positive effect on nonmotorized transportation.

Turning to Model II, which instruments for the variable *path density*, a chi-square test indicates that the estimates of the residual terms are jointly significant ($\tilde{\chi}^2 = 58.13$), which suggests rejecting the null hypothesis of no endogeneity. Nevertheless, the effect of controlling for the residuals on the other estimates appears to be moderate. The estimates of the variable *fuel price* are statistically indistinguishable between Models I and II, while the difference in the effect of *path density* between the models is more difficult to compare given the quadratic specification of the variable. One basis for comparison is given by the implied saturation point, when the estimated effect reaches zero. The saturation point for path density

equals 7.65 based on the estimates from Model II (calculated as $\beta_{path^1} / \beta_{path^2}$). This value is slightly beyond the maximum value of 7.37 observed in the data, which is recorded for the city of Munich. The corresponding value derived from Model I equals 3.92, which is in the top 3% of values observed in the data. Taken together, both models suggest that most towns in Germany have scope for eliciting additional active travel through the expansion of bicycle/pedestrian paths, even if a handful are approaching (or may have exceeded) a saturation point.

Table 2: Select coefficients, fractional response model (FRM)

	I		II	
	FRM		IV-FRM	
Away				
Path density	0.047***	(0.010)	0.015	(0.014)
Path density ²	-0.004*	(0.002)	-0.001	(0.003)
Fuel price	-0.002	(0.005)	-0.001	(0.005)
Residual			0.036**	(0.013)
Residual ²			-0.008	(0.005)
Nonmotorized				
Path density	0.243***	(0.021)	0.306***	(0.029)
Path density ²	-0.031***	(0.004)	-0.020**	(0.006)
Fuel price	0.040***	(0.012)	0.038***	(0.011)
Residual			-0.104***	(0.025)
Residual ²			-0.017	(0.010)
Motorized				
Path density	-0.110***	(0.016)	-0.113***	(0.018)
Path density ²	0.006	(0.004)	-0.007	(0.006)
Fuel price	-0.072***	(0.006)	-0.071***	(0.007)
Residual			0.028	(0.017)
Residual ²			0.024**	(0.009)
Transit				
Path density	0.395***	(0.034)	0.510***	(0.050)
Path density ²	-0.041***	(0.006)	-0.080***	(0.011)
Fuel price	0.031	(0.021)	0.029	(0.019)
Residual			-0.060	(0.038)
Residual ²			0.071***	(0.016)
Control variables	Yes		Yes	
State × Year	Yes		Yes	
N	28252		28252	

Bootstrapped standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Further insight into the effect sizes of the estimates can be gleaned by referencing the conditional expectation for each equation:

$$E [f_{ij}|x_i] = \frac{e^{(\beta'_j x_i)}}{\left[1 + \sum_{h=2}^J e^{(\beta'_h x_i)}\right]}, \quad j = 2, \dots, J \quad (5)$$

and differentiating to obtain the partial effect, PE , of the k^{th} regressor on the j^{th} share:

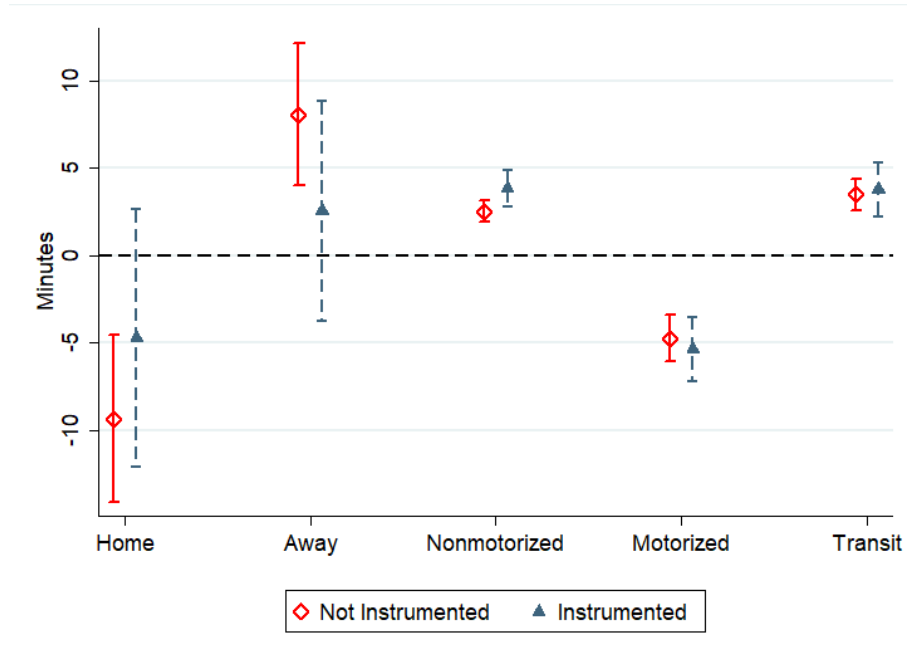
$$PE_{ijk} = \frac{\partial E [f_{ij}|x_i]}{\partial x_{ik}} = E [f_{ij}|x_i] \cdot \left[\beta_{jk} - \frac{\left[\sum_{h=2}^J \beta_{hk} e^{(\beta'_h x_i)} \right]}{\left[1 + \sum_{h=2}^J e^{(\beta'_h x_i)} \right]} \right] \quad (6)$$

We multiply Equation 6 by 1440 to enable interpretation of the PE in terms of the change in daily minutes resulting from a unit change in the explanatory variable. As this calculation yields a unique PE for every observation i in the data, we report the estimated average partial effects (APEs), $APE = \frac{1}{N} \sum_{i=1}^N PE_{ijk}$.⁶ The APE for a given explanatory variable across categories of the dependent variable logically sums to zero, reflecting the constraint of 24 hours in the day.

Figure 4 presents the APEs for *path density*. The confidence intervals of the instrumented estimates are generally larger, but in all cases overlap with the non-instrumented estimates. A unit increase in the length of paths per square kilometer is associated on average with a 3.8 minute increase in time spent on non-motorized transportation per day. The non-instrumented estimate is lower at 2.5 minutes, but the difference is not statistically significant. Path density likewise has a positive effect on time spent with transit, with the point estimates ranging between 3.5 and 3.8 minutes. This possibly reflects complementarities between rail and bike travel in Germany's public transit system, where patrons can typically pay a surcharge to travel with their bicycle. More generally, it aligns with the widely documented synergies between walkability and transit usage (Alshalifah and Shalaby, 2007; Ryan and Frank, 2009; Litman, 2024). Conversely, increases in path density is negatively associated with motorized transportation, with the reduction in daily time exceeding just over 5 minutes according to the

⁶In calculating the APE of *path density*, we adjust Equation 6 to accommodate the quadratic specification, replacing instances of β_k with $(\beta_{k_1} - 2\beta_{k_2} \textit{path density})$, where β_{k_1} is the coefficient of *path density* and β_{k_2} is the coefficient of *path density*².

Figure 4: Average Partial Effect (APE) of bike path density



instrumented estimate.

Figure 5 presents the APEs for a 10-cent increase in the fuel price, which corresponds roughly to the carbon tax on fuel recently introduced by the German government (see below). In this case, the point estimates and confidence intervals of the two models are nearly identical. As with path density, increases in the fuel price increase time spent on nonmotorized transport while decreasing time on motorized transport, with estimates of about 0.58 and -2.93 minutes, respectively.

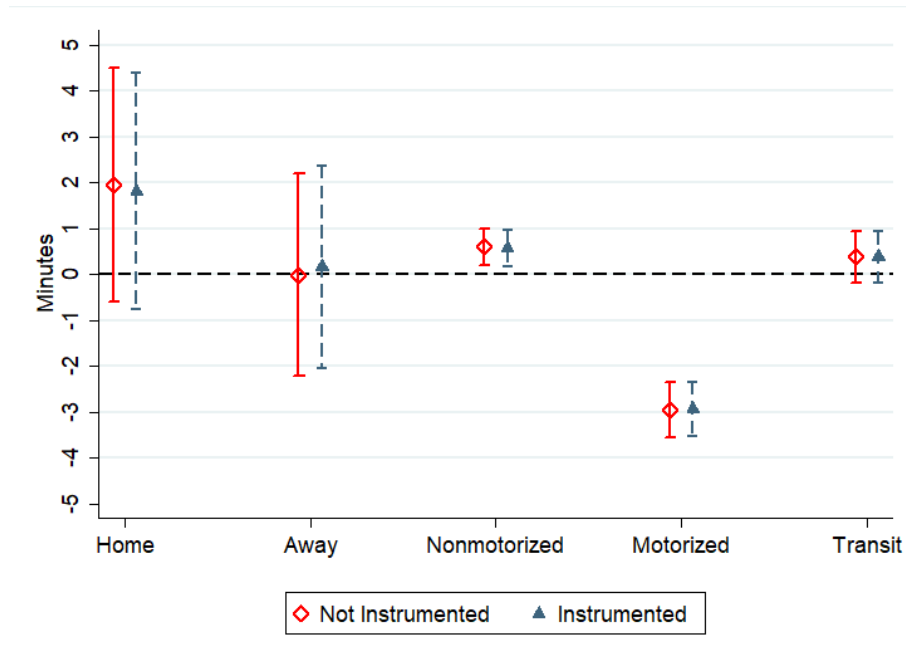
Table 3: Elasticities of *path density* and *fuel price* with respect to time allocation

	Home	Away	Nonmotorized	Motorized	Transit
Path density	-0.003	0.007	0.207	-0.097	0.228
Fuel price	0.022	0.008	0.522	-0.886	0.378

To get a further sense of the magnitude of the estimates, Table 3 presents the elasticities derived from the point estimates of the instrumented models in Figure 4 and Figure 5.⁷ A 10% increase in path density is associated with a roughly 2% increase in time with nonmotorized transport and with public transit, while it is associated with about a 1% decrease in time spent with motorized transport.

⁷The elasticities are calculated by the product: $APE * (\bar{x}/\bar{y})$, where \bar{x} is the mean value of *path density* (or *fuel price*) and \bar{y} is the mean number of minutes in the respective category.

Figure 5: Average Partial Effect (APE) of fuel price



These findings are broadly in line with the literature exploring the link between land-use factors and transportation. Many of these studies focus on vehicle kilometers traveled (VKT) as it relates to various dimensions of density, finding elasticities that typically fall well below 0.5 (see Table 7 and the associated discussion in Litman (2024) for an overview). Turning to the fuel price, the derived elasticities are larger, reaching nearly 0.9 for the motorized category. While these estimates are on the high side of fuel price elasticities found in the literature, which likewise focuses on VKT, they fall within the range of estimates from Germany (Fron del et al., 2008; Keller and Vance, 2013). Fron del et al. (2012), for example, obtain fuel price elasticities ranging between -0.56 and -0.81 using quantile regression methods.

4 Benefit-cost ratios (BCRs) of Paths and Prices

Increases in cycling and walking from infrastructure and price-based interventions result in economic benefits to society through different channels, two prominent ones being reduced premature mortality and reduced carbon emissions. At the municipal level, many cities in Germany have plans in place to increase the

network of bicycle/pedestrian paths, while at the federal level, a carbon tax was introduced in 2021 amounting to €25/ton, or roughly a 7 cent per liter increase in the price of petrol, to be increased to €55/ton by 2025 ([Wettengel, 2024](#)). This section undertakes a comparative analysis that quantifies the benefits of these two measures for the city of Munich by linking the econometric estimates with the WHO's HEAT application. While we assess each measure individually, we note that the intent is not to rank the superiority of one against the other. Indeed, the ideal policy may well involve a combination of both policies to take advantage of complementarities between them, an issue that goes beyond the scope of the present analysis.

Munich has long taken a pioneering role in the promotion of urban bicycle mobility tracing back to the first "Transport Development Plan – Bicycle Traffic (VEP-R)" in 1986, which set the framework for an extensive network of bicycle paths. By 2010, some 1,200 km of paths extended throughout the city connecting greenspaces. More recently, the city council integrated a citizen petition for more bicycle infrastructure into its new mobility strategy. To this end, the urban development plan for 2040 foresees the creation of "green" and "blue" infrastructure as a means to reduce inner city congestion and heat. The total length of extended pedestrian and bicycle paths is expected to be 450 km, which will connect both green spaces as well as the city center with outer districts ([Landeshauptstadt München, 2021](#)).

The question arises as to the net benefits of this extension, taking into account its impacts on health and carbon emissions, its costs, and the fact that Munich already has a high density of paths. To answer this question, HEAT requires baseline values of mode use and the changes therein that result from the intervention. Referring to the descriptive statistics from the sample, people in Munich travel a daily average of 18 minutes by bike or foot, 27.6 minutes by car, and 32.5 minutes by public transit. For the calculation that follows, we assume a ten-year time horizon during which 200 of the planned 450 km of paths is to be initially constructed. According to the point estimate of the econometric model evalu-

ated using the APE for the city of Munich, each kilometer per square kilometer increase in paths is associated with a roughly 2.36-minute increase in nonmotorized travel per person per day, an effect we assume is uniform across the city. Given that the size of Munich is 310 km^2 , this implies a $(200/310)*2.36 = 1.52$ minute increase in daily nonmotorized travel per person. We likewise use the econometric estimates to arrive at the changes induced by the increase in bike paths in motorized travel and public transit in Munich: -4.50 minutes and -0.59 minutes, respectively.⁸

Using these figures, HEAT calculates the number of prevented premature deaths and reduced tons of CO_2 over each year of the 10 year horizon. These are monetized using the VSL and SCC values noted in Section 2.3, from which a present value is calculated using a discount rate entered by the user. We enter the default rate of 5%. Several other assumptions pertaining to the age bracket of the affected population, local pollution exposure, crash risk, and other parameters which can be modified by the user underpin the calculation; these are presented in the appendix. We generally maintain the default values set by HEAT, though in some cases we make adjustments, erring on the side of values that result in a more conservative estimate of the net benefits.⁹ It also bears noting that the benefits of additional bike paths are likely to be more moderate in Munich than in most German cities because of its existing extensive network of paths (see [Figure 2](#)), a feature accounted for by the quadratic specification of *path density* in the econometric model.

To obtain a benefit-cost ratio (BCR), it is necessary to submit an estimate of costs, which are assumed to be incurred in full at the outset of the intervention. We draw on figures from the European Cyclists Federation (ECF 2021), which presents cost estimates of cycleways for different countries. The costs for Germany range between €0.2 and €2 million per kilometer. Pursuant to a conserva-

⁸The negative effect for public transit may appear to contradict the positive APE for transit appearing in [Figure 4](#). The discrepancy owes to the nonlinear effect of *path density*. Inserting the mean value of *path density* (0.78) into [Equation 6](#) yields the positive effect on transit in [Figure 4](#), but inserting the higher value for Munich (7.37) yields a slightly negative effect.

⁹For example, the default value for the take-up time until a new steady-state is reached following the intervention is one year. We reset this to 5 years.

tive estimate of the BCR, we enter the latter figure, converting this to dollars to align with the currency used in HEAT. We make the simplifying assumption that this money is raised from taxes that are specifically earmarked for the construction of bicycle/pedestrian paths.

The top panel of [Table 4](#) presents the main outputs of HEAT for the path expansion scenario. We implement two runs with HEAT, assuming either that the additional 1.52 minutes of nonmotorized travel is allocated completely to walking or completely to cycling.¹⁰ The calculated benefit in terms of prevented premature deaths is seen to be higher for walking than for cycling, which reflects the narrower age bracket considered by HEAT for cyclists (20 – 64 versus 20 – 74 for walking). The reduced tons of CO_2 is likewise somewhat higher for walking. The total value of discounted benefits from walking amounts to \$694 million. Dividing this figure by the total costs yields a benefit-cost ratio of 1.58. Were the increase in paths to result exclusively in an increase in cycling, the BCR would be lower at 1.07, but still indicative of a net positive benefit.

Table 4: Benefit-cost ratios (BCRs) from HEAT-calculations

	Premature deaths prevented	CO_2 reduced metric tons	Benefits millions \$	Costs millions \$	BCR
Path expansion					
Walking	185	957,251	694	440	1.58
Cycling	119	821,786	472	440	1.07
Fuel price increase					
Walking	69	513,239	281	11.5	24.43
Cycling	45	443,749	195	11.5	16.96

The lower panel of [Table 4](#) shows the outputs from HEAT when plugging in the changes in time allocation associated with a 10-cent increase in the fuel price, resulting in an additional 34.5 and 22.5 seconds of nonmotorized and public transport, respectively, and 2.9 fewer minutes on motorized transport. Unlike with the quadratic specification of *path density*, which allows the marginal effect to depend on the level of the variable and thereby renders a unique value for each locale, the linear specification of *fuel price* imposes the assumption of a uniform

¹⁰As the econometric model collapses these two categories, it is not possible to calculate a combined estimate that reflects the shares of biking and walking.

price response across Germany. We find that the increase in the fuel price yields lower reduced premature deaths than the path expansion, a consequence of the latter's stronger absolute effect in increasing nonmotorized transport. Likewise, it yields lower impacts on reduced carbon emissions. Together, these effects yield lower estimates of the benefits, which vary between \$281 and \$195 million for the walking and cycling scenarios, respectively.

To obtain the BCR, we assume that the costs of levying the tax are approximated as a percentage of the total revenue that the tax generates. As [Pomerleau \(2021\)](#) suggests, there is little empirical evidence on the administrative burden of a carbon tax, though she also notes that such taxes appear to have a relatively low administrative cost-to-revenue ratio. She cites figures from Great Britain suggesting this ratio to be on the order of 0.5%, which is somewhat higher than the 0.2% that [Peters and Kramer \(2003\)](#) report for the federal fuel tax in the U.S.. [Wachs \(2003\)](#) reports for the U.S. a share ranging between 1 and 2%. Recognizing that Germany's administrative costs may fall higher (or lower) than these figures, we settle on a cost-to-revenue ratio at the high end of these estimates, at 2%. Taking 2% of Germany's fuel tax revenue in 2022 and adjusting for the size of the tax base in Munich, we arrive at a localized administrative cost of \$11.5 million.¹¹ The resulting BCR ranges from 24.43 for walking and 16.96 for cycling, orders of magnitude higher than for the path increase, notwithstanding the lower monetized benefits of the fuel price increase.

5 Conclusion

While it has long been recognized that physically active transportation confers multiple benefits for mental and physical health ([Litman, 2013](#)), as well as for the environment, the mechanisms underpinning this linkage and their relation to policy instruments remain poorly understood. The forgoing analysis has attempted to address this void through an exploration of everyday time use by

¹¹Revenue from petrol and diesel taxes amounted to roughly €29.5 billion in 2022 ([Destatis, 2023b](#)). We assume that the share of Munich's tax base is directly proportional to the share of Munich's population in Germany, 1.77%. The average \$/€ exchange rate in 2022 was 1.1.

leveraging travel survey data from Germany, recognizing that how people allocate their time, and particularly the means by which they move about, has far-reaching implications for welfare. The analysis proceeded in two steps, beginning with the estimation of an econometric model that identified the determinants of time allocation to different travel modes: motorized, nonmotorized and public transit. Particular focus was directed at estimating the effects of bicycle/pedestrian paths and fuel prices. To allow for non-linear effects, the variable *path density* was modeled as a quadratic, thereby capturing the possibility of a diminishing effect with increases in density. The second step fed the model estimates, expressed in minutes, into the WHO's Health Economic Assessment Tool (HEAT) to facilitate an assessment of changes in premature mortality and CO₂ emissions under alternative scenarios for the city of Munich, from which a benefit-cost ratio could be estimated.

With respect to time allocated to different travel modes and the implications for health and the environment, the analysis revealed:

- Increases in bicycle/pedestrian paths and fuel prices have a statistically- and economically significant effect in increasing time spent on nonmotorized transport and decreasing time spent on motorized transport.
- An increase in paths additionally increases the time with public transport, a possible reflection of synergies facilitated by the accommodation of bicycles on public rail systems in Germany.
- Taking into account the construction costs and the upwards of \$694 million in benefits from reduced premature mortality and reduced carbon emissions, the planned expansion of bicycle/pedestrian paths in Munich yields a benefit-cost ratio (BCR) varying between 1.07 and 1.58.
- By comparison, the economic benefits of a 10 cent increase in the fuel price results in more modest benefits reaching upwards of \$281 million, but yields a considerably higher BCR ranging between 16.96 and 24.43.

Taken together, the findings show that increases in bicycle/pedestrian paths and

fuel prices not only result in substantial benefits, but do so in a cost-effective manner. This especially applies to the fuel price owing to its modest administrative costs. Indeed, the results suggest that the double-dividend sometimes ascribed to carbon taxes ([Pearce, 1991](#)) – emissions reductions and revenue generation – may warrant upgrading to a triple dividend when factoring in the health benefits that emerge from higher levels of physically active travel.

Future research may further investigate the distributive aspects of the benefits, including those associated with improvements in air quality ([Wang et al., 2023](#)). Research into policy impacts on marginalized communities is of particular interest as these populations systemically face higher-than-average negative environmental impacts ([Bluhm et al., 2022](#)).

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Appendices

A Full set of econometric estimates

The first stage estimates of the control function approach, which runs a linear regression of *path density* on the full set of exogenous variables including the instrument, *porous*, is presented in [Table A.1](#). As expected, *porous* has a positive association with *path density*, which is statistically significant.

In the second stage, we extract the residuals from the first stage model, which, along with their square, we include as an explanatory variable to control for the endogeneity of *path density* in the fractional response model. The full set of results, labeled as IV-FRM, are presented in the second column of [Table A.2](#). We also explored models with a linear specification of the variable *path density*, presented in [Table A.3](#), which confirm the direction of effects in [Table A.2](#).

Table A.1: First-stage OLS model

	(1)	
	Path density	
Porous	1.071***	(0.014)
Fuel price	0.033***	(0.006)
Female	0.023*	(0.009)
Cars	-0.213***	(0.006)
Low income	-0.045***	(0.011)
Posths	0.149***	(0.009)
Number employed	0.059***	(0.008)
Full-time	0.021	(0.014)
Part-time	-0.034*	(0.016)
Age 66	-0.017	(0.013)
Young kids	0.030	(0.015)
State \times Year	Yes	
<i>N</i>	28252	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Second stage fractional response model (FRM), full set of estimates from Table 2

	(1)		(2)	
	FRM		IV-FRM	
Away				
Path density	0.047***	(0.013)	0.015	(0.014)
Path density ²	-0.004	(0.003)	-0.001	(0.003)
Fuel price	-0.002	(0.006)	-0.001	(0.006)
Residual			0.036**	(0.012)
Residual ²			-0.008	(0.005)
Female	-0.067***	(0.010)	-0.066***	(0.008)
Posths	0.050***	(0.009)	0.055***	(0.007)
Full-time	0.776***	(0.017)	0.777***	(0.013)
Part-time	0.360***	(0.019)	0.359***	(0.015)
Age 66	-0.397***	(0.016)	-0.398***	(0.013)
Cars	0.024***	(0.006)	0.016**	(0.006)
Low income	-0.035**	(0.011)	-0.037***	(0.009)
Number employed	0.086***	(0.009)	0.088***	(0.008)
Young kids	-0.079***	(0.013)	-0.078***	(0.011)
Nonmotorized				
Path density	0.243***	(0.027)	0.306***	(0.029)
Path density ²	-0.031***	(0.005)	-0.020**	(0.007)
Fuel price	0.040**	(0.014)	0.038**	(0.012)
Residual			-0.104***	(0.025)
Residual ²			-0.017	(0.010)
Female	-0.065**	(0.022)	-0.067***	(0.016)
Posths	0.153***	(0.021)	0.136***	(0.017)
Full-time	-0.167***	(0.032)	-0.168***	(0.024)
Part-time	-0.069*	(0.034)	-0.064*	(0.028)
Age 66	-0.035	(0.030)	-0.032	(0.025)
Cars	-0.458***	(0.016)	-0.436***	(0.015)
Low income	-0.067**	(0.025)	-0.061**	(0.021)
Number employed	0.090***	(0.019)	0.084***	(0.015)
Young kids	0.169***	(0.031)	0.165***	(0.027)
Motorized				
Path density	-0.110***	(0.021)	-0.113***	(0.020)
Path density ²	0.006	(0.005)	-0.007	(0.005)
Fuel price	-0.072***	(0.007)	-0.071***	(0.006)
Residual			0.028	(0.017)
Residual ²			0.024**	(0.008)
Female	-0.169***	(0.013)	-0.168***	(0.010)
Posths	0.025*	(0.013)	0.029**	(0.011)
Full-time	0.651***	(0.020)	0.651***	(0.016)
Part-time	0.466***	(0.023)	0.465***	(0.018)
Age 66	-0.040*	(0.019)	-0.042**	(0.016)
Cars	0.334***	(0.009)	0.328***	(0.008)
Low income	-0.113***	(0.015)	-0.115***	(0.013)
Number employed	-0.115***	(0.012)	-0.113***	(0.010)
Young kids	0.042*	(0.019)	0.044**	(0.016)
Transit				
Path density	0.395***	(0.044)	0.510***	(0.055)
Path density ²	-0.041***	(0.008)	-0.080***	(0.011)
Fuel price	0.031	(0.024)	0.029	(0.022)
Residual			-0.060	(0.044)
Residual ²			0.071***	(0.015)
Female	-0.005	(0.036)	-0.007	(0.026)
Posths	0.379***	(0.039)	0.373***	(0.030)
Full-time	-0.142*	(0.060)	-0.143**	(0.049)
Part-time	-0.473***	(0.064)	-0.471***	(0.055)
Age 66	-0.314***	(0.051)	-0.317***	(0.045)
Cars	-0.831***	(0.034)	-0.822***	(0.029)
Low income	0.052	(0.041)	0.054	(0.034)
Number employed	0.501***	(0.032)	0.497***	(0.028)
Young kids	-0.347***	(0.076)	-0.345***	(0.056)
State × Year				
	Yes		Yes	
N	28252		28252	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Second stage FRM with linear specification of *path density*

	(1)		(2)	
	FRM		IV-FRM	
Away				
Path density	0.027***	(0.006)	0.001	(0.011)
Fuel price	-0.002	(0.006)	-0.001	(0.006)
Residual			0.032**	(0.012)
Female	-0.067***	(0.010)	-0.067***	(0.008)
Posths	0.051***	(0.009)	0.056***	(0.007)
Full-time	0.776***	(0.017)	0.776***	(0.013)
Part-time	0.361***	(0.019)	0.359***	(0.015)
Age 66	-0.398***	(0.016)	-0.398***	(0.013)
Cars	0.023***	(0.006)	0.016**	(0.006)
Low income	-0.035**	(0.011)	-0.037***	(0.009)
Number employed	0.087***	(0.009)	0.088***	(0.008)
Young kids	-0.079***	(0.013)	-0.078***	(0.011)
Nonmotorized				
Path density	0.095***	(0.011)	0.204***	(0.022)
Fuel price	0.041**	(0.014)	0.038**	(0.012)
Residual			-0.130***	(0.025)
Female	-0.065**	(0.022)	-0.068***	(0.016)
Posths	0.158***	(0.021)	0.137***	(0.017)
Full-time	-0.170***	(0.032)	-0.171***	(0.024)
Part-time	-0.069*	(0.034)	-0.063*	(0.028)
Age 66	-0.038	(0.030)	-0.035	(0.025)
Cars	-0.469***	(0.016)	-0.440***	(0.015)
Low income	-0.068**	(0.025)	-0.061**	(0.021)
Number employed	0.092***	(0.019)	0.084***	(0.015)
Young kids	0.172***	(0.031)	0.166***	(0.027)
Motorized				
Path density	-0.088***	(0.010)	-0.112***	(0.016)
Fuel price	-0.072***	(0.007)	-0.071***	(0.006)
Residual			0.030	(0.017)
Female	-0.169***	(0.013)	-0.168***	(0.010)
Posths	0.025	(0.013)	0.029**	(0.011)
Full-time	0.651***	(0.020)	0.652***	(0.016)
Part-time	0.466***	(0.023)	0.465***	(0.018)
Age 66	-0.040*	(0.019)	-0.041**	(0.016)
Cars	0.335***	(0.009)	0.329***	(0.008)
Low income	-0.113***	(0.015)	-0.114***	(0.013)
Number employed	-0.115***	(0.012)	-0.113***	(0.010)
Young kids	0.042*	(0.019)	0.043**	(0.016)
Transit				
Path density	0.182***	(0.017)	0.259***	(0.041)
Fuel price	0.032	(0.024)	0.031	(0.022)
Residual			-0.093*	(0.046)
Female	-0.006	(0.036)	-0.007	(0.026)
Posths	0.387***	(0.039)	0.372***	(0.031)
Full-time	-0.145*	(0.060)	-0.146**	(0.049)
Part-time	-0.472***	(0.064)	-0.468***	(0.055)
Age 66	-0.319***	(0.051)	-0.318***	(0.045)
Cars	-0.848***	(0.034)	-0.829***	(0.030)
Low income	0.053	(0.041)	0.057	(0.034)
Number employed	0.502***	(0.032)	0.496***	(0.028)
Young kids	-0.342***	(0.076)	-0.342***	(0.056)
State × Year	Yes		Yes	
N	28252		28252	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B HEAT input data

Table B.4: Input data for HEAT

	Biking	Walking	Default value
Age bracket	20-64	20-74	same
Proportion of age bracket	60%	70%	same
Proportion excluded	10%	10%	0%
Temporal and spatial adjustment	0	0	same
Take-up time in years for active travel demand	5	5	1
Proportion of new trips	0	0	same
Proportion for transport	100%	100%	50%
Proportion in "traffic"	80%	80%	50%
Substituion of physical activity	0	0	same
All-cause mortality rate: Number of deaths/100,000 inhabitants	274	480	same
PM2.5 concentration: 12 ug/m3	12	12	same
Fatality rate (fatalities per 100 million km)	1.1	1.6	same
Value of a statistical life	\$4,308,000	\$4,308,000	same
Social cost of carbon per ton	\$182	\$182	same
Discount rate	5%	5%	same