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Research Article

Unequal Journeys: Do Income and Neighborhood Influence Public Transport Travel Times in German Cities?

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Abstract

Inefficient public transport is a barrier to increased use and can contribute to time scarcity. Most comparisons of travel time across modes come from accessibility studies that compare trip data and leave several questions unanswered. These include whether the travel time disadvantage of public transport at the trip level translates into a disadvantage at the household level, given the interdependence of mobility choices among household members. Also, whether public transportation is the least time-competitive for social groups that rely on it most, particularly low-income households and those living in low-income neighborhoods.

To investigate these questions, the study employs survey data on daily mobility comprised of data from 67,455 individuals aggregated at the household level across 79 German cities in 2017. The data are supplemented by independent 1km-by-1km grid-level data on neighborhood poverty and centrality and are analyzed via multi-level regression models. Results indicate that the travel time disadvantage of public transportation is mitigated at the household level, and there is no indication that disadvantaged households experience longer travel times given equal travel distances when using public transport. However, the travel time disadvantage of low-income households is not fully explained by the use of public transport over cars, car ownership nor neighborhood centrality.

1 Introduction

To avoid the potentially catastrophic effects of unchecked climate change and to achieve the goals of the Paris Climate countries like Germany need to reduce the use of private cars (Creutzig et al., 2015). Germany, in particular, has a strong affinity for private cars: In January 2022, there were 580 registered passenger cars per 1,000 inhabitants in Germany, up from 517 in 2011 (Federal Statistical Office of Germany, 2022), which is above the European average (acea, 2024). Preferences for modes of transport depend on various factors, including the type of journey (van Eenoo & Boussauw, 2023), lifestyle (Beirão & Sarsfield Cabral, 2007), and both neighborhood location as well as neighborhood affluency (Karjalainen et al., 2022; van Eenoo & Boussauw, 2023).

A variety of reasons have been identified as motivating the preference for motorized individual transport (cars and motorcycles) over public transport, specifically, including flexibility, autonomy, comfort, and symbolizing social status (e.g., Liu et al., 2023; Pojani et al., 2018; Steg, 2003, 2004; van Eenoo & Boussauw, 2023). Despite these, some factors inhibit the uptake of public transport in particular. Among them low accessibility of public transport stations (Ewing & Cervero, 2010; de Vos et al., 2016) whereas increasing the travel time efficiency of public transportation has been shown to increase uptake (Eriksson et al., 2008; Pucher et al., 2005; Redman et al., 2012, p. 123). However, expected travel time is not necessarily the predominant motivation for individuals to opt for cars over public transportation (Kent, 2014; Steg, 2003, 2004).

Whilst the reduced competitiveness of public transport in terms of travel time may represent but one of numerous barriers to its uptake, the implications of inefficient travel times extend beyond the potential for a sustainable transportation transition. Since a considerable segment of the population depends on public transportation, time-inefficient public transportation can contribute to time scarcity (Giurge et al., 2020; Rampell, 2011). In turn, time scarcity is connected to a variety of adverse outcomes, ranging from detrimental impacts on physical and mental health to lower earning potentials (Brownson et al., 2005; Rathjen, 2014; Rose, 2017; Senia et al., 2014; Srivastava & Floro, 2017; Strazdins et al., 2015). The need to increase the uptake of public transportation to combat climate change, while it is uncompetitive in terms of travel times, poses a societal problem.

The majority of comparisons of travel time between different modes of transportation are accessibility studies that compare trip data, which leaves several questions unaddressed. To what extent does the travel time disadvantage of public transportation that has been reported at the trip level translate to disadvantages at the household level? This is of particular importance given that mobility choices are interdependent between household members that share resources and responsibilities among them. Moreover, it is important to know whether public transportation is the least time-competitive for the social groups that rely most on it, specifically low-income households and those residing in low-income neighborhoods. Finally, given the interconnection between economic deprivation and time scarcity, it would be especially problematic if public transportation is the least time-competitive for low-income households for the purpose of commuting.

Survey data on daily mobility is needed to address these questions (Karner & Golub, 2019). Presently, however, there is an absence of this kind of data to assess the travel time competitiveness of public transportation, both in Germany and beyond (Karner & Golub, 2019; Lachapelle & Boisjoly, 2023). Therefore, the current study employs one of the largest and most comprehensive representative survey on daily mobility, the "Mobilität in Deutschland" 2017 (MiD 2017) survey, comprised of individual-level travel data from 67,455 individuals in 2017 that is aggregated at the household level (30,712 households) across 79 German cities with at least 100,000 inhabitants to investigate the research questions. The data allow to distinguish between different trip purposes, including commuting, errands, and leisure mobility (An et al., 2021). This data on daily mobility is supplemented by independent, 1-kilometer-by-1-kilometer grid-level data on neighborhood poverty and centrality and analyzed via multi-level regression models.

2 Research background

2.1 Travel time contributes to time scarcity

The 24-hour time budget limiting everyone's day is roughly divided into place-based activities, such as those performed at home, school, or work, and mobility-related activities. Time spent on mobility, especially on commuting, is one of the major contributors to time scarcity (Giurge et al., 2020; Rampell, 2011). Time scarcity is commonly understood as a lack of sufficient discretionary or leisure time and a high level of time spent on other purposes like earning money or caring for dependents (Williams et al., 2015). It negatively impacts both mental and physical health in myriad ways, ranging from stress (Rose, 2017; Strazdins et al., 2015) to limiting the time available for healthy eating habits (Senia et al., 2014) or for physical activity (Brownson et al., 2005). Time scarcity potentially exacerbates economic deprivation by reducing employment opportunities (Srivastava & Floro, 2017) or by forcing individuals to pay more for products and services (Rathjen, 2014). Indeed, some of the problematic outcomes of socioeconomic deprivation may instead be attributable to time scarcity (Whillans & West, 2022).

While time scarcity has multiple causes, commuting is one of its biggest contributors (Giurge et al., 2020; Rampell, 2011). Unsurprisingly, then, the negative effects of long commutes mirror the negative effects of time scarcity: Less time for leisure activities, including those that promote well-being, better health, and greater social connectedness (Besser et al., 2008; Hilbrecht et al., 2014), as well as reduced employment opportunities (Kneebone & Holmes, 2015). In addition, the act of commuting itself (long hours of sitting, increased exposure to air pollution, etc.) leads to adverse health outcomes (Hilbrecht et al., 2014; Hoehner et al., 2012). Against that background, the need to increase the uptake of public transportation to combat climate change, while it is uncompetitive in terms of travel times, poses a societal problem affecting employment, health, and quality of life. Given these implications, it is important to accurately understand and compare travel time expenditures between cars and public transport. The next section will introduce the different methods employed to that end.

2.2 Comparing travel time between cars and public transportation

Large parts of the literature comparing travel time between different modes of transport are accessibility studies that estimate travel times for specific destinations, like workplaces or hospitals (see Stępniak et al., 2019 for a review). One limitation of accessibility studies is the degree of modeling they require, having to make assumptions about congestion and parking, which both depend on the time of day (Liao et al., 2020; Salonen & Toivonen, 2013), as well as realistic route combinations, as transit is often multi-modal (Salonen & Toivonen, 2013). As such, they often fail to take population flows, i.e., transport performance of the actual demand, into account (Liao et al., 2020). Real-time data, like geotagged social media data (Rashidi et al., 2016), taxi GPS data (Luo et al., 2017), or public transportation smart card data (if available in a country) (Pelletier et al., 2011) have been utilized to address this shortfall.

However, real-time data in most cases does not provide any additional information about the mobile population (e.g., socio-economic characteristics) nor the trips taken (e.g., travel purpose). Surveys address these shortcomings by requiring respondents to protocol each stage of their journeys throughout the day (e.g., Do Carmo et al., 2018; Durán-Hormazábal & Tirachini, 2016). Mobility surveys do not need additional modeling of various assumptions, as modal choice, route combinations, congestion, parking, etc., are all recorded as is ("revealed") (Lunke et al., 2021). Their downside is that they are only valid if representative and mobility protocols put high demands on respondents, introducing potential bias. They are, furthermore, expensive and time-consuming to conduct. Tracking daily journeys of respondents via apps or trackers can eliminate burdensome protocols (Yip et al., 2016), but they depend on the legal framework regarding data protection in a country and are, for that reason, not a valid option in Germany for large-scale surveys (innoZ, 2013).

2.3 Travel time competitiveness of public transportation

No matter the method of estimation, studies across Northern American and many European cities have concluded that motorized individual transport generally saves travel time compared to public transit (e.g., Akhavan et al., 2019; Do Carmo et al., 2018; Liao et al., 2020). Recent estimates for travel times using public transit for the purpose of commuting in major German cities are estimated to be approximately three times longer than those for cars (Mocanu et al., 2021). The authors derived their estimation by integrating aggregated commuter data with travel time data, which was calculated using a synthetic national transport model that contains all major inner and extra urban roads and takes both parking and congestion into account, as well as public transport timetable data for Germany. A different model, also relying on public transport timetables but using real-time data from a weekday in January 2020 at 8am for algorithmically estimating car travel times for all trip purposes, concludes that cars are about two times faster than public transport in the largest German cities (mib, 2021).

Currently, there exists no estimation based on revealed travel time, i.e., survey-based, to assess the travel time competitiveness of public transport versus cars in Germany. Consequently, little is known about systematic differences in time competitiveness of public transportation for different trip purposes or between different social groups. This is problematic because public transportation might be the least competitive for the social groups that rely most on it. This lack of understanding is not limited to Germany (Lachapelle & Boisjoly, 2023) leading to calls to collect survey data on daily mobility to assess equity in public transportation services (Karner & Golub, 2019).

It is known that across Europe, including in Germany, low-income households are less likely to own cars (Mattioli, 2021, p. 9) and utilize it less often, even if they own cars, because of monetary restraints (e.g. Belton Chevallier et al., 2018; Mattioli et al., 2018), rendering low-income households more dependent on public transportation. At the same time, as evidence from Germany and other countries suggests, low-income residents are priced out of the most central neighborhoods (Dohnke et al., 2012; Hochstenbach & Musterd, 2017; Srinivasan et al., 2019; Sterzer, 2017). This negatively affects their access to public transit (Buttner et al., 2013; Herrero Olarte, 2021; Sterzer, 2017; Viguié et al., 2022) but also leads to the problem of long distances to key points of interest (Park et al., 2021) including places of work (e.g., Alba et al., 2021; Kneebone & Holmes, 2015), or cultural centers and hospitals (Siqueira-Gay et al., 2019). In Germany, for instance, about a quarter of the urban population lives more than 1000 meters from the nearest grocery store (Kokorsch & Küpper, 2019). This spatial inequality has the potential to increase travel times independent of mode of transport for low-income residents and/or those residing in low-income neighborhoods and might also reduce their travel time efficiency with public transportation, but this potential consequence has not yet been studied in detail.

Moreover, low-income residents that use public transport might frequent buses or other slow modes of public transit more often than other groups, as has been shown with regard to Montreal/Canada (Lachapelle & Boisjoly, 2023), which might negatively impact their public transit travel speed. With regard to Germany, qualitative interviews so far indicate that this might indeed be a problem for disadvantaged urban groups (George et al., 2025). Furthermore, the experience of public transportation of low-income residents might depend more on the time of day compared to other residents, as they often work schedules outside of regular nine-to-five schedules (eight-to-four depending on the region in Germany), which may negatively impact their experience with public transport (Benenson et al., 2016; Vermesch et al., 2021). Low-income residents' greater reliance on public transit and their potentially poorer experiences with may partially explain why time scarcity can both be a consequence of but also compound economic deprivation (e.g., Srivastava & Floro, 2017).

2.4 Model choices and hypotheses

For comparing travel time with public transportation between low-income residents and others, three considerations are important:

1. Low-income residents travel shorter distances on average and cover smaller activity spaces with their daily mobility (Morency et al., 2011; Tao et al., 2019) and consequently may experience shorter overall transit travel times (Deboosere & El-Geneidy, 2018). It is therefore important to differentiate between travel time and *travel time expenditures*, with the latter looking at the travel time required for similar distances traveled when comparing modes of transport and/or mobility behavior of different social groups, which allows to assess the quality of transport more directly. From a statistical perspective, regression models that utilize travel time as the dependent variable must incorporate travel distance as a control variable to accurately assess the impact of independent variables on travel time under the assumption that travel distances remain constant.
2. Trips throughout the day for any given individual are interdependent (Lunke & Engebretsen, 2023). Using daily distances traveled as a metric accounts for these interdependences.
3. Even if low-income households own cars, these vehicles are likely to be shared among members (Lachapelle, 2015). Even more than for households with average or high incomes, daily mobility decisions of members of low-income households condition each other. It is therefore essential to consider the aggregate mobility patterns of residents not only throughout the day but also at the *household level* to assess if public transportation requires low-income residents to invest more time in their public transit. Only by looking at the household's mobility as its entirety and throughout the given day can the conditioned mobility of household members be accounted for. This, of course, necessitates survey data.

Against the background of the literature, it can be expected that low-income households use public transportation more often throughout the day than other households, as do households in low-income neighborhoods (Hypothesis 1). The revealed travel time expenditure of public transportation averaged across households throughout the day is expected to be higher compared to cars (including motorcycles) across trip purposes in German cities (Hypothesis 2). In addition, there is an open question as to how longer travel times for public transport reported at the trip level translate to the household level, given the sharing of cars, responsibilities, schedules, etc. between members. Furthermore, it can be expected that low-income households and households in low-income neighborhoods experience especially high travel time expenditures with public transportation compared to other households' travel time expenditures using public transportation (Hypothesis 3). Given the less standardized working schedules of low-income residents, the travel time disadvantage when using public transportation might be especially pronounced for low-income households for commutes (Hypothesis 4).

3 Data and methods

3.1 Data, sampling, weighting, and validity

Household-level data on the daily mobility behavior of German urban residents, their socioeconomic status, and their sociodemographic background come from the "Mobilität in Deutschland" (MiD) survey. The MiD was conducted between May 2016 and September 2017 by *infas*, a commercial social research institute, on behalf of the *Federal Ministry for Digital and Transportation* [sic]. Access to the data must be requested from the *German Aerospace Center* (DLR, 2023).

The survey is representative of all residents in Germany across all ages and was conducted as a triple-frame survey (infas et al., 2018, 15–33). Households were randomly selected based on population registers as well as random-digit-dialing of both landline and mobile phone numbers. Each household that was contacted was asked to answer questions about the household and was informed of a more detailed follow-up interview with each person in the household, available either by mail, CATI, or online, and in several languages. For children under the age of ten, the parent/guardian was interviewed in the follow-up interview. All those surveyed agreed to their anonymized data being used for scientific studies on mobility behavior. Questions about individuals' daily mobility behavior were asked on a random day of the week over a period of more than fifteen months to ensure the data is neither affected by day-of-week nor seasonal biases. The standard ("RP3") net response rate (AAPOR, 2016) is 6 percent at the individual level, with the estimated proportion of cases of unknown eligibility that are eligible assumed to be equal to the proportion of eligible cases among all cases in the sample.

Out of the realized sample of 316,361 individuals, a total of 225,847 respondents (71 percent) agreed to waive their privacy rights in order to determine which 1km-by-1km grid they live in based on their addresses. These grids are determined by the German *Federal Agency for Cartography and Geodesy* (BKG, 2020). Using the geometric centroid of these grids, I found that 94,810 of those respondents (42 percent) live in the 79 German cities with a population of 100,000 or more in 2017 (see Appendix A, Figure 4). As an example, Figure 1 shows the spatial distribution of respondents from Berlin, Germany's capital city, compared to the known residential areas of the city. As expected, the MiD covers the inner-city areas almost completely, but not all areas in the city's outer regions. This phenomenon is consistent across all major cities in the sample, with smaller cities frequently experiencing complete coverage by the MiD.

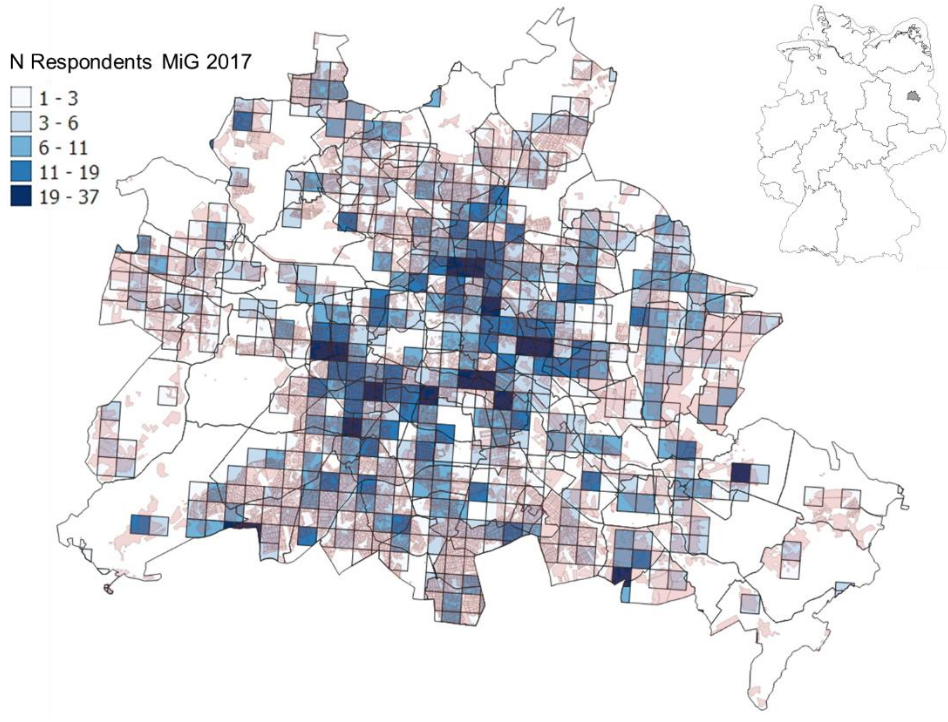

Figure 1. Spatial Distribution of MiD 2017 Respondents across Berlin. Exemplifies the distribution of MiD 2017 respondents in Berlin (blue) compared to residential areas (red). Residential areas are areas of residential or mixed commercial and residential use as recorded in the OpenStreetMap land use data Germany 2021.

The urban respondents of the MiD are clustered in 48,572 households. From these, certain households were excluded from the analytical sample for having no household member that was mobile on the day of questioning, having only members that were mobile outside of Germany, or only reported trips that are part of regular work (e.g., self-employed persons visiting clients directly from home). If one household member failed to provide (valid) answers to relevant questions about daily mobility, the household was excluded, too. From the remaining 42,454 households, a further 11,742 households that are entirely composed of respondents who are (self-reported) retired were excluded. The remaining 30,712 households are the analytical sample. They are comprised of 67,455 individual respondents that together took 237,674 distinct trips and live in 5,032 different 1km-by-1km neighborhood grids in 79 German cities. The MiD survey was complemented with independent contextual data on poverty rates, population density, and the distance to the city center at 1km-by-1km neighborhood grid level (see below).

A weighting procedure at the household level adjusts for the season and day of the week of the survey, the state, city area, and regional population size of the respondent's place of residence according to the 2011 census, as well as for household size, and the household composition with regard to employment status, educational attainment, age, and gender. The weighting procedure also takes into account the different selection probabilities associated with the triple frame design and adjusts for non-response rates of specific sub-populations (infas et al., 2018, pp. 35–50). For additional information on how the survey dealt with the difficulty of measuring daily mobility behavior and potential sampling biases, see Appendix B.

3.2 Variables

In order to test the aforementioned hypotheses, several measures of the aggregated mobility behavior of household members and the socio-economic as well as socio-demographic composition of households were computed. These measures are based on individual-level and trip-level data from the MiD. This data is enriched with additional independent measures of the socio-economic composition of neighborhood grids, and, as two measures of centrality, their population density and geographical distance from the city center. The primary variables are elucidated in greater detail below.

Mobility behavior

Travel distance (km). Total travel distance on the day of the survey is the sum of the length of each trip in kilometers from start to end point, by any transport mode. If missing (initially 8.91 percent of all trips) travel distance was imputed based on the start and end point of each trip and its duration and/or mode of transportation. Responses were capped at the 99th percentile and aggregated at the household level as the average. The distribution is log-linear and was log-transformed for inclusion in regression analyses.

Travel time (min). Total travel time on the day of the survey is the sum of the duration of each trip in minutes from the start to end point by any transport mode. Individual level responses were capped at the 99th percentile and aggregated at the household level as the average of daily travel time expenditure per household member. Its distribution is log-linear and was log-transformed for inclusion in regression analyses.

Travel distance by modal choice. Percentage of total daily distances traveled by mode of transport as the *main* mode of transport per household: motorized individual transport (cars, motorcycles, etc.), public transportation (train, bus, metro, etc.), or foot/bicycle (%). Together, they describe 100 percent of all trips recorded by the MiD, as air transport was recorded in a separate dataset.

Trip purposes. For travel time/distance (by mode) different purposes are distinguished: commuting (getting to or from one’s place of work/education/training), errands (for running errands, shopping, or escorting others to school, doctors, etc.), and leisure (trips for recreational activities, such as going to concerts or dining out, but not mobility as leisure like jogging).

Household context

Income. Categorization of households according to their disposable income (after taxes, deductions), in 15 categories. Adjusted for household size, where the first person aged 14 or over is weighted by a factor of 1, each additional person in that age group is weighted by a factor of 0.5, and each child under 14 is weighted by a factor of 0.3 (according to the OECD modified scale, see Hagenaars et al., 1994). Adjusted household disposable income was divided into five categories (quantiles) based on the entire MiD sample, including non-urban, non-mobile, retired, and those who did not agree to be included in the localized sample. For the current analysis, the two lowest and the two highest quantiles were combined into one category each.

Previous research has shown that a number of demographic factors are associated with the likelihood of using a car or public transportation. Male, employed individuals, and those in multiple-member households are more likely to use motorized individual transport (e.g., Dėdelė et al., 2020; Goel et al., 2023; Kwan & Kotsev, 2014; Roos et al., 2020) and men tend to travel longer distances (e.g., Cassel et al., 2013; Dėdelė et al., 2020). Household size and whether there are children in the households also affect model choice (Olabarria et al., 2013). Older residents have been found to be both more (Roos et al., 2020) or less likely (Dėdelė et al., 2020) to rely on motorized individual transport.

Consequently, these characteristics will be statistically controlled in the analysis. That is, they are included in the regression models as control variables (see below) to account, for example, for an unequal distribution of family households across income groups and to ensure that the statistical effect of household income on the dependent variables is independent of these potentially unequal distributions. The control variables are: the percentage of female members in the household, percentage of members in different age groups (below 18 years, 18 to 29 years, 30 to 59 years, 60 years and older), if there are children below the age of 18 in the household (family household), the percentage of members of certain employment status (employed, student/trainee, homemaker, retirees, other). The number of cars in the household and whether the household has a car-sharing membership are also included as control variables, as it is well established that low-income households own fewer cars, and the paper is interested in differences in travel time and public transportation experience that go beyond that.

Neighborhood context

Poverty rate (%). The proportion of individuals receiving social assistance for the unemployed (i.e., who have been unemployed for more than one year) or for low-income workers, as a percentage of all residents aged under 65 for each grid in 2017. Like similar studies, this index includes the working poor (e.g., Macintyre et al., 2008) but unlike others it excludes those that are "comfortable" between jobs. (Source: Special enquiry at the German Federal Employment Agency, data on residents per grid aged under 65 commercially obtained from *GfK Geomarketing.* The latter are projections based on the 2011 census data.

Centrality. Two measures of neighborhood centrality are employed (Louf & Barthelemy, 2016). First, the inverted distance from the geographic center of each 1km-by-1km grid where respondents live to the geographic center of each city (Source: own calculations). Second, the grid population density (Source: commercially obtained from *GfK Geomarketing*). Both measures of centrality serve as control variables.

3.3 Statistical approach

A series of random-intercept-fixed-slope multilevel linear OLS regression models was applied to get an estimation of the daily travel time of public transportation compared to motorized individual transport and (with regard to hypothesis 1) the likelihood of households to use public transportation for daily travels depending on income levels and neighborhood status. Data are stratified at three levels: households are nested within neighborhoods, which are nested within cities. The multi-level OLS regression models were fitted using the MIXED routine of Stata 17. They are defined as follows (equation 1):

$$Y_{jkl} = b_{000} + b_{q00} * W_{qkl} + u_{j00} + b_{0s0} * Z_{sl} + v_{0k0} + t_{00l} \quad (1)$$

Where Y_{jkl} is the daily travel time expenditure (separate for commutes, errands, leisure) of household j averaged across all household members, that reside in neighborhood k in city l and b_{000} is the grand across-city intercept. 1 … Q are predictors W at the household level (e.g., household income), with each of their slopes b_{q00} fixed across neighborhoods and cities; 1 … S are predictors Z at the neighborhood level (e.g., poverty levels) and their slopes b_{0s0} fixed across cities; u_{j00} are residual errors at household level, v_{0k0} residual errors at the neighborhood level and t_{00l} residual errors at the city level.

4 Results

For context, Figure 2 provides the average percentage of the total daily travel distance for households per mode of transport, separate for different trip purposes and by household income. Public transportation is especially common for commutes, while households prefer traveling by car and foot/bicycle over public transport for both errands and leisure activities. Without controlling for any additional factors, Figure 2 shows that low-income households use cars less often than high-income households across all trip purposes.

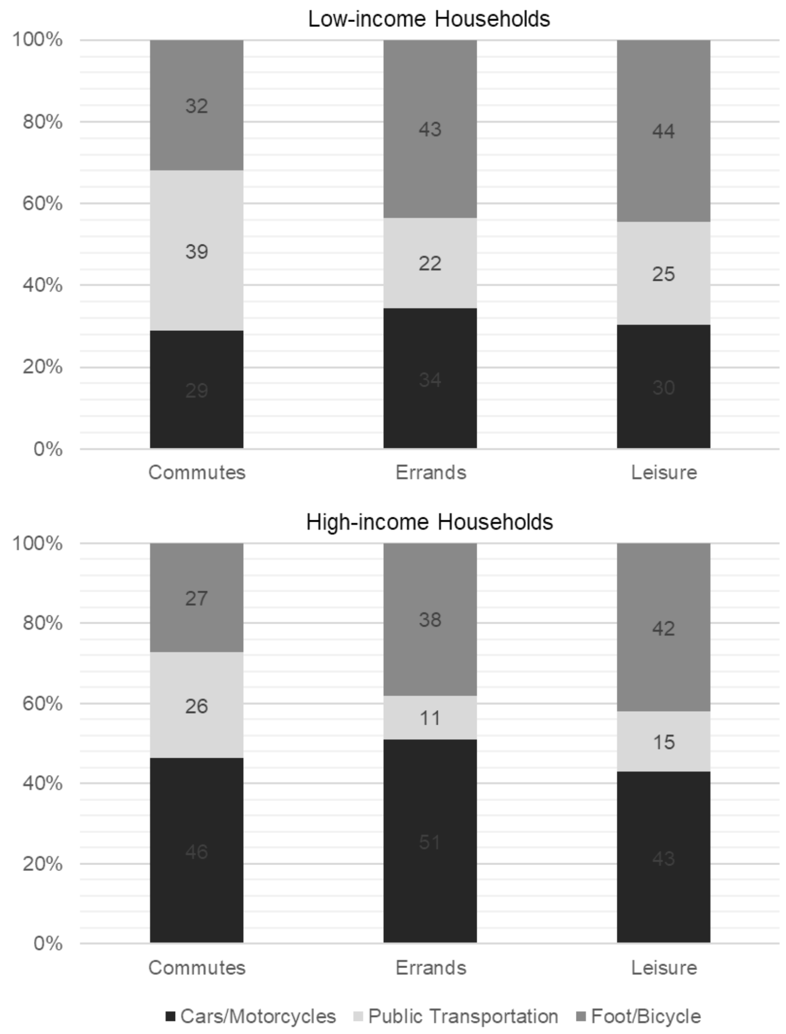

Figure 2. Percentage of the total daily travel distance per mode of transport by purpose and household income, deviation from 100% due to rounding errors

4.1 *H1: Low-income households and those in low-income neighborhoods use public transportation more often*

Results concerning Hypothesis 1 are presented in Table 1 and confirm the descriptive findings shown in Figure 2 above. As Modal M1 indicates, low-income households travel, on average, 8.7 percent more kilometers on public transportation out of their daily total travel distance than high-income households, as opposed to traveling by car or by bicycle/foot (the effect of low household income on the dependent variable, travel distance by public transit, is .087. Since the dependent variable represents percentages but is coded from 0 to 1, the coefficient is multiplied by 100 for interpretation). This finding is net of all differences between low- and high-income households in terms of gender and age composition, occupation, etc.

Model M1 further demonstrates that for every ten-percentage-point increase in neighborhood poverty at the grid level, local households travel 2.2 percent more kilometers on public transportation out of their total daily travel distances. For the five percent of households residing in neighborhoods with a poverty rate of 30 percent and higher, the model thus predicts that they travel about 6.6 percent more kilometers on public transportation out of the total daily travel distance than the 35 percent of households in the sample that live in neighborhoods with a poverty rate of zero. This finding lends support to Hypothesis 1.

Model M1A in Table 1 shows that the impact of household income becomes statistically insignificant when the number of cars in a household and its car-sharing membership are statistically controlled for. The effect of neighborhood poverty on public transportation use becomes less pronounced under these conditions but remains statistically significant.

Table 1. Effects of household income and neighborhood poverty on daily travel distance by public transit (%)

	M1: All Purposes		M1A: All Purposes	
Households	Coef.	SE	Coef.	SE
Income (Reference: High)				
Low	.087 ***	.010	.002	.010
Average	.031 ***	.007	-.003	.007
Size (Reference: 2 members)				
1 member	.025 **	.008	-.043 ***	.008
3 members	-.011	.011	.025 *	.011
4+ members	-.020	.015	.033 **	.011
Female members (%)	.027 *	.011	.024 *	.010
Age (Reference: 60+)				
below 18 (%)	.009	.026	-.029	.027
18-29 (%)	.038 *	.017	-.005	.015
30-59 (%)	.005	.011	-.013	.010
Family household	-.059 ***	.016	-.059 ***	.013
Occupation (Reference: Other)				
Employed (%)	.007	.020	.047 **	.017
Student/Trainee (%)	.104 ***	.017	.112 ***	.020
Homemaker (%)	-.059	.032	-.046	.030
Pensioner (%)	-.065 **	.024	-.025	.023
Cars (Reference: no cars)				
1			-.266 ***	.009
2+			-.345 ***	.013
Car sharing membership			-.035 ***	.009
Constant	.107 ***	.022	.367 ***	.022

Neighborhoods				
Poverty (%)	.222 ***	.051	.177 ***	.037
Centrality (km)	-.002	.001	.003 *	.001
Population (per 10,000 capita)	.025	.015	-.006	.013
Constant	.028	.006	.024	.005
Cities				
Constant	.003	.001	.002	.000

**p* < .05; ***p* < .01; ****p* < .001 (two-tailed tests), random-intercept-fixed-slope multilevel linear OLS regression models. The independent variable travel distance by public transit (%), and all measures in percentages are coded 0-1 and represent averages across households. Interpretation example: Low-income households travel 8.7 percent more (.087×100) out of their daily distances traveled by public transportation as opposed to other modes of transport compared to high-income households.

4.2 *H2: Travel time expenditure of public transportation is higher compared to cars across trip purposes.*

The results of the evaluation of Hypothesis 2 are presented in Table 2 and Figure 3. The dependent variable, daily travel time (in minutes), is averaged across household members. Furthermore, the dependent variable has been log-transformed, indicating that for a one-unit change in the independent variable, travel times in minutes increase by *(exp(b)-1)×100* percent. Results in Table 2 indicate that households in German cities, for the purpose of commuting experience, on average, a 6.1 percent increase in travel times for every 10 percent more kilometers they travel mainly on public transportation compared to those traveling the same distances by car, which is the reference category, and controlled for travel distances by bicycle/foot (Model M2).

In terms of daily mobility related to errands (Model M3), the use of public transportation results in a similar 6.1 percent increase in travel time expenditures for each 10 percent increase in travel distance (6.1 = exp(.478)-1)×100). In the context of daily mobility related to leisure activities (Model M4), the travel time expenditure disadvantage associated with public transportation increases to 7.2 percent for 10 percent more traveled kilometers by public transportation compared to traveling the same distances by car. Results lend support to Hypothesis 2.

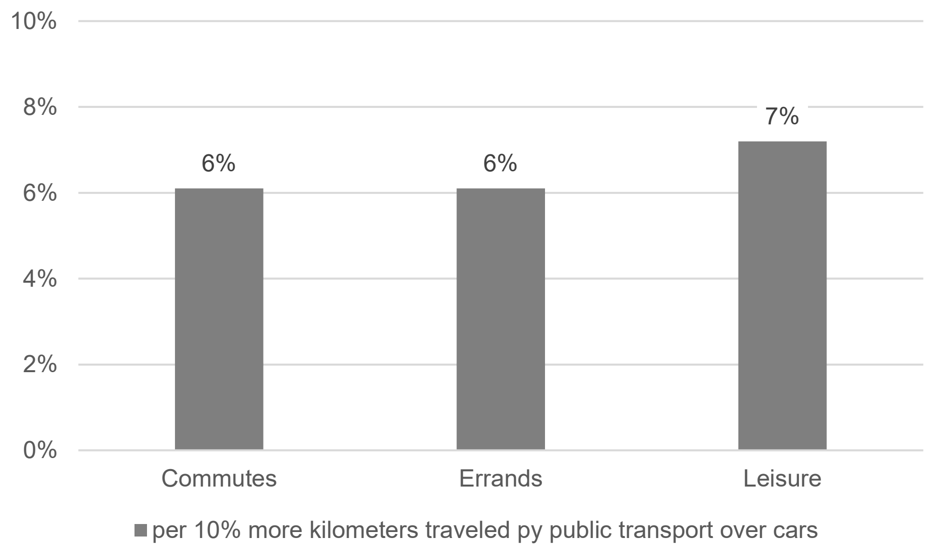

Figure 3. Added Travel Time for Average Household, estimates taken from regression models M2 to M3 in Table 2.

The main effects of low household income (and average household income for errands and leisure) are positive and statistically significant (and smaller for average household income) in models M2 to M2 (Table 2). This is independent of the number of cars in the household, whether the household is a car-sharing member, the use of public transport compared to private cars, and neighborhood centrality. The disadvantage is largest for commutes, where low-income households incur an additional 6.7 percent travel time compared to high-income households throughout the day (4.4 percent and 4.7 percent for errands and leisure-related mobility, respectively).

Table 2. Effects of household income and neighborhood poverty on daily travel time (min)

	M2: Commutes		M3: Errands		M4: Leisure	
Households	Coef.	SE	Coef.	SE	Coef.	SE
Income (Reference: High)						
Low	.065 **	.020	.043 *	.021	.046 *	.023
Average	.019	.014	.035 *	.015	.046 **	.016
Size (Reference: 2 members)						
1 member	.105 ***	.013	.116 ***	.020	.061 ***	.016
3 members	-.072 ***	.018	-.057 **	.019	-.047 *	.024
4+ members	-.059 **	.018	-.061 **	.022	-.041	.025
Female members (%)	.081 ***	.015	.050 *	.021	.071 **	.023
Age (Reference: 60+)						
below 18 (%)	-.069	.073	-.437 ***	.075	-.158 *	.070
18-29 (%)	-.106 ***	.026	-.149 ***	.033	-.128 ***	.034
30-59 (%)	-.064 **	.024	-.063	.034	-.072 **	.031
Family household	.068 *	.032	.204 ***	.041	.066 *	.031
Occupation (Reference: Other)						
Employed (%)	.144 **	.054	-.177 ***	.050	-.099 **	.037
Student/Trainee (%)	.180 ***	.040	-.173 ***	.047	-.222 ***	.042
Homemaker (%)	-.090	.076	.014	.060	.051	.063
Pensioner (%)	-.144 *	.058	-.035	.094	-.004	.083
Cars (Reference: no cars)						
1	-.026	.016	-.007	.019	-.002	.022
2+	-.041	.024	-.038	.026	-.001	.027
Car sharing membership	.000	.011	-.013	.022	.018	.025
Travel distance (log)	.646 ***	.008	.720 ***	.007	.708 ***	.006
Travel distance by (Reference: by Car)						
Public transit (%)	.476 ***	.025	.478 ***	.020	.543 ***	.022
Bicycle/Foot (%)	.594 ***	.032	.849 ***	.027	1.005 ***	.024
Constant (Households)	2.144 ***	.054	2.255 ***	.082	2.153 ***	.076
Neighborhoods						
Poverty (%)	.048	.064	.056	.088	.108	.066
Centrality (km)	-.003	.002	-.003	.002	-.002	.002
Population (per 10,000 capita)	.037 *	.017	.072 ***	.019	.041 *	.017
Constant	.082	.017	.082	.017	.082	.017
Cities						
Constant	.001	.001	.003	.001	.001	.001

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$ (two-tailed tests), random-intercept-fixed-slope multilevel linear OLS regression models. Daily travel time is averaged across household members and has been log-transformed. All measures in percentages are coded 0-1 and represent averages across households. Interpretation example: Regarding commutes, households that exclusively (to 100 percent) rely on public transportation as main mode of transport incur (exp(.476)-1×100)= 61 percent higher travel times as opposed to traveling the same distances exclusively by car (i.e., for each 10 percent more kilometers they travel in public transportation their travel time expenditure increases by 6.1 percent for commutes).

4.3 *H3: Low-income households and those in low-income neighborhoods experience especially high travel time expenditures when using public transportation.*

Results with regard to Hypothesis 3 can be found in Table 3. The data does not support Hypothesis 3, as there is neither a statistically significant interaction effect between the percentage of travel distance traveled by public transportation with low household income nor the neighborhood poverty rate. However, Model M6 reveals that in regard to errands, for every 10 percent increase in daily travel distance covered by public transportation as opposed to cars, *average-income* households experience an increase in travel time of 1.1 percent compared to high-income households. This is in addition to the main effect of an average household income on travel time (which is statistically insignificant in this case) and the main effect of the travel distance by public transit.

The findings reveal that the main effect of low household income on travel time becomes statistically insignificant when the interaction between household income and travel mode is included in the regression model (compare Table 2 to Table 3), implying that the greater dependence of low-income households on public transport (see Table 1) statistically fully explains their generally higher travel time expenditures. (In other words, the effect of low household income disappears of modes of transportation are kept constant between income groups).

Table 3. Effects of household income and neighborhood poverty on daily travel time (min) in interaction with travel distance by public transit (%)

	M5: Commutes		M6: Errands		M7: Leisure	
Households	Coef.	SE	Coef.	SE	Coef.	SE
Income (Reference: High)						
Income: Low	.065	.039	.016	.033	.035	.039
# Travel distance: Public Transit (%)	.022	.049	.090	.064	-.011	.065
# Travel distance: Bicycle/Foot (%)	.059	.052	.041	.046	.036	.057
Income: Average	.019	.023	-.002	.017	.037 *	.018
# Travel distance: Public Transit (%)	-.010	.031	.104 *	.047	.013	.037
# Travel distance: Bicycle/Foot (%)	.032	.030	.063 *	.029	.016	.031
Size (Reference: 2 members)						
1 member	.105 ***	.013	.114 ***	.021	.061 ***	.016
3 members	-.071 ***	.018	-.057 **	.018	-.049 *	.024
4+ members	-.057 **	.018	-.062 **	.022	-.042	.024
Female members (%)	.081 ***	.015	.050 *	.021	.072 **	.023
Age (Reference: 60+)						
below 18 (%)	-.070	.072	-.437 ***	.075	-.164 *	.069
18-29 (%)	-.106 ***	.027	-.149 ***	.033	-.129 ***	.034
30-59 (%)	-.065 **	.025	-.063	.034	-.074 *	.031
Family household	.068 *	.031	.203 ***	.042	.070 *	.031
Occupation (Reference: Other)						
Employed (%)	.145 **	.055	-.175 ***	.050	-.100 **	.036
Student/Trainee (%)	.179 ***	.040	-.171 ***	.047	-.222 ***	.041
Homemaker (%)	-.087	.077	.013	.060	.048	.062
Pensioner (%)	-.142 *	.058	-.030	.094	-.008	.082
Cars (Reference: no cars)						
1	-.026	.016	-.001	.019	-.001	.022

2+	-.042	.024	-.040	.026	-.002	.027
Car sharing membership	.000	.011	-.010	.022	.018	.025
Travel distance (log)	.646 ***	.008	.719 ***	.007	.708 ***	.006
Travel distance by (Reference: by Car)						
Public Transit (%)	.481 ***	.028	.394 ***	.038	.576 ***	.032
Bicycle/Foot (%)	.575 ***	.033	.752 ***	.036	.969 ***	.029
Constant	2.146 ***	.053	2.294 ***	.082	2.162 ***	.077
Neighborhoods						
Poverty (%)	.060	.064	-.166	.094	.082	.110
# Travel distance: Public Transit (%)	-.017	.148	.198	.309	-.294	.167
# Travel distance: Bicycle/Foot (%)	-.020	.164	.583 **	.168	.239	.179
Centrality (km)	-.003	.002	-.004	.002	-.002	.002
Population (per 10,000 capita)	.038 *	.017	.076 ***	.019	.040 *	.017
Constant	.048	.009	.079	.016	.082	.017
Cities						
Constant	.002	.001	.003	.001	.001	.001

**p* < .05; ***p* < .01; ****p* < .001 (two-tailed tests), random-intercept-fixed-slope multilevel linear OLS regression models. Daily travel time is averaged across household members and has been log-transformed. All measures in percentages are coded 0-1 and represent averages across households.

4.4 *H4: The travel time disadvantage when using public transportation is especially pronounced for low-income households when commuting.*

Results for testing Hypothesis 4 are presented in Table 3 above. Hypothesis 4 is not supported by the data; the only statistically significant interaction of household income and travel distance by public transport was found with regard to errands and for households with *average* household income compared to high-income households (Model M6).

5 Discussion and conclusion

A substantial body of research has demonstrated that public transportation systems in urban areas across North America and Europe lack competitiveness in terms of travel time when compared to cars (e.g., Akhavan et al., 2019; Do Carmo et al., 2018; Liao et al., 2020). Although the expected travel time expenditures may not represent the predominant motivation for individuals to opt for cars over public transportation (Kent, 2014; Steg, 2003, 2004), increasing its time efficiency has been shown to increase uptake (Eriksson et al., 2008; Pucher et al., 2005; Redman et al., 2012, p. 123). Arguably just as important, a considerable segment of the population depends on public transportation. Time-inefficient public transportation can contribute to time scarcity (Giurge et al., 2020; Rampell, 2011) which is connected to a variety of adverse outcomes (Brownson et al., 2005; Rathjen, 2014; Rose, 2017; Senia et al., 2014; Srivastava & Floro, 2017; Strazdins et al., 2015).

The majority of comparisons of travel time between different modes of transportation are accessibility studies. Presently, there is an absence of an estimation that is based on revealed travel time – that is to say, survey-based and as is (Lunke et al., 2021) – to assess the travel time competitiveness of public transportation in Germany. This state of affairs leaves various questions unaddressed: first, to what extent does the travel time disadvantage of public transportation that has been reported at the trip level translate to disadvantages at the at the household level and throughout the day? This is of particular importance given that mobility choices are interdependent throughout a given day and depend on and affect other household members that share resources and responsibilities among them. Moreover, public transportation may be the least competitive in terms of travel time for the social groups that rely most on it, specifically low-income households and those residing in low-income neighborhoods.

The study employed representative individual-level travel data from 67,455 individuals, aggregated at the household level (30,712 households) across 79 German cities with at least 100,000 inhabitants from a survey in 2017 to investigate the research questions. The data have been supplemented by independent, 1km-by-1km grid-level data on neighborhood poverty and centrality (population density and distance to the geographical city center).

It has been previously established that public transportation for *commuting* in German cities is not competitive with cars in terms of travel time at the trip level (Mocanu et al., 2021). The current study shows that this disadvantage translates to daily mobility aggregated at the household level and throughout the day. Specifically, for every 10 percent increase in the number of kilometers traveled on public transportation throughout the day, households experience an increase in travel time of 6 to 7 percent, contingent upon the purpose of the travel. Despite the sustained focus of researchers on the issue of excessive commuting (e.g., Bwire & Zengo, 2019), findings indicate that the travel time advantage of cars remains relatively stable across different trip purposes. This indicates that there is not a mismatch regarding the efficiency of public transportation that is specific to commuting from home to work in German cities.

Accessibility studies for German cities have shown that travel time disadvantage at the trip level is twice as long in the largest cities (mib, 2021) and up to three times as long for commuting specifically (Mocanu et al., 2021). The revealed travel time disadvantage aggregated at the household level throughout the day reported here is much less pronounced. This discrepancy is indicative of the manner in which household members endeavor to optimize the utilization of household resources, such as available cars, but also the distribution of responsibilities among them. In partner or family households, women often have less access to the household car than men (e.g., Rogalsky, 2010; Tiikkaja & Liimatainen, 2021). The advantage that some members (more likely to be male) have in relying on cars for daily transportation is, to a certain extent, negated by other members (more likely to be female) in the household who then must rely on public transportation in one-car households. While a valid method for assessing the potential of public transportation to be time-competitive, comparing the travel times of different modes of transportation at the trip level may exaggerate the extent of the societal problem of non-time-competitive public transportation. This method disregards the fact that the decision of an individual traveling by car is embedded in the broader decision-making process of the entire household.

Previous research has produced considerable, although circumstantial, evidence that low-income households and such residing in disadvantaged neighborhoods may experience lower public transportation quality, including higher travel times (Buttner et al., 2013; Lachapelle & Boisjoly, 2023; Herrero Olarte, 2021; Sterzer, 2017; Viguié et al., 2022) and may experience infrastructural disadvantages (Alba et al., 2021; Kneebone & Holmes, 2015; Park et al., 2021; Siqueira-Gay et al., 2019). The present study's findings in German cities do not provide evidence that low-income households or those residing in disadvantaged neighborhoods incur higher travel times when using public transportation compared to other income or neighborhood groups, independent of travel purposes.

Contrary to the hypothesis, the present study revealed that average-income households experience a slight travel time disadvantage when using public transportation for errands in comparison to high-income households. As Mattioli (Mattioli, 2021) explains, average and especially high-income households have the capacity to circumvent the externalities associated with transportation (e.g., noise and emissions emanating from bustling streets, railways, streetcars, and bus stations) when selecting a place of residency. This phenomenon potentially places them at a disadvantage with respect to the accessibility of public transportation. While high-income households appear not to be affected, average-income households may lack the necessary resources to completely overcome these challenges, which could explain the observed slightly elevated travel times when utilizing public transportation.

However, neither public transportation use compared to private car use, the number of cars in the household, whether the household is a car-sharing member, nor neighborhood centrality fully explains the travel time disadvantage of low-income households. These households experience 6.7 percent higher travel times for commuting and between 4 and 5 percent higher travel times for errands and leisure mobility throughout the day. Since the time it takes to get to a public transit station is included in the public transit travel time, this is not likely to be due to the accessibility of public transit, but rather to a specific mismatch between these households' places of interest and where they live.

The findings of this study may not be universally applicable to all German cities. Future research and urban planners might want to consider whether high levels of residential segregation (Jähnen & Helbig, 2023), geographical features that divide cities (e.g., Hamburg owing to the river Elbe), or other features might impact the travel time equity of public transportation. Furthermore, if subsequent research demonstrates that low-income households and low-income neighborhoods are disproportionately exposed to the externalities of public transportation in Germany – which might be the case for specific cities (König et al., 2024) – the inequity may lie in the fact that these households do not enjoy any consequent travel time *advantages* when using public transport. It would mean that more affluent households get the best of both, less exposure to noise and emissions and equal access and service of public transport compared to low-income households.

Furthermore, while there might not be significant disparities in the travel time of public transportation between income groups or neighborhoods with different poverty levels, there might be disparities between other social groups. Studies from other countries have found that, e.g, immigrants are disadvantaged in their daily mobility, especially in terms of commuting (Gao et al., 2021; Golub et al., 2013; Kneebone & Holmes, 2015). There is a disparity in travel time between native and immigrant populations in urban Germany as well that cannot be fully attributed to the higher propensity of immigrants to utilize public transportation (George et al., 2025). Although the MiD records respondents' immigration history, it was not possible to obtain this information from the *German Aerospace Center* for the localized MiD (the data needed for analyses at the neighborhood level), given the problem of potential re-identification and Germany's strict data protection laws. While this limitation is understandable to a degree, future research might be able to obtain information on the immigrant background for at least the very largest German cities to at test for any potential problems in the delivery of public transportation for immigrants in metropolitan Germany.

In addition to the examination of immigrants, the public transportation experience of specific demographic groups could serve as a fruitful avenue for future research. Such groups may include single mothers residing in low-income neighborhoods, low-income seniors, and other relevant demographics. Such detailed analysis might reveal pockets of resistance to expanding public transit or to limiting the use of private cars.

In summary, the travel time disadvantage of public transportation in German cities is less severe when the daily mobility behavior of the entire household is taken into account compared to estimates of previous accessibility studies. This disadvantage is consistent across all trip purposes and is not more pronounced for low-income households or households residing in low-income neighborhoods. There is no pervasive evidence indicating that the public transportation system caters to disadvantaged households in a manner that is less comprehensive than that of other groups in terms of resulting travel times. Nevertheless, investing in public transportation would benefit both low-income households and those residing in low-income neighborhoods disproportionately, as these groups utilize public transportation for greater travel distances throughout the day than other urban residents in Germany. Conversely, disregarding the lower reliance of low-income households and households in low-income neighborhoods on cars in evaluating the projected consequences of car-restrictive policies could potentially amplify the concerns of affluent households and neighborhoods. However, these households possess greater resources to adapt to policy-mandated limitations on private car usage.

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Data Access Statement

Access to the MiD data must be requested from the German Aerospace Center (DLR). All other data may be obtained from the author upon request.

Author and Contributor Statement

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Conflict Of Interest (COI)

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References

AAPOR. (2016). *Standard definitions: Final dispositions of case codes and outcome rates for surveys*. 9th edition. https://aapor.org/wp-content/uploads/2022/11/Standard-Definitions20169theditionfinal.pdf

acea. (2024). *Motorisation rates in the EU, by country and vehicle type*. https://www.acea.auto/figure/motorisation-rates-in-the-eu-by-country-and-vehicle-type/

Akhavan, A., Phillips, N. E., Du, J., Chen, J. Y., Sadeghinasr, B., & Wang, Q. (2019). Accessibility Inequality in Houston. *IEEE Sensors Letters*, *3*(1), 4. https://doi.org/10.1109/lsens.2018.2882806

Alba, D. F. M., Figueroa, O., & Gurdon, C. (2021). Urban inequalities: Travel costs and travel times in the Santiago Metropolitan Area. *Revista Invi*, *36*(102), 54–79. https://doi.org/10.4067/s0718-83582021000200054

An, Z., Heinen, E., & Watling, D. (2021). The level and determinants of multimodal travel behavior: Does trip purpose make a difference? *International Journal of Sustainable Transportation*, *17*(2), 103–117. https://doi.org/10.1080/15568318.2021.1985195

Beirão, G., & Sarsfield Cabral, J. A. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy*, *14*(6), 478–489. https://doi.org/10.1016/j.tranpol.2007.04.009

Belton Chevallier, L., Motte-Baumvol, B., Fol, S., & Jouffe, Y. (2018). Coping with the costs of car dependency: A system of expedients used by low-income households on the outskirts of Dijon and Paris. *Transport Policy*, *65*, 79–88. https://doi.org/10.1016/j.tranpol.2017.06.006

Benenson, I., Ben-Elia, E., Rofé, Y., & Geyzersky, D. (2016). The benefits of a high-resolution analysis of transit accessibility. *International Journal of Geographical Information Science*, *31*(2), 213–236. https://doi.org/10.1080/13658816.2016.1191637

Besser, L. M., Marcus, M., & Frumkin, H. (2008). Commute time and social capital in the U.S. *American Journal of Preventive Medicine*, *34*(3), 207–211. https://doi.org/10.1016/j.amepre.2007.12.004

BKG. (2020). *Geographische Gitter für Deutschland: GeoGitter.* Federal Agency for Cartography and Geodesy. https://sg.geodatenzentrum.de/web_public/gdz/dokumentation/deu/geogitter.pdf

Brownson, R. C., Boehmer, T. K., & Luke, D. A. (2005). Declining rates of physical activity in the United States: What are the contributors? *Annual Review of Public Health*, *26*, 421–443. https://doi.org/10.1146/annurev.publhealth.26.021304.144437

Buttner, B., Wulfhorst, G., Ji, C., Crozet, Y., Mercier, A., & Ovtracht, N. (Eds.) (2013). *The impact of sharp increases in € mobility costs analysed by means of the vulnerability assessment*. https://www.mos.ed.tum.de/fileadmin/w00ccp/sv/PDF/1_projects-reports/Buettner_Veroeffentlichungen/wctr2013_Vulnerability_Assessment_final.pdf

Bwire, H., & Zengo, E. (2019). Comparison of efficiency between public and private transport modes using excess commuting: An experience in Dar es Salaam. *Journal of Transport Geography*, *82*, 102616. https://doi.org/10.1016/j.jtrangeo.2019.102616

Cassel, S. H., Macuchova, Z., Rudholm, N., & Rydell, A. (2013). Willingness to commute long distance among job seekers in Dalarna, Sweden. *Journal of Transport Geography*, *28*, 49–55. https://doi.org/10.1016/j.jtrangeo.2012.10.011

Creutzig, F., Jochem, P., Edelenbosch, O. Y., Mattauch, L., van Vuuren, D. P., McCollum, D., & Minx, J. (2015). Energy and environment. Transport: A roadblock to climate change mitigation? *Science (New York, N.Y.)*, *350*(6263), 911–912. https://doi.org/10.1126/science.aac8033

de Vos, J., van Acker, V., & Witlox, F. (2016). Urban sprawl: neighbourhood dissatisfaction and urban preferences. Some evidence from Flanders. *Urban Geography*, *37*(6), 839–862. https://doi.org/10.1080/02723638.2015.1118955

Deboosere, R., & El-Geneidy, A. (2018). Evaluating equity and accessibility to jobs by public transport across Canada. *Journal of Transport Geography*, *73*, 54–63. https://doi.org/10.1016/j.jtrangeo.2018.10.006

Dėdelė, A., Miškinytė, A., Andrušaitytė, S., & Nemaniūtė-Gužienė, J. (2020). Dependence between travel distance, individual socioeconomic and health-related characteristics, and the choice of the travel mode: a cross-sectional study for Kaunas, Lithuania. *Journal of Transport Geography*, *86*, 102762. https://doi.org/10.1016/j.jtrangeo.2020.102762

DLR. (2023). *Clearing house of transport data at the Institute of Transport Research (DLR)*. https://www.dlr.de/en/research-and-transfer/projects-and-missions/mid2023

Do Carmo, R. M., Santos, S., & Ferreira, D. (2018). Unequal mobilities in the Lisbon Metropolitan Area: Daily travel choices and private car use. *Finisterra-Revista Portuguesa De Geografia*, *52*(106). https://doi.org/10.18055/Finis10102

Dohnke, J., Seidel-Schulze, A., & Häußermann, H. (2012). Segregation, Konzentration, Polarisierung - sozialräumliche Entwicklung in deutschen Städten 2007-2009 [Segregation, concentration, polarization - socio-spatial development in German cities 2007–2009]. *Difu-Impulse 2012, 4*. Deutsches Institut für Urbanistik.

Durán-Hormazábal, E., & Tirachini, A. (2016). Estimation of travel time variability for cars, buses, metro and door-to-door public transport trips in Santiago, Chile. *Research in Transportation Economics*, *59*, 26–39. https://doi.org/10.1016/j.retrec.2016.06.002

Eriksson, L., Friman, M., & Gärling, T. (2008). Stated reasons for reducing work-commute by car. *Transportation Research Part F: Traffic Psychology and Behaviour*, *11*(6), 427–433. https://doi.org/10.1016/j.trf.2008.04.001

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. *Journal of the American Planning Association*, *76*(3), 265–294. https://doi.org/10.1080/01944361003766766

Federal Statistical Office of Germany. (2022). *Car density at record high in 2021: Press release No. N 058* [Press release]. https://www.destatis.de/EN/Press/2022/09/PE22_N058_51.html

Gao, Q. L., Yue, Y., Tu, W., Cao, J. Z., & Li, Q. (2021). Segregation or integration? Exploring activity disparities between migrants and settled urban residents using human mobility data. *Transactions in Gis*, *25*(6), 2791–2820. https://doi.org/10.1111/tgis.12760

George, S., Salomo, K., & Pfaff, T. (2025). Socio-spatial inequalities in urban mobility: the immigrant-native travel time gap in German cities – a mixed method study. *Journal of Ethnic and Migration Studies, 51*(13), 3218-3242. https://doi.org/10.1080/1369183X.2025.2492346

Giurge, L. M., Whillans, A. V., & West, C. (2020). Why time poverty matters for individuals, organisations and nations. *Nature Human Behaviour*, *4*(10), 993–1003. https://doi.org/10.1038/s41562-020-0920-z

Goel, R., Oyebode, O., Foley, L., Tatah, L., Millett, C., & Woodcock, J. (2023). Gender differences in active travel in major cities across the world. *Transportation*, *50*(2), 733–749. https://doi.org/10.1007/s11116-021-10259-4

Golub, A., Marcantonio, R. A., & Sanchez, T. W. (2013). Race, Space, and Struggles for Mobility: Transportation Impacts on African Americans in Oakland and the East Bay. *Urban Geography*, *34*(5), 699–728. https://doi.org/10.1080/02723638.2013.778598

Hagenaars, A. J. M., Vos, K. de, Zaidi, M. A., & Statistical Office of the European Communities. (1994). *Poverty statistics in the late 1980s : research based on micro-data*. Office for Official Publications of the European Communities.

Herrero Olarte, S. (2021). ¿Qué variables de movilidad están asociadas con la pobreza urbana? El caso de Santiago de Chile y Quito [Which mobility variables are related to urban poverty? The Case of Santiago de Chile and Quito]. *ACE: Architecture City and Environment*, *16*(47), Article 9510. https://doi.org/10.5821/ace.16.47.9510

Hilbrecht, M., Smale, B., & Mock, S. E. (2014). Highway to health? Commute time and well-being among Canadian adults. *World Leisure Journal*, *56*(2), 151–163. https://doi.org/10.1080/16078055.2014.903723

Hochstenbach, C., & Musterd, S. (2017). Gentrification and the suburbanization of poverty: changing urban geographies through boom and bust periods. *Urban Geography*, *39*(1), 26–53. https://doi.org/10.1080/02723638.2016.1276718

Hoehner, C. M., Barlow, C. E., Allen, P., & Schootman, M. (2012). Commuting distance, cardiorespiratory fitness, and metabolic risk. *American Journal of Preventive Medicine*, *42*(6), 571–578. https://doi.org/10.1016/j.amepre.2012.02.020

infas, DLR, IVT, & infas 360. (2018). *Mobilität in Deutschland (im Auftrag des Bundesministeriums für Verkehr und digitale Infrastruktur)* [Mobility in Germany (on behalf of the Federal Ministry of Transport and Digital Infrastructure)]. https://www.mobilitaet-in-deutschland.de/archive/pdf/MiD2017_Methodenbericht.pdf

innoZ (2013). *GPS-Tracking als Instrument der Mobilitätsforschung* [GPS tracking as a tool for mobility research]. Innovationszentrum für Mobilität und gesellschaftlichen Wandel. Workshop im Rahmen des Praxisforums Verkehrsforschung 2013, Berlin.

Jähnen, S., & Helbig, M. (2023). The dynamics of socio-economic segregation: What role do private schools play? *Urban Studies*, *60*(4), 734–751. https://doi.org/10.1177/00420980221119385

Karjalainen, L. E., Tiitu, M., Lyytimäki, J., Helminen, V., Tapio, P., Tuominen, A., Vasankari, T., Lehtimäki, J., & Paloniemi, R. (2022). Going carless in different urban fabrics: socio-demographics of household car ownership. *Transportation*, *50*(1), 107–142. https://doi.org/10.1007/s11116-021-10239-8

Karner, A., & Golub, A. (2019). Comparison of two common approaches to public transit service equity evaluation. *Transportation Research Record: Journal of the Transportation Research Board*, *2531*(1), 170–179. https://doi.org/10.3141/2531-20 (Original work published 2015)

Kent, J. L. (2014). Driving to save time or saving time to drive? The enduring appeal of the private car. *Transportation Research Part a-Policy and Practice*, *65*, 103–115. https://doi.org/10.1016/j.tra.2014.04.009

Kneebone, E., & Holmes, N. (2015). *The growing distance between people and jobs in metropolitan America.* Brookings. https://www.brookings.edu/articles/the-growing-distance-between-people-and-jobs-in-metropolitan-america/

Kokorsch, M., & Küpper, P. (2019). Trends der Nahversorgung in ländlichen Räumen [Local supply trends in rural areas]. *Thünen Working Paper, 126*. https://doi.org/10.3220/WP1564566619000

König, C., Salomo, K., & Helbig, M. (2024). *Understanding variation in neighbourhood environmental inequalities: The influence of residential segregation, gentrification, and other city-level factors.* OSF. https://doi.org/10.31235/osf.io/j4tf2

Kwan, M.-P., & Kotsev, A. (2014). Gender differences in commute time and accessibility in Sofia, Bulgaria: a study using 3D geovisualisation. *The Geographical Journal*, *181*(1), 83–96. https://doi.org/10.1111/geoj.12080

Lachapelle, U. (2015). Walk, bicycle, and transit trips of transit-dependent and choice riders in the 2009 United States National Household Travel Survey. *Journal of Physical Activity & Health*, *12*(8), 1139–1147. https://doi.org/10.1123/jpah.2014-0052

Lachapelle, U., & Boisjoly, G. (2023). Breaking down public transit travel time for more accurate transport equity policies: A trip component approach. *Transportation Research Part a-Policy and Practice*, *175*, Article 103756. https://doi.org/10.1016/j.tra.2023.103756

Liao, Y., Gil, J., Pereira, R. H. M., Yeh, S., & Verendel, V. (2020). Disparities in travel times between car and transit: Spatiotemporal patterns in cities. *Scientific Reports*, *10*, 4056. https://doi.org/10.1038/s41598-020-61077-0

Liu, Q., Liu, Y., Chen, C.-L., Papa, E., Ling, Y., & Cao, M. (2023). Is it possible to compete with car use? How buses can facilitate sustainable transport. *Urban Planning*, *8*(3). https://doi.org/10.17645/up.v8i3.6368

Louf, R., & Barthelemy, M. (2016). Patterns of residential segregation. *PLoS ONE*, *11*(6), Article e0157476. https://doi.org/10.1371/journal.pone.0157476

Lunke, E. B., Fearnley, N., & Aarhaug, J. (2021). Public transport competitiveness vs. the car: Impact of relative journey time and service attributes. *Research in Transportation Economics*, *90*, 101098. https://doi.org/10.1016/j.retrec.2021.101098

Lunke, E. B., & Engebretsen, Ø. (2023). Public transport use on trip chains: Exploring various mode choice determinants. *Findings.* https://doi.org/10.32866/001c.74112

Luo, X., Dong, L., Dou, Y., Zhang, N., Ren, J., Li, Y., Sun, L., & Yao, S. (2017). Analysis on spatial-temporal features of taxis' emissions from big data informed travel patterns: a case of Shanghai, China. *Journal of Cleaner Production*, *142*(2), 926–935. https://doi.org/10.1016/j.jclepro.2016.05.161

Macintyre, S., Macdonald, L., & Ellaway, A. (2008). Do poorer people have poorer access to local resources and facilities? The distribution of local resources by area deprivation in Glasgow, Scotland. *Social Science & Medicine*, *67*(6), 900–914. https://doi.org/10.1016/j.socscimed.2008.05.029

Mattioli, G. (2021). Transport poverty and car dependence: A European perspective. *Advances in Transport Policy and Planning. Social Issues in Transport Planning*, *8*, 101–133. https://doi.org/10.1016/bs.atpp.2021.06.004

Mattioli, G., Wadud, Z., & Lucas, K. (2018). Vulnerability to fuel price increases in the UK: A household level analysis. *Transportation Research Part A: Policy and Practice*, *113*, 227–242. https://doi.org/10.1016/j.tra.2018.04.002

mib. (2021). *Travel Time Index.* Mobility Institute. https://mobilityinstitute.com/en/impulses/travel-time-index

Mocanu, T., Joshi, J., & Winkler, C. (2021). A data-driven analysis of the potential of public transport for German commuters using accessibility indicators. *European Transport Research Review*, *13*, 54. https://doi.org/10.1186/s12544-021-00507-0

Morency, C., Paez, A., Roorda, M. J., Mercado, R., & Farber, S. (2011). Distance traveled in three Canadian cities: Spatial analysis from the perspective of vulnerable population segments. *Journal of Transport Geography*, *19*(1), 39–50. https://doi.org/10.1016/j.jtrangeo.2009.09.013

Olabarria, M., Pérez, K., Santamariña-Rubio, E., Aragay, J. M., Capdet, M., Peiró, R., Rodríguez-Sanz, M., Artazcoz, L., & Borrell, C. (2013). Work, family and daily mobility: A new approach to the problem through a mobility survey. *Gaceta Sanitaria*, *27*(5), 433–439. https://doi.org/10.1016/j.gaceta.2012.08.008

Park, S., Oshan, T. M., El Ali, A., & Finamore, A. (2021). Are we breaking bubbles as we move? Using a large sample to explore the relationship between urban mobility and segregation. *Computers Environment and Urban Systems*, *86*, Article 101585. https://doi.org/10.1016/j.compenvurbsys.2020.101585

Pelletier, M.-P., Trépanier, M., & Morency, C. (2011). Smart card data use in public transit: A literature review. *Transportation Research Part C: Emerging Technologies*, *19*(4), 557–568. https://doi.org/10.1016/j.trc.2010.12.003

Pojani, E., van Acker, V., & Pojani, D. (2018). Cars as a status symbol: Youth attitudes toward sustainable transport in a post-socialist city. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 210–227. https://doi.org/10.1016/j.trf.2018.06.003

Pucher, J., Park, H., Kim, M. H., & Song, J. (2005). Public transport reforms in Seoul: Innovations motivated by funding crisis. *Journal of Public Transportation*, *8*(5), 41–62. https://doi.org/10.5038/2375-0901.8.5.3

Rampell, C. (2011, October 14). World of commuters. *The New York Times*. https://economix.blogs.nytimes.com/2011/10/14/world-of-commuters/

Rashidi, T. H., Abbasi, A., Maghrebi, M., Hasan, S., & Waller, T. S. (2016). Exploring the capacity of social media data for modelling travel behaviour: Opportunities and challenges. *Transportation Research Part C: Emerging Technologies*, *75*, 197–211. https://doi.org/10.1016/j.trc.2016.12.008

Rathjen, T. (2014). Time poverty and price dispersion: Do time poor individuals pay more? *Time & Society*, *24*(1), 27–53. https://doi.org/10.1177/0961463X14533281

Redman, L., Friman, M., Gärling, T., & Hartig, T. (2012). Quality attributes of public transport that attract car users: A research review. *Transport Policy*, *25*, 119–127. https://doi.org/10.1016/j.tranpol.2012.11.005

Rogalsky, J. (2010). Bartering for basics: Using ethnography and travel diaries to understand transportation constraints and social networks among working-poor women. *Urban Geography*, *31*(8), 1018–1038. https://doi.org/10.2747/0272-3638.31.8.1018

Roos, J. M., Sprei, F., & Holmberg, U. (2020). Sociodemography, geography, and personality as determinants of car driving and use of public transportation. *Behavioral Sciences*, *10*(6), Article 93. https://doi.org/10.3390/bs10060093

Rose, J. (2017). "Never enough hours in the day": Employed mothers' perceptions of time pressure. *Australian Journal of Social Issues*, *52*(2), 116–130. https://doi.org/10.1002/ajs4.2

Salonen, M., & Toivonen, T. (2013). Modelling travel time in urban networks: comparable measures for private car and public transport. *Journal of Transport Geography*, *31*, 143–153. https://doi.org/10.1016/j.jtrangeo.2013.06.011

Senia, M. C., Jensen, H. H., & Zhylyevskyy, O. (2014). Time in eating and food preparation among single adults. *Review of Economics of the Household*, *15*(2), 399–432. https://doi.org/10.1007/s11150-014-9258-5

Siqueira-Gay, J., Giannotti, M. A., & Sester, M. (2019). Learning about spatial inequalities: Capturing the heterogeneity in the urban environment. *Journal of Cleaner Production*, *237*, Article 117732. https://doi.org/10.1016/j.jclepro.2019.117732

Srinivasan, S., Guan, C., & Nielsen, C. P. (2019). Built environment, income and travel behavior: Change in the city of Chengdu, China 2005-2016. *International Journal of Sustainable Transportation*, *14*(10), 749–760. https://doi.org/10.1080/15568318.2019.1625088

Srivastava, A., & Floro, M. S. (2017). The dual problem of unemployment and time poverty in South Africa: Understanding their linkages. In R. Connelly & E. Kongar (Eds.), *Gender and time use in a global context* (pp. 193–230). Palgrave Macmillan. https://doi.org/10.1057/978-1-137-56837-3_8

Steg, L. (2003). Can public transport compete with the private car? *IATSS Research*, *27*(2), 27–35. https://doi.org/10.1016/S0386-1112(14)60141-2

Steg, L. (2004). Car use: Lust and must. Instrumental, symbolic and affective motives for car use. *Transportation Research Part A: Policy and Practice*, *39*(2-3), 147–162. https://doi.org/10.1016/j.tra.2004.07.001

Stępniak, M., Pritchard, J. P., Geurs, K. T., & Goliszek, S. (2019). The impact of temporal resolution on public transport accessibility measurement: Review and case study in Poland. *Journal of Transport Geography*, *75*, 8–24. https://doi.org/10.1016/j.jtrangeo.2019.01.007

Sterzer, L. (2017). Does competition in the housing market cause transport poverty? Interrelations of residential location choice and mobility. *European Transport Research Review*, *9*(3), Article 45. https://doi.org/10.1007/s12544-017-0259-3

Strazdins, L., Welsh, J., Korda, R., Broom, D., & Paolucci, F. (2015). Not all hours are equal: Could time be a social determinant of health? *Sociology of Health & Illness*, *38*(1), 21–42. https://doi.org/10.1111/1467-9566.12300

Tao, S., He, S. Y., Kwan, M.-P., & Luo, S. (2019). Does low income translate into lower mobility? An investigation of activity space in Hong Kong between 2002 and 2011. *Journal of Transport Geography*, *82*, Article 102583. https://doi.org/10.1016/j.jtrangeo.2019.102583

Tiikkaja, H., & Liimatainen, H. (2021). Car access and travel behaviour among men and women in car deficient households with children. *Transportation Research Interdisciplinary Perspectives*, *10*, Article 100367. https://doi.org/10.1016/j.trip.2021.100367

van Eenoo, E., & Boussauw, K. (2023). "That's not feasible without a car": An exploration of car-dependent practices. *Transport Policy*, *144*, 1–10. https://doi.org/10.1016/j.tranpol.2023.09.021

Vermesch, P., Boisjoly, G., & Lachapelle, U. (2021). Commuting mode share and workplace-based public transport services: An equity perspective. *Case Studies on Transport Policy*, *9*(2), 590–599. https://doi.org/10.1016/j.cstp.2021.02.013

Viguié, V., Liotta, C., Pfeiffer, B., & Coulombel, N. (2022). Can public transport improve accessibility for the poor over the long term? Empirical evidence in Paris, 1968–2010. *Journal of Transport Geography*, *106*, Article 103473. https://doi.org/10.1016/j.jtrangeo.2022.103473

Whillans, A., & West, C. (2022). Alleviating time poverty among the working poor: A pre-registered longitudinal field experiment. *Scientific Reports*, *12*, Article 719. https://doi.org/10.1038/s41598-021-04352-y

Williams, J. R., Masuda, Y. J., & Tallis, H. (2015). A measure whose time has come: Formalizing time poverty. *Social Indicators Research*, *128*(1), 265–283. https://doi.org/10.1007/s11205-015-1029-z

Yip, N. M., Forrest, R., & Xian, S. (2016). Exploring segregation and mobilities: Application of an activity tracking app on mobile phone. *Cities*, *59*, 156–163. https://doi.org/10.1016/j.cities.2016.02.003

Appendix A

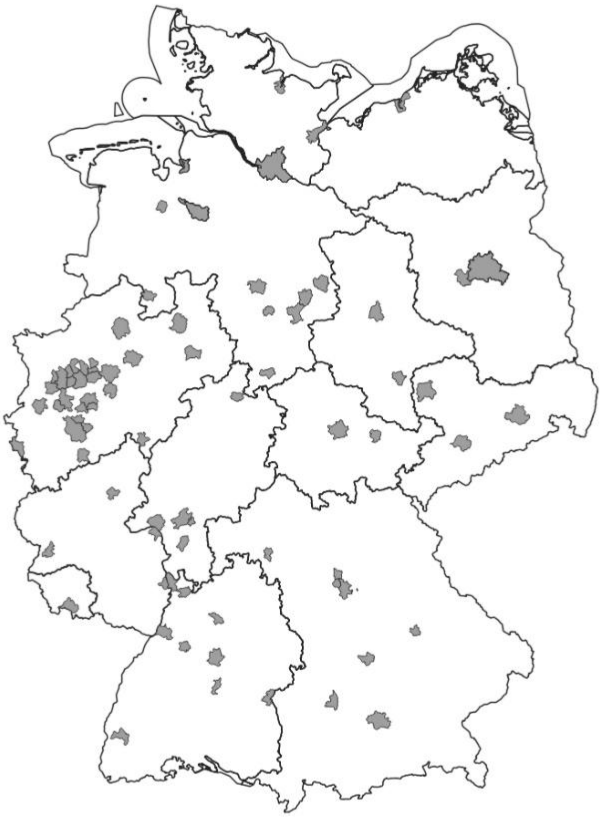

Figure 4. Locations of cities in Germany composing the analytical sample

Appendix B

Dealing with difficult questions on daily mobility

Questions about daily mobility – start and end points, length, duration, mode, etc. of each trip made – are notoriously difficult. Respondents were given small notebooks to carry with them during the day to record their trips, or they could complete them online on mobile devices. When completed retrospectively, an interviewer was usually present. Trip endpoints were determined in online and face-to-face interviews using interactive lists of cities, street names, and approximately 2.5 million points of interest; otherwise, respondents had to write down addresses. A telephone hotline and live chat provided support throughout the field phase. The length and duration of individual trips were calculated in part from the information provided (start/end points and length or duration given the mode of transportation recorded).

Non-response survey

A non-response survey was used to collect some basic information on initial non-responses. No significant differences were found between the main MiG survey and non-respondents in terms of being mobile in general or total distance in kilometers per day. However, respondents with a high volume of daily trips were found to be slightly underrepresented in the main survey (infas et al., 2018, pp. 41–47).

Potential biases of analytical sample

Our analytical sample could be biased in two additional ways: first, with respect to individuals who were immobile on the day of the survey, and second, with respect to individuals who refused to waive their privacy rights regarding the grid location of their homes. Table A2 compares the sociodemographic characteristics of immobile and mobile individuals among urban residents who are not yet retired, using unweighted data. As expected, those who are immobile are less likely to be employed but also have lower levels of education.

Table A2 compares respondents with known grid location with those whose grid location is not known, across all settlement types, excluding retired respondents. Those whose grid location is unknown have slightly lower levels of education and live in smaller households, but are otherwise not significantly different from those whose grid location is known. The weighting procedure conservatively accounts for both of these biases. Overall, however, we conclude that individuals with many trips per day and individuals with very low mobility levels are somewhat underrepresented in our sample.

Table 4. Comparison of mobile and immobile respondents

	Mobile	Immobile
Employed (%)	65.56	48.19
Education: A-levels or higher (%)	60.33	46.83
Age: 17 years or younger (%)	17.73	21.21
Age: 18-39 years (%)	31.89	31.13
Age: 39 years or older (%)	50.40	47.71
Household: 3 or more members (%)	54.79	57.04
Household: above-average income (%)	58.83	48.79
Gender: female (%)	51.31	53.82

Notes. Comparison of mobile and immobile MiG 2017 respondents with known grid location that live in cities and are not yet retired, unweighted data.

Table 5. Table A2. Comparison sample with and without grid-ID

	Grid location	No grid location
Employed (%)	65.65	65.99
Education: A-levels or higher (%)	51.34	39.57
Age: 17 years or younger (%)	17.95	19.77
Age: 18-39 years (%)	25.72	20.93
Age: 39 years or older (%)	56.35	59.35
Household: 3 or more members (%)	59.32	67.38
Household: above-average income (%)	59.31	59.58
Gender: female (%)	51.58	50.95

Notes. Comparison of MiG 2017 respondents whose grid location is known with those whose grid location is not known, all settlement types, excluding retired respondents, unweighted data.