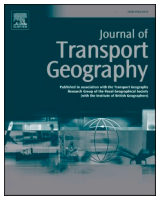
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How public transport costs influence the residential location choice of German commuters

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ABSTRACT

The negative utility of commuting arises from the time spent and the costs incurred. While numerous studies have examined the effect of commuting time on residential location choice, only a few studies published in recent decades have included commuting costs in their analyses, especially public transport costs. We used the official commuter statistics listing the number of commuters by residential and workplace municipality, i.e. a revealed preference origin-destination commuter matrix, for the Frankfurt region in Germany. We estimated multinomial logit models examining residential location choice as the explained variable and using public transport commuting costs as an explanatory variable. The results indicate that public transport commuting costs have an impact on residential location choice, but should not replace public transport commuting time as an explanatory variable. We calculated the value of travel time for commuting by public transport as a function of the number of working days per month. It ranges from 4.3 €/hour for ten working days per month to 8.6 €/hour for twenty working days per month. These results fall in line with existing research, despite the fact that our data and methods diverge from the approaches used in previous studies. Our results show that public transport commuting costs should be taken into account when analysing residential location choices, especially in the light of new pricing policies such as fare-free public transport or nationwide transit passes.

1. Introduction

Classical models see residential location choice as a trade-off between housing and commuting costs (Alonso, 1964; Mills, 1967; Muth, 1969). As commuting is one of the least enjoyable daily activities (Kahneman et al., 2004), the most accurate way of including commuting costs in residential location choice models would be to use a combination of actual monetary costs and time spent. Early studies did just this, including monetary commuting costs – hereafter called commuting costs – and commuting time as explanatory variables in models of residential location choice (Anas, 1981; Anas and Chu, 1984; Lerman, 1976). In recent decades, models have often used car commuting time or distance as explanatory variables, in some cases public transport (PT) commuting time, and hardly any commuting costs, neither for car nor for PT (Schirmer et al., 2014). However, it is questionable to what extent the results of studies published decades ago are still valid, as commuting behaviour has changed in the meantime (Reinfeld and Hagen, 2025). Recent studies tend to focus on the car because, as a result of decreasing transport costs relative to wealth and the consequent increase in car ownership and use, the car nowadays accounts for the majority of household transport costs (Scheiner, 2018). The fact that many studies do not include commuting costs in their models may be related to focusing on the car. For cars, travel time and operational costs (mainly fuel costs) are strongly correlated (Kuhnimhof and Eisenmann, 2023). For statistical reasons, it may even be a good advice to omit one of the two variables. As travel time is more readily available in transport models, most models use car commuting time instead of monetary costs.

Both the focus on the car and the focus on commuting time need to be questioned. On the one hand PT is an alternative for commuting, especially in urban areas of Central Europe. In large cities in Germany, for example, almost as many people commute by PT (31%) as by car (33%) (BMDV, 2019). On the other hand, commuting time and cost may not be as strongly correlated for PT as for car commuting, as PT commuters tend to use monthly or annual transit passes. Therefore, it seems reasonable to consider including the PT commuting time and cost as an explanatory variable in addition to car commuting time in a model of residential location choice.

With the introduction of nationwide transit passes in a number of

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European countries, the issue has become even more relevant. Austria (1400 €/year), Germany (63 €/month), Hungary (18,900 HUF/month, equivalent to ~49 €/month), and Portugal (20 €/month) have such an offer, allowing the holder to use PT throughout the country at a fixed price (BMK, 2026; Comboios de Portugal, 2026; DB, 2026; MAV, 2026). Some details vary from country to country: Germany does not allow the ticket to be used on long-distance trains, Portugal does not allow the ticket to be used in certain metropolitan areas, and Hungary does not allow the ticket to be used on local transport. Overall, such nationwide transit passes extend the geographic coverage of previous transit passes, which were typically tied to fare zones, and reduce transit costs for their holders, potentially influencing residential location choices.

Against this background, the aim of this paper is to estimate the impact of PT commuting costs on residential location choice. Furthermore, we focus on the underlying relationships between PT commuting costs and commuting time as well as location characteristics. The paper is structured as follows. In the next section, we review the existing literature on residential location choice models that use commuting costs as an explanatory variable. We then describe our data and methodological approach. Finally, we present and discuss the results.

2. Literature

McFadden (1977) introduced discrete choice models (DCM) to model residential location choice. This allowed the characteristics of individual, household, dwelling, and location to be related. Schirmer et al. (2014) reviewed studies using DCM to model residential location choice, focusing on the location variables used. They classified these variables into four groups: the built environment, the socioeconomic environment, the availability of points of interest, and accessibility. All of these characteristics are often summarised as 'amenities'. Bieri et al. (2023) compiled data on 75 amenities influencing the quality of life and consequently residential location choice. However, models of residential location choice typically only consider a few of these factors. Commonly used variables include those describing the residential or population density (e.g. Bhat et al., 2016; Salon, 2009; Waddell et al., 2007), housing costs (e.g. Pagliara et al., 2006; Srour et al., 2002; Zondag and Pieters, 2005), the availability or quality of educational facilities (e.g. Chen et al., 2008; Pinjari et al., 2009; Zhou and Kockelman, 2008), the availability of open spaces (e.g. Chen et al., 2008; Guo and Bhat, 2007; Zondag and Pieters, 2005), and land use mix (e.g. Bhat and Gossen, 2004; Guo and Bhat, 2007; Pinjari et al., 2009). An alternative approach is to summarise several types of amenities into a categorical variable describing amenity availability more broadly, as Robbennolt et al. (2024) did. Additionally, accessibility is a widely studied topic in residential location choice. However, there are divergent results regarding its effects due to the use of different analysis levels, variables, model types, and accessibility measures (see Baraklianos et al., 2020, for an overview). These measures include distance (Palma et al., 2007), cumulative opportunities (Lee et al., 2010; Srour et al., 2002), and potential or gravity-based accessibility (Hu and Wang, 2019; Ibeas et al., 2013).

Accessibility is typically analysed in the context of employment. Rather than considering the aforementioned accessibility measures, various studies consider an individual's specific commute. The most accurate way would be to include the individual generalised commuting costs as an explanatory variable in residential location choice models. When interpreted as generalised costs, time costs are added to monetary costs. For car users, the cost of commuting consists of the fixed and operational costs, while for PT users it is the ticket price (usually a transit pass such as a monthly pass). The time cost for both types of users is the time spent commuting.

In recent decades, most studies have used commuting time or distance to describe access to work. As the car is the dominant mode of commuting in many countries, studies often include car commuting time (Frenkel et al., 2013; Guo and Bhat, 2007; Ibeas et al., 2013; Lee et al., 2010; Zhou and Kockelman, 2008; Zolfaghari et al., 2012). The strong correlation between distance, travel time, and operational costs for the car means that the car commuting time variable is a good proxy for generalised costs, with the limitation that PT users are neglected. To avoid this, there are also studies that include commuting time differentiated by car and PT (Guidon et al., 2019; Habib and Miller, 2009). Alternatively, commuting distance is used in the form of the road network-based distance or Euclidean distance between residence and workplace (Chen et al., 2008; Haque et al., 2019; Haque et al., 2020; Srour et al., 2002; Zhang et al., 2019). However, PT users cannot be included in the study in this way because the PT network is less dense than the road network. In general, the estimated parameter of the commuting time/distance variable is negative. This means that the probability of choosing a residential location increases as commuting time/distance decreases and vice versa.

While early studies of residential location choice often included commuting costs and time as explanatory variables (Anas, 1981; Anas and Chu, 1984; Lerman, 1976), commuting costs have only been included in a few studies in recent decades. Table 1 gives an overview of these studies. We have only taken into account studies published from 2000 onward and based on data collected in defined study areas. We excluded theoretical models (e.g. Eliasson and Mattsson, 2000; Ho and Wong, 2007).

In most of the studies mentioned in Table 1, the use of a commuting cost variable is a means to an end and not the key objective of research. The research focuses on the impact of road pricing (Andani et al., 2021; Arentze and Timmermans, 2007; Tillema et al., 2010a, 2010b) or autonomous driving (Krueger et al., 2019; Zhang and Guhathakurta, 2018) on residential location choices or the dependency between short and long term decisions (Guo et al., 2020; Pagliara et al., 2006; Pinjari et al., 2009; Rouwendal and Meijer, 2001; Salon, 2009; Yang et al., 2013). In general, the commuting cost variable is statistically significant and the probability of choosing a residential location decreases as the commuting cost variable increases and vice versa. This is independent of the type of data (revealed or stated preference), the study area, and the variable(s) used to describe commuting costs.

Several studies investigated the decision makers' sensitivity to commuting costs. Habib and Miller (2009) found that decision makers are more sensitive to commuting costs than to commuting time. Salon (2009) comes to the opposite conclusion. This may be because the studies were conducted in fundamentally different areas. While Salon's study area was New York City, Habib and Miller used data collected in Ontario, which is a much larger and overall very sparsely populated area with some dense urban centres. Guo et al. (2020) added that the sensitivity to commuting costs differs between modes. Car users are less sensitive to commuting costs, while the opposite is true for PT users. Tillema et al. (2010b) compared the sensitivity to commuting and housing costs and concluded that the sensitivity to commuting costs is higher than to housing costs. In another study, the same authors found that about 5% of the households would consider moving if commuting costs increased as a result of the introduction of road pricing (Tillema et al., 2010a). In a study by Arentze and Timmermans (2007), also using data collected in the Netherlands, about 10% of the households would consider moving. Zhang and Guhathakurta (2018) found that households may move to find better location characteristics due to lower generalised commuting costs if autonomous driving is established.

According to the existing literature, the impact of (components of) generalised commuting costs on residential location choice is small. Households accept long commutes in order to meet their housing needs (Rouwendal and Meijer, 2001) or to pay lower housing costs (Palm et al., 2014). De Vos and Witlox (2013) see the reason for this in technological developments and the expansion of transport infrastructure, which have led to lower transport costs. The increase in housing costs over the same period reinforced the impact of a proportional decrease in transport costs. Scheiner (2018), on the other hand, argues that although high commuting costs force households to save elsewhere, they may not be

Table 1
Literature overview on residential location choice models including commuting costs as an explanatory variable.

Data type	Paper	Topic	Study area	Commuting time variable	Commuting cost variable
RP	Habib and Miller, 2009	Reference dependence: relocation gains and losses	Ontario, Canada	Car + PT	Total household's commuting costs
RP	Pinjari et al., 2009	Residential self-selection	Alameda County, U.S.	Car	Total household's commuting costs
RP	Salon, 2009	Interaction between car ownership, commute mode, and location choice	NYC, U.S.	Car (driver, passenger) + bus + subway + bicycle/walk	Car (driver, passenger) + bus + subway + bike/walk
RP	Yang et al., 2013	Interaction between travel mode, departure time, and location choice	Beijing, China	Car + PT + bicycle	Total travel cost (Car: fuel costs, PT: ticket price)
RP	Zhang and Guhathakurta, 2018	Autonomous driving	Atlanta metropolitan area, U.S.	Car (time cost, combining commuting time and salary)	Car (vehicle cost relative to income)
SP	Rouwendal and Meijer, 2001	Interaction between housing, job, and commuting	Netherlands	Car	Household disposable income (net income – housing cost – operational car commuting costs)
SP	Pagliara et al., 2006	Interaction between housing, amenities, and commuting	Oxfordshire, UK	Car + PT	Car + PT
SP	Arentze and Timmermans, 2007	Congestion pricing	Netherlands	–	Car (base, congestion increase) + train (base increase)
SP	Tillema et al., 2010a	Road pricing	Netherlands	Car	Toll costs
SP	Tillema et al., 2010b	Road pricing	Netherlands	Car	Operational costs (car) + toll costs
SP	Krueger et al., 2019	Autonomous driving	Sydney metropolitan area, Australia	Car + PT	Car + PT
SP	Guo et al., 2020	Interaction between housing, job, and commuting	Shenyang, China	Car + PT (metro, bus) + bike + walk	Car + PT (metro, bus)
SP	Andani et al., 2021	Road pricing	Jakarta-Bandung region, Indonesia	Total travel time	Total travel cost

Notes: RP = Revealed preference, SP = Stated preference, PT = Public transport

less satisfied overall as long as they meet their location needs.

The increase in working from home during the Covid-19 pandemic also suggests that commute-related characteristics are becoming less important (see Ilham et al. (2024) for an overview of the effects of working from home on relocation). As people commute less frequently, they are more willing to accept greater distances between home and work (Böhnen and Kuhnimhof, 2024; Salon et al., 2022; Stefaniec et al., 2022). Additionally, as people spend more time at home and in their neighbourhood (Huang et al., 2023; Song et al., 2023), the characteristics of their dwelling and neighbourhood become more important (e.g. dwelling size or access to green spaces) (Melo, 2022). The effects are already evident in the housing market. One notable trend is the migration from metropolitan areas to their suburbs, known as the 'donut effect' (Ramani and Bloom, 2021). Ahrend et al. (2023) specify this by identifying rising demand for housing in both low-density metropolitan area suburbs and high-density rural settlements.

The findings can be summarised as follows: First, the number of studies published in recent decades examining the impact of commuting costs on residential location choice is limited. To our knowledge, there is no study including PT commuting costs that is based on regional revealed preference data, including both dense urban centres and rural areas. Second, when commuting costs were used as an explanatory variable, the likelihood of choosing a location as a residential location increased as commuting costs decreased. However, the sensitivity to commuting costs varies according to the transport mode used to commute and the area in which people live and work. Third, households give more weight to location characteristics than to commute-related characteristics.

Against this background, this study complements existing research by including PT commuting costs as an explanatory variable in a residential location choice model based on a regional revealed preference commuter matrix. We tested the hypothesis that lower PT commuting costs increase the likelihood of a municipality being chosen as a residential location. By including both commuting time and commuting costs, we were able to examine the interrelationship between both variables.

3. Methodology

3.1. Data

Our study area is the Frankfurt metropolitan transport association region (in German: Rhein-Main-Verkehrsverbund (RMV)) (Fig. 1). Around five million people live in the RMV area, which is divided into 60 fare zones, each of which typically covering several municipalities. In total, the RMV area consists of 287 municipalities. The transport association's boundaries have been chosen so that most commuter traffic takes place within the area. Due to the population density in this region, certain restrictions are unavoidable. Notably, the area borders the employment centres of Mannheim and Ludwigshafen to the south. This is why the adjacent municipalities of these cities are not included in the transport association. As the study area is large, the proportion of cross-border commuters is low, so we do not expect our analysis to be significantly affected. The only available information on modal share in this region relates to the entire state of Hesse. In 2017, cars accounted for almost two-thirds of commute trips in Hesse, compared to 16% for PT (BMDV, 2019).

We used origin-destination (OD) commuting data from the Federal Employment Agency. The data contain information on the place of residence and place of work at the municipal level for each employee subject to social insurance contributions (about three quarters of the German workforce). Only OD combinations of municipalities with at least ten commuters are included. In total, the commuting data for the study area cover 1,723,575 employees. The data are from 2018, i.e. before the COVID-19 pandemic and the associated increase in working from home. The lines between the centroids of each municipality in Fig. 2 illustrate OD commuting relations in the study area. The darker the line, the larger the number of commuters. Most commuters live and work in and around Frankfurt am Main, with the larger cities of Wiesbaden, Mainz, and Darmstadt.

We sourced the characteristics of the OD commutes from various databases. Travel times between the municipalities were extracted from a regional transport model and differentiate between car and PT. Since the transport model operates at the level of traffic cells, which cover smaller geographical areas than the municipalities, we determined the travel times used in our model as follows. First, we assigned the

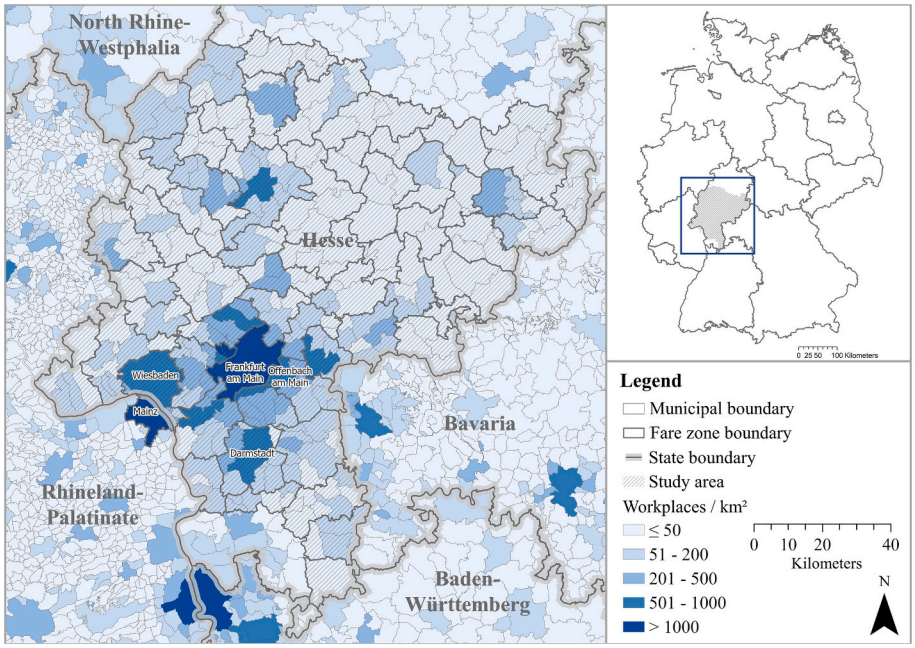


Fig. 1. Study area (own illustration using electronic maps from the Federal Agency for Cartography and Geodesy and data from the Federal Employment Agency. The hatched area covers the municipalities of the RMV, our study area).

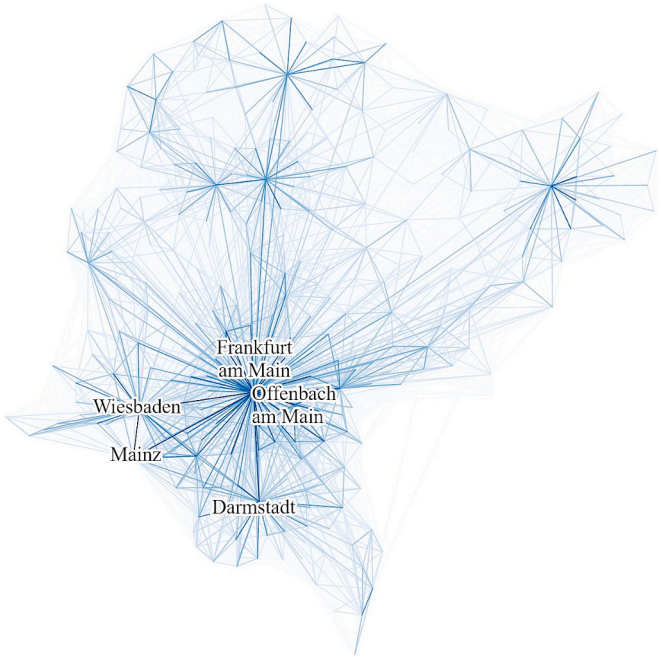


Fig. 2. Origin-destination commuting relations in the study area (own illustration using electronic maps from the Federal Agency for Cartography and Geodesy and data from the Federal Employment Agency).

transport model's traffic cells to the municipalities. Next, we calculated the average travel time between municipalities, weighting the travel times between respective traffic cells according to the number of trips. We calculated the transport network distance based on the OpenStreetMap road network. We determined the PT commuting costs between each municipality from the RMV's 2018 general fare plan.[1] This includes a matrix of price levels for the shortest connection between all 60 fare zones and a price list with the ticket prices for each price level, differentiated by ticket type. By transferring the price levels to the municipalities included in each fare zone, we assigned a price level to all combinations of municipalities in the study area. Using the price list, we determined a price for a monthly pass for all combinations of municipalities in the study area. Table 2 lists the price of a monthly pass for each of the five price levels. The higher the price level, the higher the price of the monthly pass and the larger the geographic area covered by the pass. A price level 3 monthly pass entitles the holder to use PT in one fare zone. Comparing columns three and four of Table 2 shows that price level 3 only covers a small number of OD combinations. However, these OD combinations accounted for more than half of employee commutes in 2018. This shows that the majority of commuters live close to their place of work. 38% of employees even live and work in the same municipality, based on the OD commuter matrix.

To characterise the municipalities, we considered housing and spatial data. We used housing cost data from the Research Data Centre Ruhr (FDZ Ruhr)[2] and spatial data from the German regional database

Table 2
Distribution of origin-destination combinations and commuters by price level in 2018.

Price level	Monthly pass price [€][a]	Proportion of OD combinations [%]	Proportion of commuters [%][b]
3[c]	89.60	2.1	53.1
4	136.30	9.2	32.5
5	183.10	15.6	10.6
6	229.30	18.6	2.5
7	275.80	54.5	1.3

[a] Data from RMV's 2018 general fare plan
[b] Own calculation using data from the Federal Employment Agency
[c] Monthly pass price for the Mainz/Wiesbaden fare zone was 81.5 €

[1] See RMV's latest general fare plan as an example: https://www.rmv.de/c/fileadmin/documents/PDFs/_RMV_DE/Fahrkarten/Regeln/Tarifgesamtplan.pdf

[2] See for an overview of the available data sets: https://www.rwi-essen.de/en/research-advice/further/research-data-center-ruhr-fdz/data-sets

(Federal Statistical Office and the statistical offices of the Länder, 2024). The spatial data include, for each municipality, the number of dwellings, the settlement area, the total area, the share of recreational area, and the share of area covered by residential, commercial/industrial respectively other land use. All these data refer to our studies reference year 2018.

3.2. The multinomial logit model

Based on McFadden (1973), we used a multinomial logit model to explain residential location choice based on the characteristics of the alternatives. The utility of alternative j for decision maker n is composed of a deterministic component, V_{nj}, and a random error term, ε_{nj}: $U_{nj} = V_{nj} + \varepsilon_{nj}$. The underlying assumption is that individuals aim to maximize their utility. If an alternative i provides greater utility than any other alternative j, then the individual will choose i, thereby satisfying the condition $U_{ni} > U_{nj}$, $\forall j \neq i$. Assuming independent and identically distributed (IID) error terms and a Gumbel distribution for ε, the probability of decision maker n choosig alternative i can be expressed as $P_{ni} = e^{V_{ni}} / \sum_j e^{V_{nj}}$.

We only used alternative specific variables with generic coefficients. Since it can be assumed that the effect of the variables does not depend on the specific municipality, generic coefficients are sufficient. Accordingly, we have not included alternativ specific constants in our model. We were not able to account for characteristics of individual decision makers due to the structure of the commuting data used. The dependent variable of the multinomial logit model represents the decision maker's actual choice of a particular municipality as a residential location. The basic choice set for each decision maker consisted of 287 municipalities representing the potential residential locations. We considered the workplace as exogenous, i.e. the commute-related characteristics resulted from the combination of the municipality of the workplace and the potential residential locations. Due to this and the lack of individual characteristics in the commuting data, the values of the characteristics describing the alternatives are the same for decision makers working in the same municipality. We estimated all models with the Apollo package (version 0.3.5) for R (Hess and Palma, 2019).

3.3. Explanatory variables

The commute-related variables taken into account were the commuting time and the commuting costs for both car and PT and a dummy variable indicating if residence and workplace are in the same municipality. As described in section 3.1, we extracted both travel times from a regional transport model and determined the PT commuting costs from the RMV's general fare plan. We calculated the car commuting costs by multiplying the net distance between the centroids of the municipalities by 0.1. 0.1 €/km corresponds to the marginal cost (fuel cost) of private car use in Germany (Kuhnimhof and Eisenmann, 2023). The car commuting costs used were essentially operational costs. We neglected the fixed car costs, as these are often underestimated by car users. Table 3 shows the correlation matrix of the commute-related variables. However, we decided not to include car commuting costs in the analysis as they have a strong positive correlation with car commuting time. Despite the fact that the variables car commuting time and PT commuting costs are strongly correlated, we included both variables in our models due to their high relevance to the research question. The relatively low correlation between the variables PT commuting time and PT commuting costs indicates that commuting time and costs in the case of PT are less coupled than for the car.

In order to obtain coefficients for the commute-related variables that are only minimally confounded by factors at the municipal level, municipality-specific characteristics were included. The number of dwellings as a proxy for municipality size, housing costs, and the share of recreational areas are key characteristics assumed to influence residential choice. As a proxy for housing costs on the municipal level, we used an index that reflects the deviation from the average rent per square metre in Germany, based on asking rents sourced from the FDZ Ruhr (Schaffner and Thiel, 2022). To fill in missing values, we calculated averages from neighbouring municipalities. Although 47.5% of dwellings in Hesse are owner-occupied (Federal Agency for Civic Education/bpb, 2021), we interpreted rental prices as a general measure of housing costs.[3] From the area shares by land use, we calculated an index of land use diversity according to Bhat and Gossen (2004). The index value can range from 0 to 1. The higher the value, the more mixed the land use.

In general, there are two reasons why we preferred to use a simpler, more stable model with fewer explanatory variables. First, at the municipal level in particular, the variables typically used to determine a place's liveability are often highly correlated (e.g. housing density, the number of educational facilities, and housing costs). Second, since we are working with a large number of observations, there is far less variance in the explanatory variables. This could lead to overfitting if too many variables are estimated.Table 4 presents the descriptive statistics of the variables used in the model.

Table 3
Correlations between the commute-related variables.

	Car commuting time	Car commuting costs	PT commuting time	PT commuting costs
Car commuting time	1.00	0.92	0.67	0.86
Car commuting costs		1.00	0.76	0.89
PT commuting time			1.00	0.69
PT commuting costs				1.00

Notes: PT = Public transport

4. Results

The estimation results are presented in Table 5. We estimated three different models: M1 included all variables except the PT commuting costs variable, M2 included the PT commuting costs variable but not the PT commuting time variable, and M3 included all variables.

The signs of the estimated parameters did not differ between the models, except for share of recreational area and the dummy variable indicating a low land use diversity. All the variables were significant at the 0.001 level, except the low land use diversity dummy variable. The commuting time variables were negative. The effect of car commuting time exceeded that of PT commuting time in all models, showing that commuters are more sensitive to changes in car commuting time than in PT commuting time. However, this may be influenced by two factors. First, cars are the dominant mode of transport for commuting in the study area. Second, the car commuting time coefficient implicitly contains the effect of car commuting costs, whereas these are separated for PT in M3. The PT commuting costs variable is also negative. As expected, the probability of choosing a municipality as a residential location decreases as PT commuting costs increase. We included a dummy variable to take into account whether home and work were located in the same municipality. This dummy variable was always positive, even when

[3] According to the theory of rental equivalence, the user cost of owner-occupied housing can be estimated using the rental price of a similar dwelling in the same area and over the same period. Since Germany has a large rental market, this approach is well suited to the country and is also used to calculate the national consumer price index (Eurostat, 2023).

Table 4
Summary of variables used in residential location choice model.

Variable	Min	Median	Mean	Max	SE
Commute-related characteristics					
Car commuting time (hours/trip)	0.00	0.27	0.34	2.27	0.24
PT commuting time (hours/trip)	0.10	1.00	1.12	4.80	0.45
PT commuting costs (€/month)	81.50	89.60	120.01	275.80	40.72
Dummy internal commuting relation	0.00	0.00	0.38	1.00	0.49
Municipality-specific characteristics					
Number of dwellings	723.00	13,629.00	84,969.15	393,186.00	136,267.30
Housing cost index	−46.00	12.00	12.91	63.00	28.55
Land use index	0.41	0.77	0.74	0.97	0.10
Recreational area (%)	3.95	14.29	14.58	32.74	5.37

Notes: PT = Public transport, Number of observations = 1,723,575

including car and PT commuting time as explanatory variables. This suggests that people tend to live and work in the same municipality regardless of commuting time and costs. However, it should be noted that the estimated cost and time parameters for short distances may be inaccurate. Since short commuting distances mostly occur within one municipality, the dummy variable could capture this uncertainty or the impact of non-linearities.

The effect of most municipality-specific variables is clear: the probability of choosing a municipality as a residential location decreased with lower housing supply, higher housing costs and high land use diversity. However, housing supply is most likely a proxy for a municipality's attractiveness in terms of amenities, as housing supply in itself does not carry any information about housing availability. The negative sign of the dummy variable indicating high land use diversity is probably because high land use diversity is associated with a high proportion of industrial land use. The fact that the variable describing the share of recreational area is not robust across the three models suggests that it may be unsuitable for use at municipal level. However, this inconsistency only occurs in the low land use diversity category. It is therefore possible that people simply do not value these areas significantly differently to areas with medium diversity.

The main objective of this paper was to analyse how PT commuting costs affect residential location choices. Comparing M1 and M2, we found that the PT commuting costs variable is not suitable to replace the PT commuting time variable, as this reduces the explanatory power of the model. When both PT commuting time and PT commuting costs were included (M3), the model achieved the best values for log likelihood and AIC of all the models estimated. Comparing M1 and M3, the estimated parameters of the municipality-specific characteristics hardly differ. The dummy variable indicating whether a person lives and works in the same municipality remains almost unchanged. The effect of the PT commuting time is reduced by about 6%, whereas the effect of car commuting time is reduced by about 18%. This is reasonable, given that, in our data, PT commuting costs are much less correlated with PT commuting time than with car commuting time.

To test whether our results are robust despite the strong correlation between commute-related variables, we estimated our model (M3) several times in a selective way. First, we included the logarithm of the net distance between the centroids of the municipalities as a second-order distance effect (R1). The idea behind this is that an additional kilometre is more significant for short trips than for long ones. While this increased the model's explanatory power, it had little effect on the PT commuting costs variable (see Table 6 in the appendix). This does not

Table 5
Estimation results.

Variable	M1		M2		M3	
	Coef. (SE)	t-stat.	Coef. (SE)	t-stat.	Coef. (SE)	t-stat.
Commute-related characteristics						
Car commuting time (hours/trip)	−4.528 (0.008)	−541.578	−5.167 (0.008)	−659.738	−3.702 (0.010)	−369.578
PT commuting time (hours/trip)	−1.093 (0.004)	−281.067	-	-	−1.032 (0.004)	−260.615
PT commuting costs (€/month)	-	-	−0.008 (0.000)	−190.663	−0.006 (0.000)	−147.448
Dummy internal commuting relation	0.734 (0.003)	285.502	0.770 (0.003)	287.011	0.702 (0.003)	272.313
Municipality-specific characteristics						
Log(number of dwellings)	0.926 (0.001)	732.306	0.920 (0.001)	703.770	0.921 (0.001)	717.483
Housing cost index	−0.031 (0.000)	−380.782	−0.030 (0.000)	−347.298	−0.032 (0.000)	−380.060
Land use index (*ref.: medium (0.6-0.8)*)						
low (0.4-0.6)	0.015 (0.003)	4.875	−0.001 (0.003)	−0.329	−0.000 (0.003)	−0.106
high (≥0.8)	−0.130 (0.002)	−65.014	−0.081 (0.002)	−39.099	−0.121 (0.002)	−59.663
Recreational area (%)	0.007 (0.000)	32.337	−0.001 (0.000)	−5.614	0.008 (0.000)	35.692
Log likelihood	−5,187,477		−5,218,617		−5,176,705	
Akaike's information criterion	10,374,969		10,437,249		10,353,427	
Number of observations	1,723,575		1,723,575		1,723,575	
Number of alternatives	287		287		287	

Notes: PT = Public transport

entirely rule out the possibility that the commuting costs variable is merely a second-order distance effect. Nevertheless, it is encouraging that the effect remains robust even when accounting for a reasonable second-order distance effect. Second, we estimated our model using different subsamples (R2-R5) to determine whether changes to the sample significantly affect the estimated coefficients. As the coefficients of the commute-related variables remained consistent across the selected subsamples, it is reasonable to conclude that the significant correlation between these variables does not affect the main findings of our analysis (see Table 7 and Table 8 in the appendix for detailed estimation results).

The results show that commuting costs, in combination with commuting time, can be key for the choice of residential locations. For the car, distance, travel time, and operational costs are strongly correlated. Therefore, it is sufficient to use one of these variables, in our case the car commuting time. This is not the case for PT, as commuters usually use a monthly or annual transit pass. Such tickets decouple the price from the distance travelled and the time spent. In order to capture generalised commuting costs as comprehensively as possible, and thus improve the explanatory power of the model, it seems reasonable to include PT commuting costs in addition to PT commuting time. However, when doing so, a potentially strong correlation between the commute-related variables should be accounted for.

As we have estimated a parameter for both PT commuting time (β_{PTct} [hours/trip]) and PT commuting costs (β_{PTcc} [€/month]), we were able to calculate the value of travel time for PT (VTT_{PT} [€/hour]). Therefore, we had to work with assumptions as to how often commuters make the journey to the workplace as the one-way or daily commute time does not relate to the monthly PT pass price. Hence, the respective VTT is a function of the assumed number of working days per month (W): $VTT_{PT} = \beta_{PTct}/(\beta_{PTcc} \times W \times 2)$. Fig. 3 shows the resulting hyperbolic graph. The fewer days per month one works, the higher the VTT for commuting by PT. The relevant range goes from 8.6 €/hour for ten working days per month to 4.3 €/hour for 20 working days per month.

Using stated preference data collected in Germany, Ehreke et al. (2015) found a VTT of 4.47 €/hour for PT and work trips, very similar to our findings. The similarity of these VTT values, based on substantially different data bases, is mutually reassuring that the findings of both studies can not be too far off ground truth. As most people work less than 20 days a month, our average VTT is probably slightly higher than the one found by Ehreke et al. This is reasonable because stated preference studies tend to find lower values than revealed preference studies (van Ommeren and Fosgerau, 2009).

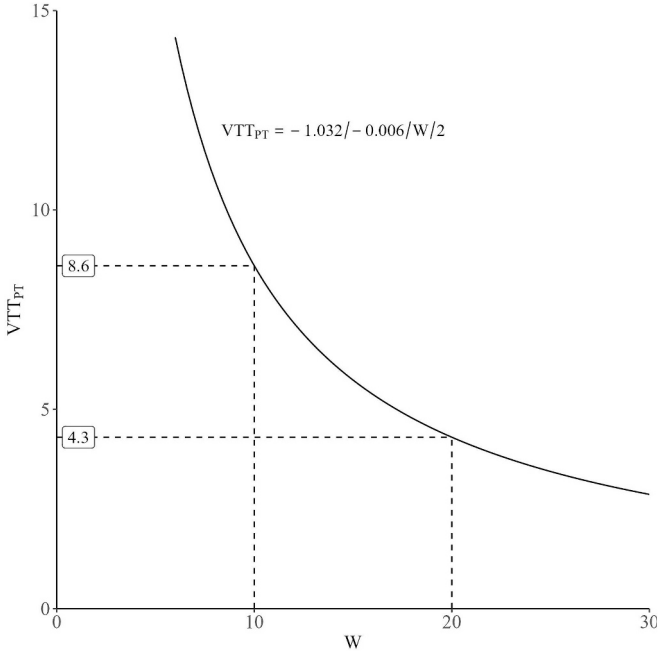


Fig. 3. Value of travel time for commuting by public transport (VTT_{PT}) as a function of number of working days per month (W).

PT commuting costs may influence the choice of where to live. In general, the PT accessibility of the location may be the main consideration. However, once PT accessibility is given, then costs may play a role. A significant reduction in PT commuting costs, e.g. as a result of the introduction of nationwide transit passes, as has happened in recent years in several European countries, could either encourage households to consider moving or at least influence the choice of where to live, if this is to be done anyway for other reasons. This is particularly the case for PT users, who are more sensitive to changes in commuting costs than car users (Guo et al., 2020). However, despite the relevance of PT commuting costs, it is unlikely that substantially lower PT costs would have the impact on residential choices as the decline in the total cost of ownership of cars relative to income since the middle of the last century. The main reason is that most people commute by car. Significantly lower PT commuting costs will not fundamentally change this, although they help to increase the share of PT in the modal split of commuting journeys (Santos et al., 2013). A very likely implication of lower PT costs are longer average commutes, but contrary to car users PT users are tied to fixed points such as transit stations when moving out of the centres. Hence, locations outside the centres with high quality PT supply and relatively low housing costs, some of which are already experiencing increased housing demand due to more people working from home, may become more attractive as residential locations.

5. Limitations and future research

Although our sample size is large, the data is selective in terms of employment, as it only includes employees subject to social insurance contributions. On average, there is no significant difference in income between employees in the sample and those who are not. However, the incomes of some groups of employees not included are significantly different. As marginally employed workers have substantially lower incomes, they probably live closer to work and use PT more frequently for their commute. In contrast, officials have higher incomes on average, probably meaning they live further away and use PT less frequently for their commute.

Due to the structure of our commuter matrix data set, there is no information on individual or household characteristics in the data. In particular, information on the actual mode of transport for commuting would provide useful insights. An alternative would be to use the car availability, as Guidon et al. (2019) did. These variables could be used as interaction term with the corresponding commuting time or commuting costs. However, this information was not available to us. The same applies to individual characteristics such as income or age. Their inclusion would improve the level of detail of the results and allow a differentiated analysis according to individual characteristics. In reality, residential location choice for multi-person households is the result of a compromise between all household members. In particular, for households with more than one employee, longer commutes may be accepted individually in order to reduce the sum of commuting time or costs. However, there is only a slight difference in commuting distance between households with one employee and households with several employees in Germany (one employee: 15 km, more than one employee: 16 km) (Nobis and Kuhnimhof, 2018).

The place of work was assumed to be exogenous. This means that the residential location is always chosen depending on the place of work. In reality, however, both are possible and often intertwined: households may choose their place of residence after their place of work, or vice versa. To reflect this in the model, the decision could be computed simultaneously. However, this would lead to high computational complexity when using multinomial logit models (Waddell et al., 2007).

Another possibility would be hierarchical modelling, e.g. with a nested logit model, as done by Waddell et al. (2007) or Lee and Waddell (2010). Alternatively, rather than focusing on accessibility to a specific location (e.g. the workplace), one could use a more general accessibility measure, such as a logsum approach (Zondag and Pieters, 2005).

The cost of commuting by PT was based on the price of a monthly pass, as this was the standard ticket used by PT commuters in 2018, when the data was collected. However, employers often subsidise the monthly pass, such that the actual cost to the individual employee may be lower. Moreover, each additional PT trip made by a monthly pass holder in addition to their commute comes with no marginal cost and thus represents an additional financial incentive for obtaining a PT pass.

Our choice set consisted of 287 municipalities. The municipality is often used as the unit of residential choice. However, a smaller unit would allow, for example, the integration of detailed information about the dwelling or the neighbourhood characteristics.

In future research, it would be useful to determine the effect of PT commuting costs on residential location choice on the basis of surveys that ask about individual and household characteristics. That way, the results of this study could be further verified. Finally, there are many applications for a residential location choice model that takes into account commuting costs, especially for PT, with developments such as nationwide transit passes or fare-free PT. Our study shows that PT commuting costs can influence residential location choice. The long-term effects of a permanent reduction in these costs, and how this can be reconciled with the goals of denser settlement development, would be topics for future research. In contrast to the private car, the combination of commuting costs and time must always be considered, as PT is not an alternative in many places due to poor accessibility, even if the costs are low. Therefore, future research could examine the effect of PT commuting costs in combination with PT supply, for example by using an interaction term in model estimation.

6. Conclusion

We estimated models of residential location choice with and without PT commuting costs as an explanatory variable. Including PT commuting costs increased the explanatory power of the model. As expected, the probability of choosing a residential location decreases as PT commuting costs increase. PT commuting costs therefore have an impact on residential location choice. However, their inclusion in the model had little effect on the importance of location characteristics such as housing costs or housing supply. Our findings show that in the case of PT, the commuting cost variable should not replace the commuting time variable. Instead, it should be included in the model in a complementary manner. By including both the time and the cost of commuting by PT as explanatory variables, we were able to establish the VTT for commuting by PT as a function of the number of working days per month. The resulting VTT varies from 8.6 €/hour for ten working days per month to 4.3 €/hour for 20 working days per month. This is in line with existing research, although other studies have used different methods or data. Our study provides empirical evidence that the integration of PT commuting costs into a residential location choice model can be useful, especially in the light of novel PT tickets that have been introduced in European countries in recent years. These nationwide transit passes, which result in comparatively low costs for commuters, can have long-term effects. They could either encourage households to consider moving or at least impact on residential choice decisions when these are to be made anyway due to other reasons.

CRediT authorship contribution statement

Johannes Nießen: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Tobias Kuhnimhof:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

None.

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Appendix A

Table 6
Estimation results for a model including net distance between centroids of the municipalities.

Variable	R1	
	Coef. (SE)	t-stat.
Commute-related characteristics		
Car commuting time (hours/trip)	−3.128 (0.011)	−274.442
PT commuting time (hours/trip)	−0.963 (0.004)	−242.373
Log(net distance)	−0.290 (0.003)	−105.133
PT commuting costs (€/month)	−0.005 (0.000)	−124.824
Dummy internal commuting relation	0.435 (0.003)	124.824
Municipality-specific characteristics		
Log(number of dwellings)	0.925 (0.001)	715.279
Housing cost index	−0.032 (0.000)	−386.689

(*continued on next page*)

Table 6 (*continued*)

Variable	R1	
	Coef. (SE)	t-stat.
Land use index (*ref.: medium (0.6-0.8)*)		
low (0.4-0.6)	−0.004 (0.003)	−1.156
high (≥0.8)	−0.145 (0.002)	−69.928
Recreational area (%)	0.008 (0.000)	37.207
Log likelihood		−5,171,203
Akaike's information criterion		10,342,426
Number of observations		1,723,575
Number of alternatives		287

Notes: PT = Public transport

Table 7
Estimation results based on subsamples (R2: without internal commuting relations, R3: car commuting distance ≤50 km).

Variable	R2		R3	
	Coef. (SE)	t-stat.	Coef. (SE)	t-stat.
Commute-related characteristics				
Car commuting time (hours/trip)	−3.997 (0.011)	−368.108	−3.880 (0.011)	−350.144
PT commuting time (hours/trip)	−0.873 (0.004)	−200.656	−0.940 (0.004)	−224.066
PT commuting costs (€/month)	−0.006 (0.000)	−141.364	−0.006 (0.000)	−143.214
Dummy internal commuting relation	-	-	0.682 (0.003)	245.173
Municipality-specific characteristics				
Log(number of dwellings)	1.022 (0.005)	731.319	0.902 (0.001)	677.380
Housing cost index	−0.034 (0.000)	−348.432	−0.029 (0.000)	−325.185
Land use index (*ref.: medium (0.6-0.8)*)				
low (0.4-0.6)	0.021 (0.003)	6.477	0.016 (0.003)	5.153
high (≥0.8)	−0.094 (0.002)	−39.171	−0.121 (0.002)	−57.732
Recreational area (%)	0.009 (0.000)	36.062	0.008 (0.000)	38.544
Log likelihood		−4,037,857		−4,572,197
Akaike's information criterion		8,075,730		9,144,411
Number of observations		1,068,702		1,653,391
Number of alternatives		286		15–106

Notes: PT = Public transport; R2 excludes internal commuting relations. R3 excludes commuting relations where the net distance between the centroids of the municipalities exceeds 50 kilometres.

Table 8
Estimation results based on subsamples (R4: northern part, R5: southern part).

Variable	R4		R5	
	Coef. (SE)	t-stat.	Coef. (SE)	t-stat.
Commute-related characteristics				
Car commuting time (hours/trip)	−5.047 (0.020)	−253.891	−3.464 (0.014)	−239.997
PT commuting time (hours/trip)	−0.839 (0.006)	−151.262	−1.284 (0.007)	−176.595
PT commuting costs (€/month)	−0.008 (0.000)	−94.753	−0.004 (0.000)	−79.735
Dummy internal commuting relation	0.731 (0.005)	153.089	0.638 (0.003)	194.655
Municipality-specific characteristics				
Log(number of dwellings)	0.691 (0.004)	187.783	0.952 (0.002)	625.084
Housing cost index	−0.036 (0.000)	−155.285	−0.028 (0.000)	−281.013

(*continued on next page*)

Table 8 (*continued*)

Variable	R4		R5	
	Coef. (SE)	t-stat.	Coef. (SE)	t-stat.
Land use index (*ref.: medium (0.6-0.8)*)				
low (0.4-0.6)	0.037 (0.007)	5.419	0.024 (0.004)	6.630
high (≥0.8)	−0.069 (0.006)	−11.652	−0.090 (0.002)	−38.716
Recreational area (%)	0.013 (0.000)	33.969	−0.001 (0.000)	−2.158
Log likelihood	−1,125,700		−3,364,849	
Akaike's information criterion	2,251,419		6,729,716	
Number of observations	428,066		1,202,075	
Number of alternatives	159		128	

Notes: PT = Public transport; R4 only includes municipalities in the northern, more rural part of the study area, while R5 only includes those in the southern, more urban part. The boundary is formed by the RegioStaR2 urban region.

Data availability

Data on commuting times sourced from a transport model are not publicly available. Data on the housing cost index is available to researchers upon request. The remaining data is publicly available.

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