

*Abstract*— *This research investigates the preference of residents in the province of Utrecht, the Netherlands, to move to the Merwedekanaalzone, which is a planned residential area with a mobility system supported by mobility hubs... Several advanced discrete choice models with systematic taste variation were adopted to analyze the residential self-selection of individuals along with their commute mode choice. A mixed Revealed and Stated preference online survey was designed to collect the proper data for the analysis purposes. The data consists of three hundred ninety-nine observations, where respondents were presented with the choice between residing in their current residential location or moving to a residential location with mobility hubs. Simultaneously, respondents were asked to choose their preferred commuting mode. The results show that while the respondent’s preferences differ based on their sociodemographic charact-eristics, housing costs and travel costs are important factors in their combined residential and modal choice.*

Keywords—Mobility hub, Residential self-selection, Commute mode choice, Single household worker, Latent class nested logit model, Nested logit model, Multinomial logit model

# Introduction

Within the European Union (EU) a quarter of the greenhouse gas emissions comes from the transportation sector. If left unchecked, the pollution stemming from transportation is expected to grow even further to 50% of all emissions in Europe over the next decades [1]. The EU has voiced the ambition to battle the negative effects of mobility by stimulating automated and connected multimodal transportation and work towards a sustainable and integrated transport system in both freight and passenger transportation [2].

Passenger transportation can be introduced to multimodal travel options by developing mobility hubs in residential neighborhoods in urban areas [3]. In the context of this paper mobility hubs are defined as multimodal transportation nodes which facilitate intermodal transfers by providing access to a bundle of mobility options through an integrated virtual platform [4]. The concept of mobility hubs is built on the principles of shared mobility and Mobility as a Service (MaaS), which is an alternative approach to mobility where vehicle ownership is replaced by access to shared vehicles [3]. Users of MaaS are given access to vehicles provided by intermediary parties which combine transaction, information and booking in a single service [5].

Multimodal mobility hubs are proposed as an alternative transportation option in a mobility regime dominated by private car use, but it is unknown whether the intended users are willing to follow along. Urry [6] states that automobility has become “*…impossible to break from*” because the car is *“…simultaneously immensely flexible and wholly coercive*” , flexible for the individual who seeks connectivity, and coercive for Western societies, which are forced to build further on a modernist legacy of car-oriented infrastructure [6]. However, since the start of the millennium, the growth of car use has started to stagnate in Europe [7]. Especially younger urban residents have started to shift away from the car as their preferred mode [8]. The lifestyle offered by neighborhoods with mobility hubs may thus be of interest for this demographic group.

Neighborhoods with mobility hubs may also be of particular interest for working singles. Single households have been shown to favor central-city living and they are more keen on job proximity than other household types [9]. Mobility hubs have the potential to improve the inner-urban accessibility, giving working singles accessibility to both their job location and the recreational activities in the inner city.

The aim of this research is to capture the attractiveness of mobility hubs by estimating the willingness of working singles to move to a residential area with mobility hubs. Through this estimation demographic segmentations and their preferences can be defined. The research is operationalized through the analysis of discrete choice data. This data is consists of three hundred ninety-nine observations of single worker households within the province of Utrecht, the Netherlands. For the collection of the data a dynamic online survey is designed which features a choice scenario. Here, the respondent is given a simultaneous residential choice and mode choice. This research has two additional objectives. The first objective is to test the hypothesis that young individuals are more interested in mobility hubs than older individuals. The second objective is to test the application of an innovative discrete choice model. A latent class nested logit model is applied to see whether it provides better results than more basic discrete choice models.

Mobility hubs have received quite some attention in the existing literature, although they are frequently referred to with different terms, such as multimodal hubs, intermodal hubs, mobility stations and more. Studies have focused on defining typologies [10], distinguishing user requirements [11], [12], capturing user preferences [4] and investigating planning practices [13]. Additionally, a more elaborate and comprehensive work is provided by Miramontes [3]. While these studies focus on providing a knowledge base for the characteristics and requirements of successful mobility hubs, little attention is devoted to the definition of the users themselves, the exception being Miramontes et al. [4]. A large body of literature has shown that individuals self-select their residential location to fit their travel preferences [14], [15]. Knowledge on the differences between the preferences of user groups is valuable, because it gives researchers a better understanding of the attractiveness of mobility hubs.

An ambition of the European Union is to promote multimodal mobility solutions such as mobility hubs. However, the integration of mobility hubs in residential areas requires urban planners to dedicate their commitment, considerable financial investments, and valuable urban space to a mobility concept that is still in its infancy. Those involved with such development projects encounter a multifaceted challenge with various uncertainties. This work aids in facing this challenge by providing knowledge about the target groups for mobility hubs. This knowledge allows urban planners to better predict the demand for housing in residential areas with mobility hubs and their commute transport mode choice.

The rest of this paper is structured as follows: Firstly, the relevant literature is reviewed, where mobility hubs are further defined and the concepts of residential choice and commute mode choice are further explored. Secondly, the methodology, including the development process of the online joint RP-SP survey and the model descriptions, is elaborated upon. Thirdly, the collected data is described with descriptive measures and a sensitivity analysis. Fourthly, the results of the best fitting are presented and discussed. Finally, the paper is concluded.

# BACKGROUND AND STUDY CONTEXT

## Background

The functionality of mobility hubs originates from the concept of transit-oriented development (TOD). TOD is an urban development approach where residential, commercial, and business spaces are located close to public transport facilities to improve walkability, promote sustainable mobility and reduce the amount of space allocated to car use [16]. TOD-inspired policies have been established in American, Asian and Oceanian planning contexts to counteract the effects of urban sprawl and to facilitate urban intensification [17]. It did not have the same revolutionary effect in Europe, where cities have a long history of integration of public transit in their transportation systems . Nonetheless, European scholars and planners have started to pay attention to TOD and the solutions that stem from the concept.

One of these solutions is the mobility hub. emphasized the multimodal facilitation aspect by defining mobility hubs as *“…multimodal transport nodes that facilitate intermodal transfers by providing different mobility options in close proximity”* [4]. However, they do not make a distinction between mobility hubs and similar mobility stations. Miramontes [3] noted that mobility hubs and mobility stations share the same core function of providing multimodal mobility, but that mobility hubs have a stronger focus on the integration of land use and transportation. Pfaffenbichler & Vorstandlechner [10] noted a further typology of four different types of hubs: 1) stations of national significance, 2) stations of regional significance, 3) stations of local significance, and 4) transfer points of urban public transit.. Hubs supporting neighborhoods with a primarily residential function would belong to either the third or the fourth category [10].

Several studies focus on identifying user requirements [11], [12]. With a principal component analysis, Monzón et al. [12] identified information, transfer conditions, safety & security, emergency situations, design & image, environmental quality, services and facilities, and comfort of waiting time to be essential factors in a user’s assessment of a hub’s quality. Based on a focus group study Bell [11] argued that, for users to accept mobility hubs, mobility hubs should, in the very least, provide enough information and be well-located, comfortable, and accessible. Beyond these basic requirements, user demands are heterogeneous and depend on the individual and the purpose of the trip [11].

Since travel preferences differ based on socio-economic characteristics [8], [18] and on lifestyle preferences [19], neighborhoods with mobility hubs are likely to attract some while deterring others. More specifically, mobility hubs are designed to facilitate a multimodal mobility lifestyle, which has been associated with the lifestyle preferences of ‘millennials’, individuals born in the tail end of the twentieth century [20]. Expectations are that the ‘millennial’ age group will take particular interest in neighborhoods with mobility hubs. However, residential choice does not only hinge on travel preferences. In fact, as mentioned before, accommodation of the preferred travel modes is relatively low on the priority list of house seekers.

Research on residential location choice has accumulated an excellent knowledge base on what factors influence the utility of anyone location [21]. The distance to the work location has been consistently found as an essential locational factor and usually has a negative influence on the residential location choice [22]–[24]. Capturing the influence of the distance to the workplace becomes more complex in multiple worker households. Researchers have dealt with this complexity by considering the angle between the workplaces with the residential location as center point [25] and by analyzing the commuting dynamics within the household [26]. Continuing on the theme of accessibility, the proximity of the central business district (CBD) is regularly found to have a significant effect on utility, although its direction can differ [27]. Evidence suggests a CBD-related directional bias in movers. The majority of moves was found to occur in a line from the CBD, meaning they either move towards or away from the city center, rather than a lateral move [28]. The housing costs are also an often recurring negative factor in residential location choice [24], [29]. Research has found that income and housing costs are positively correlated, which suggests that, while the cost of housing in itself negatively affects the utility, households with a higher income are biased towards more high-end housing options [30].

Within the body of knowledge on travel behavior, a notable proportion is dedicated to mode choice. Like with research on residential choice, studies on modal choice have garnered a collection of recurring factors [31]. Research often finds income, age and gender, education level to have a significant effect on mode choice [26], [32], [33]. In the case of gender, however, evidence shows that differences are becoming decreasingly pronounced [34].

It is commonly accepted that residential location choice and travel preferences are related and that this relationship is nonrandom [14], [15]. Households actively consider the availability and facilitation of transportation modes in the selection of their residential location and seek to match their choice with the travel preferences of the individual household members. This phenomenon is known as residential self-selection (RSS). Because of its nonrandom nature, RSS is a source of bias in the effects of the built environment on travel behavior, which is why transportation research often needs to consider the impact of RSS on these effects. Studies capture RSS effects through direct questioning, statistical control, propensity score models and simultaneous models, such as joint discrete choices and structural equation models [15]. They generally find that travel attitudes only have a weak effect on residential location choice. Other factors not related to travel play a stronger role in the residential choice [15], [35]–[37]. Although the effects of RSS are generally well-understood, self-selection is still subject to ongoing research because questions remain on the magnitude of the causal mechanisms, regional differences and self-selection effects among immigrants [38]. Van Wee [39] argues that consideration of self-selection should not be considered to the residential dimension only, but that also the work location and locations of other activities are important.

A number of studies address the effects of RSS by simultaneously estimating residential choice and mode choice. Guo, Feng, and Timmermans [40] apply an error component mixed logit model for the simultaneous estimation of the residential location, the work location, and the commuting mode and find significant interdependencies between the three different life domains. Ardeshiri & Vij [41] adopt a hierarchical latent class model to simultaneously capture the influence of household and modality lifestyles on household-level residential choice and individual level modal choice in California. They define separate latent classes for the household’s utility of a residential location and for the individual’s utility of a transportation mode and then relate these through correlation. They find strong evidence for a relation of suburban residential choice and a car-oriented lifestyle. They also note that for high level income migrant households and median level income white households are likely to be either car-oriented or to have a strong preference for the bicycle.

## Study context

The attractiveness of mobility hubs is researched with a case study. In the city of Utrecht, the Netherlands, city plans are in place to build a new neighborhood, namely the Merwedekanaalzone [42]. This neighborhood provides living spaces for between 6,000 and 10,000 residents on a surface area of 65 hectares, which means space is scarce. Hence, the development works with a parking norm of 0.3 parking spaces per household. To compensate for the lack of parking, the neighborhood is planned entirely around mobility hubs, which provide quick access to public transit, shared cars, shared bicycles, and a variety of mobility services. At the time of writing, 6,000 dwellings are planned for development between 2020 and 2025.

Past studies have made use of dynamic survey designs containing a choice experiment for the collection of discrete choice data [43]. This research follows a similar data collection methodology. Following the examples of Ardeshiri & Vij [41] and Guo et al. [40] the choice experiment poses the respondent with a combined choice of a residential location and a transportation mode to account for RSS-effects.

# METHODOLOGY

## Survey design

For data collection purposes, in this study inhabitants from the province of Utrecht, the Netherlands, are recruited for an online joint Revealed and Stated preference (RP-SP) survey. Participants are required to be actively employed, live in a single worker household and reside in the province of Utrecht, the Netherlands. Only fully completed responses are considered for analysis. To capture the influences of multiple work locations in a household requires elaborate techniques [25], [26], [44], which are beyond the scope of this research. The focus on single worker households eliminates this complexity while also maintaining validity.

Using LimeSurvey, a dynamic RP-SP survey is designed which captures commuting travel behavior, information about the existing and preferred residential location, work location, and socioeconomic variables. In the RP part of the survey, participants’ recent work trip information (of the respondent’s last work day), accompaniment type, current housing cost, etc. are asked.

For the SP part of the survey, as Louviere et al. [45] discussed in their study, participants in most studies are presented with one to six choice sets where three to seven attributes have to be considered so that the scenarios would be more realistic and less complex [45], [46]. Hence, in this part of our survey, respondents are presented with three joint residential and commute mode choice sets/scenarios in total. Additionally, for our design, seven key variables focusing on residential and commute mode were carefully chosen to be considered in the SP survey experimental design (TABLE 3.1). Each SP attribute varies across three levels for non-linear utility function analysis. The values of these attribute levels should not only be reasonable but also be related to participant’s experience and allow the alternatives to compete with each other [45], [46]. Hence, these values are defined relative to respondents’ current residential location, proposed mobility hub neighborhood location, and their work location pairs. This information was gathered for available commute modes separately and added to the survey as secondary data to generate accurate values for each origin-destination pairs. In the SP experimental design, to avoid the non-attendance problem in our study; which occurs when a variable is considered in a SP experiment but is not used by the participant in the preference choice process which results in its parameters’ signification’s reduction; the respondents are asked to rank each SP attribute level of importance from their perspective from a scale of 1 to 5 (1 as unimportant and 5 as very important)[43], [47]. At the end, the variables with rates more than and equal to 3 (Neutral (3), important (4) or very important (5)) are considered to be included in the SP experiment design question/scenario (see [43]). Then in the next step, in each scenario, respondents are asked to choose between their current residence and a residential location in a neighborhood with mobility hubs while accounting for their preferred commute transportation mode, where the respondent can choose between the car, public transport, cycling and walking (Fig. 3.1). For the option of the current residential situation, only the observed commute mode which the respondent specified in the RP part of the experiment is presented. In total, the respondent can either choose to stick with their current residential and commute mode situation or choose to move to the mobility hub neighborhood and pick one of the four available commute modes (See Fig. 3.2).

During the survey design, several challenges and complexities needed to be addressed. In the SP part of the survey, one of the challenges in the design was making sure the respondent understands what a mobility hub is. Hence, the respondent is introduced to mobility hubs through a combination of text, images, and a video clip of a 3D animation (Fig. 3.3a and Fig. 3.3b respectively). An additional challenge was to accommodate the availability of modes (not all modes are available for all origin-destination pairs) and the base value of attributes for a certain commute mode (which are context-dependent). Also, the success of the survey depends on how realistically the survey can be presented so that potential biases in the data are minimized.

## Model structure

Given the nature of the data, discrete choice (DC) models were considered to model the joint residential and commute mode choices. Mostly, DC models are based upon Random Utility Theory (RUT) [48], [49], which postulates that a given individual *q* selects the alternative *i* out of a choice-set *Aq*, which maximizes its expected utility; hence, individual *q* opts for alternative *i* if and only if its utility *Uiq* is larger than the utility of all remaining alternatives *j ϵ Aq*. As the analysist does not count with perfect information, *Uiq* is modeled as a latent variable consisting of a deterministic component - known as representative utility, accounting for all elements of the decision that are known to the modeler - and of an error term, accounting for all elements that are ignored by the analyst including stochastic processes. Consequentially, and assuming a linear additive representation, *Uiq* can be expressed as:

 *(1)*

where the first summand stands for the representative utility and co nsist of a (1 x *K*) row vector *iq* of parameters to be estimated (which may or may not be alternative and/or individual specific) multiplied with a (K x 1) column vector of attributes (including a constant) *Xiq*. The second summand correspond to the error coefficient for unobserved variation. Assuming independent and identically distributed error terms following an Extreme Value Type 1 distribution (EV1), with scale parameter **and equal mode, leads to the well-known Multinomial Logit (MNL) kernel [50], which is characterized by the following probabilities [51], [52]:

 *(2)*

where **is not identifiable and can be fixed at 1 without loss of generality. Note that no restriction applies to the vector *Xiq* as long as it is linearly independent across alternatives and across observations. Consequentially, it may be specified in such way that a certain element is given by the product of other elements. A particular case is given when a certain element stands for the product of a numerical variable with a dichotomous variable representing a given group of individuals. This specification allows capturing systematic taste variations across the population.

The main limitation of this framework is, however, the assumption of i.i.d error terms. Given the nature of our experiment, four out of five alternatives are associated with a change of the home location to a house located near a mobility hub, while two alternatives (the current alternative and one of the new location alternatives) are associated with the same transportation mode. Consequentially, it is possible that the alternatives associated with the same location or the same transportation mode may be correlated.

The Nested Logit (NL) model [53] allows to treat correlation by grouping the alternatives into non overlapping-nests *n* and by specifying the error terms as:

 *(3)*

where the error term *\*iq* is independently and identically distributed across alternatives belonging to the same nest *n*, and it follows an EV1 distribution with equal mode and same nest-specific scale parameter **. *n*, in turn, is common to all alternatives belonging to *n* and follows a distribution such that added up with the distribution of *\*iq*, it leads to an EV1 distribution with equal mode and scale parameter *[[1]](#footnote-1)* Consequentially, the choice probability of alternative *i* belonging to the nest *n* is given by [54]:

 *(4)*

where *N* stands for the set of non-overlapping-nests. Here, all ** and *n* parameters but one are identifiable. Consequentially, it is convenient to normalize ** at 1 without loss of generality and to estimate the parameters*n*, which are defined between 0 and 1 (as *n* is forcedly larger than ** given that the variance of *\*iq* is smaller than the variance of *iq* – see eq. 3). When all *n* approach 1, the NL collapses to the MNL; i.e. no correlation exists.

While the MNL allows capturing systematic taste variations across population groups that can be directly observed by the analysist (and therefore be classified making use of dichotomous variables as part of *Xiq*), systematic taste variation can also exist across groups that are not directly identifiable. The treatment of so-called latent groups or latent classes requires an additional modeling step. First, an additional latent variable a.k.a. classifying function is considered, which can be represented as:

 *(5)*

Note that in eq. (5), opposite to eq. (1), elements do not depend on the alternatives (as only individuals are being classified into distinct unobserved behavioral classes), but the internal logic is analogous. Hence, assuming EV1 error terms, the likelihood that an individual belong to class *c* (opposite to class *d*)is given by:

 *(6)*

Then, assuming that both classes are characterized by different sets of behavioral parameters *ic* and *id* the choice probability of alternative *i* is given by (assuming uncorrelated error terms):

 *(7)*

Note that eqs. (5-7) have been derived for two latent classes only, but its straightforward to extend the formulation for more behavioral classes, making use of e.g. an ordered Logit model. Note also, that the choice probabilities given by eq. (2) are equivalent to the choice probabilities within each latent class in eq. (7). Consequentially, it is also straightforward to replace the choice probabilities associated the MNL by the choice probabilities arising from the NL, so that:

*(7)*

which is called a latent class nested logit model (LCNL). Note that the nest structure may vary across latent classes and also that the model may collapse to the MNL for a given latent class, while still exhibiting a nested structure for the other.

Finally, the model is estimated by maximizing the log-likelihood across the entire sample making use of PandasBiogeme 3.2.3 [55].

# Data and empirical analysis

## Sample format and descriptive analysis

TABLE 4.1 presents the descriptive analysis of the data. In the sample, the average age is 44 years old (σ = 13 years), with 43% of the data above 50 years old. Moreover, 61% of the data are females. The group with an income between €20,000 and €40,000 accounts for over half the sample (53%) and the data is consistent with more educated people (58%) (postgraduate and above).

Respondents are observed to live an average of 12 kilometers away from the CBD of the city of Utrecht (σ = 9.9 km), while the choice results indicate that on average, the respondents preferred to leave closer to the center (9.9 km, σ = 9.3 km). The inverse is happening with the parking costs, observed averaging at €4.50 per month (σ = €17). The results from the choice preferences show that parking costs jump up to an average of €22.20 per month (σ = €40). The finding that the parking costs are higher in current observed data (RP) than in preference choice (SP) data falls within the line of expectation since a distinct feature of mobility hubs is the high costs for parking. An interesting finding is that in general, an increase in travel time is observed when the mobility hub alternatives are presented. The car is an exception, where a reduction of 3% from RP to SP can be observed. In the three other commute modes, the travel time strongly increases, indicating that overall the accessibility of the work location of the respondent is negatively affected by moving to the neighborhood with mobility hubs. These results are unexpected since the existing literature shows results where the travel distance and travel time to work negatively affect the value of a residential location [24]. Another interesting finding is a decrease in preference toward apartments (10%) and an increase in preference toward detached houses (9% ) between data. This finding shows that, if given the possibility, the respondents would move away from apartments. The monthly commuting costs are similar between RP and SP in the car as a commute mode choice. In public transportation as a mode choice, the monthly commuting costs decrease by 13%, indicating an improvement from RP to SP.

## Sensitivity analysis

The neighborhood with mobility hubs mostly attracts younger respondents. 34% of the younger respondents move to the neighborhood with mobility hubs (Fig. 4.1a). Half of this group chooses the bicycle as their mode. Among middle-aged respondents, 22% decides to move. Respondents with an age of over 50 years old have the biggest tendency to stick with their current situation, with 15% of this group switching to the mobility hub neighborhood. The data show that within the current situation and the car as a mode the most prominent group is older people (56%), within the public transport the largest group is middle-aged people (43%), and within the bicycle, as mode, younger people are the most prevalent (46%). This pattern is less pronounced among the respondents who choose the mobility hub neighborhood.

The middle income and high-income groups are the most likely to move to the proposed residential area, with respectively 27% and 24% of the groups opting to move (Fig. 4.1b). Among low-income respondents, 15% decide to move. The move can be costly with potentially high housing costs, travel costs and parking costs, which may have deterred the low-income group from moving. The bicycle option mitigates the parking costs and travel costs and is a popular choice among all three income groups.

27% of the respondents with higher education and 23% with no higher education move to the mobility hub residential location (Fig. 4.1c). An interesting finding is that public  
transit is observably more prevalent among respondents with higher education (22%) than among those with no higher education (10%). The inverse happens for the car as mode, where car users account for 54% within the no higher education group and 43% in the higher education group.

The revealed housing costs are frequently lower than the housing costs in the proposed neighborhood (Fig. 4.1d). The house prices in the mobility hub neighborhoods are derived from the current housing market. Due to the demand-driven housing market, house prices have risen in the last years. This seems to have deterred many respondents from moving

When looking at the effect of travel time on the choice to move it again becomes apparent that in general, the location of the residential location with mobility hubs provides worse accessibility to the work locations of the respondents (Fig. 4.1e). This is more pronounced in the groups with the car and bicycle as a mode choice. Within the current situation/car group, 32% has a commuting time of 15 minutes or shorter, while this percentage is 19% within the mobility hub/car group. Among the bicycle groups, a similar pattern appears, with 57% of the current/bicycle group having a travel time of 15 minutes or less opposed to 29% in the mobility hub/bicycle group.

The distances to the city center in the current situation show an interesting distribution. Within the group with the car as mode, 29% of the respondents live within 5 kilometers of the city center (Fig. 4.1f). This percentage is 34% for public transit, 43% for the bicycle and 57% for walking.

When respondents choose to move, they most frequently move to a detached house or terraced house. In 42% of the moves, the house type is a detached house and in 37.5%, the house type is a terraced house. The apartment is not favored among the respondents as a house type, which occurs in 20.5% of the moves (Fig. 4.1g).

In summary, the data shows that the respondent is reluctant to move to the neighborhood with mobility hubs. Only in 23% of the choice scenarios does the respondent opt to move to the proposed residential location. The total costs and commuting time look to be the most significant deterrents. Factors that in general stimulate a move are a terraced or detached house as house type and a shorter distance to the city center. Among respondents, older adults, and respondents with a low income, the frequency of moving are lower than in their counterparts. Differences between education level groups do not occur between neighborhoods, but rather between modes.

# Empirical results

The LCNL, NL, and MNL frameworks were employed on the described dataset to model the residential self-selection and commute mode choice of employed individuals living in a single-member household in the Dutch context. In the following sections, the variables used for modeling purposes are defined, the best-fitted model is selected based on the model fit measures, and finally, the results of the MNL model as the outperformed model are discussed.

## Variables

Based on the literature, four categories of variables are defined and collected in our survey for each respondent to be used in the model. *First*, data on the one round commute trip between home and work on the respondent’s last workday was collected in the RP part of the designed survey. This category of variables consists of departure and arrival time, travel costs, modal choice, fuel costs, accompaniment type, parking costs, distance to nearest parking, number of stops, access and egress mode, and duration information. *Second*, residential and work location information was gathered. This category consists of housing costs, age of the residential building, residential location, work location. *Third*, data related to the SP choice experiment are gathered. This includes the level of SP variables represented in each alternative in each SP scenario, and the chosen alternative is recorded. *Fourth*, data on the individual socioeconomic characteristics of the respondent are collected. This category includes income, age, gender, education level, employment status (part-time or full-time), car ownership, and driving license.

It should be noted that for modeling proposes, in addition to estimating a variable’s impact on residential self-selection and commute mode choice (dependent variable), the deviations of reasonable variables were evaluated and estimated through interaction variables, for example, income \* house cost. The model specification was arrived at through a systematic process of removing statistically insignificant variables and combining variables when their effects were not significantly different. All continuous variables were tested with dummy variables in different ranges in order to give a better fit model in comparison with the equivalent linear variables.

## Model parameters and elasticity

The following section presents the results of the best-fitted model among LCNL, NL, and MNL models. TABLE 5.1 presents the estimated parameters which correspond to the exogenous variables that have an impact on the baseline utility specification for employed adults in the one-member household type in the Dutch context. It presents the variable coefficients and t-statistics. Based on this table, joint residential self-selection, and commute model choice decisions for this type of adults are influenced by different individual demographics, residential and travel attributes explained below. Each column is dedicated to different variables and inertia that affect an individual's choice for each joint choice are estimated; every row defines residential and commute mode choice. Moreover, a ‘-’ entry signifies no significant effect of a variable on the particular choice utility. TABLE 5.2, and TABLE 5.3 represent the parameters elasticity and trade off.

Three sets of models were estimated with the variables identified above for employed adults in a one-member household samples: (1) LCNL model, (2) NL model, (3) and MNL model.

The comparison of the log-likelihood, BIC, AIC and AICc measures for the three frameworks indicates that the MNL model outperforms the other two models substantially. Due to space concerns, we restrict ourselves to discussing the MNL results.

1. *Inertia variables*

The inertia variables account for biases in the sample towards staying with their current location and their current mode. The inertia is significant for the current residential location (t = 5.28), which shows that respondents are indeed biased towards their current residence. Inertia also occurs in the car, public transport and walking as mode choices. These biases are expected since individuals experience additional reluctance when they have to break their travel habits [56]. The bicycle is the only part of the choice scenario where no inertia effect appears.

1. *Individual demographics*

The age of the respondents is introduced to the model with three dummy variables (less than 35 years old, 35-50 years old, more than 50 years old). The model shows that older adults (50 years and older) have a weaker preference for the other commute modes than the car/current option (β=-0.78, t=1.89). This finding supports studies that observe that older people prefer cars compared to younger people [7], [8].

The same pattern can be seen for higher educated individuals (β=-0.79, t=-2.18). Surprisingly, the model results show the opposite of what would be expected based on the descriptive statistics, where the less-educated respondents are shown to opt more often for the car. In other words, while the proportion of car users among individuals with no higher education is higher than among individuals with higher education, the car users with a higher education are more rigid in their residential self-selection, significantly more often opting to stay in their current situation compared to individuals with no high education and individuals that use another commute mode.

The income variable representing an annual income of over €40,000 also shows surprising results. In the existing residential location and the mobility hub choice, the options with the car are found to have a negative effect on the joint choice utility (respectively β=1.78, t=2.67 for all combinations except current/car and β=-1.92, t=-2.6 for mobility hub/car). This can be due to the fact that among individuals with a higher income car use is less preferred than the other modes when compared to other income groups. In the literature, the effects of income on mode choice are inconclusive. Studies show both positive and negative directions for the effects of high income on mode choice [32], [57], [58]. However, a better explanation of this result would be that car users with a high income opt to move to the

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | **TABLE 5.1: MNL REGRESSION RESULTS ON JOINT RESIDENTIAL SELF-SELECTION AND COMMUTE MODE CHOICE** | | | | | | | | | | | |
|  | | | **Inertia** | | **Socioeconomic** | | | **Attribute** | | | | | | **Inter-**  **action** |
| *Residential location* | *Mode* | *Age*  *>55 yrs* | *College and above* | *Income >*  *€40,000* | *Distance to CBD (km)* | *Housing costs*  *(€)* | *Terraced house* | *Detached house* | *Travel costs (€)* | *Travel time (Minutes)* | *Travel time (Minutes) Income >*  *€40,000* |
| **Current situation** | *Car* | | 1.26  (5.28) | 1.44  (2.65) | - | - | - | - | - | -- | - | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| *Public Transport* | | 1.26  (5.28) | 1.92  (3.21) | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | - | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| *Bicycle* | | 1.26  (5.28) | - | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | - | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| *Walking* | | 1.26  (5.28) | 2.75  (2.13) | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | - | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| **Mobility hub situation** | *Car* | *General* | - | 1.44  (2.65) | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | - | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| *Alt. specific* | - | - | - | - | -1.92  (-2.6) | - | - | - | - | - | - | - |
| *Public Transport* | | - | 1.92  (3.21) | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | - | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| *Bicycle* | | - | - | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | -0.14  (-1.82) | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |
| *Walking* | | - | 2.75  (2.13) | -0.78  (-1.89) | -0.79  (-2.18) | 1.78  (2.67) | - | -0.17  (-3.77) | 0.51  (2.38) | 0.91  (3.23) | -0.39  (-1.68) | -0.11  (-3.11) | -0.39  (-2.58) |

|  |  |  |  |
| --- | --- | --- | --- |
| **TABLE 5.2: ELASTICITIES** | | | |
| **Variable** | | | **Elasticity** |
| *Housing costs* | *Current* | | -77% |
| *Mobility hub* | | 0% |
| *Travel costs* | *Current* | *Car* | -13% |
| *Public transport* | -6% |
| *Mobility hub* | *Car* | -29% |
| *Public transport* | -42% |
| *Travel time* | *Current* | *Car* | -19% |
| *Public transport* | -41% |
| *Bicycle* | -38% |
| *Walking* | -51% |
| *Mobility hub* | *Car* | -20% |
| *Public transport* | -43% |
| *Bicycle* | -44% |
| *Walking* | -61% |
| *Travel time  Income  >€40,000* | *Current* | *Car* | -28% |
| *Public transport* | -24% |
| *Bicycle* | -11% |
| *Walking* | -4% |
| *Mobility hub* | *Car* | -27% |
| *Public transport* | -28% |
| *Bicycle* | -10% |
| *Walking* | -4% |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TABLE 5.3: TRADE-OFF EFFECTS** | | | | |
|  | **Housing costs**  ***(€)*** | **Travel costs**  ***(€)*** | **Travel time**  ***(Min-utes)*** | **Travel time (Minutes)   Income  >€40,000** |
| **Housing costs**  ***(€)*** | 1 | 2.24 | 0.06 | 0.23 |
| **Travel costs**  ***(€)*** | 0.45 | 1 | 0.03 | 0.10 |
| **Travel time**  ***(Minutes)*** | 16.11 | 36.02 | 1 | - |
| **Travel time (Minutes)   Income  >€40,000** | 4.42 | 9.87 | - | 1 |

mobility hub neighborhood more often than car users in other income groups and choose another mode than the car for commuting in the new situation.

1. *Residential location attributes*

The distance to the city center is found to negatively affect the utility of the bicycle as a commute mode choice in the mobility hub residential location (β=-0.14, t=-1.82). This suggests that bicycle users appreciate being closer to the city center. This result is similar to findings from past studies [59].

The housing costs are also found to negatively affect all options except the current/car option (β=-0.17, t=  
-3.77). This means that a decrease in the housing costs increases the probability of all other alternatives to be chosen significantly more than the probability of the current/car option. Looking at the elasticity of the housing costs (TABLE 5.2), it becomes clear that those who choose the neighborhood with mobility hubs are insensitive to price changes. However, when in the current residential situation, the housing costs increase by €100,- per month, the utility of this location reduces by 13.4% (i.e. change in the elasticity). This shows that the move of respondents is dependent on their current housing costs. Past studies generally found that housing costs have a negative influence on the utility of a residential location [22], [60].

In the discussion of the descriptive statistics, it is highlighted that respondents prefer terraced houses and detached houses over apartments. This result holds in the model. With the apartment dummy as the reference, the terraced house and detached house dummies have a positive effect on the utility (respectively β=0.51, t=2.38 and β=0.91, t=3.23). Since the car/current option is the reference for all other options, this result can be interpreted as having the exact opposite effect than all other alternatives. In the existing body of literature, no exclusive results are available on preferences towards housing type and differences exist between studies based on geographical location [21].

1. *Travel attributes*

Model results show that travel costs have a negative influence on all alternatives (β=-0.39, t=-0.108). The directionality is to be expected since a flat increase in the costs should logically lower the utility of an alternative. Within the current residential situation, car users are more sensitive to a price change of €100,- per month than users of public transit (elasticity of 13.4% and 6.1% respectively). Within the mobility hub neighborhood, the car users and public transit users are more sensitive to the same price change (elasticity of 28.8% and 42.3% respectively). Notably, the sensitivity of public transit users to changes in the travel cost is higher in this case, which indicates that the respondents are more sensitive to the price of public transit when they take up public transit use after moving than when they continue using public transit.

Travel time also has a negative influence on all alternatives (β=-0.11, t=-3.11). This finding is not surprising, since a lower accessibility of the work location is generally found to negatively influence the value of a residential location [21], [24]. When the travel time is increased with 10 minutes, the utility of the car decreases the least while the utility of walking increases the most in both the current situation (Elasticity of 19% and 51% respectively) and the mobility hub situation (Elasticity of 20% and 61% respectively). The remaining residential area/mode combinations have a travel time elasticity ranging from 38% to 44%. The interaction between a high income and travel time also returns significant (β=-0.39, t=-2.58), which shows that for those with a high income travel time has an even stronger negative effect.

1. *Trade-off effects*

The effects of the continuous variables are further analyzed by looking at the trade-offs between them (TABLE 5.2). Practically speaking, this means observing the change in the value of one variable when 1 unit is added to the value of another while keeping the utility constant. Interestingly, a change of €1,- in the housing costs requires a change of €2.24 in the travel costs to reach the same utility value. This means that the respondents are more sensitive to changes in housing costs than in travel costs. Since the trade-off is not 1, which should be expected since both costs add up to the total of monthly costs, the respondents show to have an irrational bias towards housing costs. Looking at the other trade-offs, when the housing costs increase with €1,- the travel time needs to decrease with 3.6 seconds (0.06 minutes) to keep the utility constant. Then, a change of €100,- is generally worth 6 minutes to the respondents. For high income respondents a €1,- change in housing costs requires an additional travel time change of 13.8 seconds (0.23 minutes). Similarly, a €1,- change in travel costs requires a larger trade-off among individuals with a higher income than among individuals with a lower or middle income: The general trade-off is 1.8 seconds (0.3 minutes) against €1,-, while the trade-off among high-income respondents is an additional 6 seconds (0.1 minutes). These observations are unexpected, since it would seem logical that individuals with a higher income would be more willing to trade a flat amount of their income for better work accessibility than individuals with a lower or middle income. These findings are left unexplained.

# conclusion, limitations and reflection

This research has identified several factors that should be taken into consideration during the identification of target groups of mobility hubs in the Dutch context. First, the model results indicate that older adults reduce the probability of moving to the mobility hub residential area. This result supports the expectation that primarily the millennial group would be interested in the mobility hub lifestyle. Second, high-income respondents show to be particularly sensitive to travel time in their combined mode and residential choice. Moreover, high-income respondents show a preference for public transit, cycling or walking over the car. An explanation lies in the fact that this study only targeted single worker households. The high-income singles in this study prefer not to maintain costly car ownership just for themselves. The results on the travel time and mode choice signal a possible preference of high-income respondents for using their income to improve their situation in other ways than mode choice, such as improving their accessibility by moving to higher priority residential locations. Third, the respondents do not seem to prioritize the parking conditions when considering a move. During the estimation of the model, these dropped for all alternatives, meaning this study could not find a significant effect of parking conditions on the combined residential and mode choice. Fourth, housing costs and travel costs are found to be important factors in the choice to move or not. Especially the housing costs are found to be a strong factor.

Based on the results in this study, it can be recommended that urban planners looking to attract households with working singles make a distinction between high-income households and other households in the Dutch context. High-income singles are shown to prefer anything but the car and to be more sensitive to high travel times than the other income groups and could, therefore, be ideal candidates for living in a residential area with mobility hubs. This research has not found any indication that differences within parking facilities have a significant impact on the willingness of respondents to move to a mobility hub. Rather, self-selection occurs where car users are relatively less often willing to switch to the mobility hub in the Dutch context. It could, therefore, be recommended that policymakers do not try to get car users to get rid of their car to move to mobility hubs but rather to target individuals who are currently not showing a preference for the car. These individuals are more likely to appreciate the lifestyle that mobility hubs offer.

The current study is not without limitations. Firstly, only single households are investigated, which means that the results are not relatable to any other household type. Neighborhoods with mobility hubs are not restricted to single households. Secondly, the sample size of the survey is small, limiting the number of explanatory variables the model could hold. As a result, only the most substantial factors are identified in this study while relevant lower-tier factors might remain unnoticed.

Future studies are encouraged to pick up where this study left off. We believe that research on the demand for mobility hubs is an avenue well-worth pursuing. This paper has shown that combining residential self-selection and modal choice is a valid approach in this pursuit. Future research could expand on this by investigating the demand among multiple worker households, by studying non-work related travel and housing demand in mobility hub neighborhoods, or by further integrating the complexity of multimodal travel in the research design.

# contributions

This paper was produced by the author, Eric Top. Support, feedback, and guidance was given by dr. Anae Sobhani, who supervised the entirety of the research process and contributed to the survey design and data analysis. Dr. Francisco Bahamonde Birke also made contributions to the data analysis. Dr. Ahmad Sobhani and Dr. Sina Shokoohyar assisted in the research design. Dr. Nico Dogterom contributed to the data collection process.

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1. Note that the EV1 distribution is not closed under addition. Consequentially, the shape of the distribution followed by *nq* changes depending on the values ** and **. This distribution guarantees that *iq* be identically (but not independently) distributed across all alternatives in the choice-set, following an EV1 distribution with equal mode and with scale parameter **. [↑](#footnote-ref-1)