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Mobility constraints and accessibility to work: Application to Stockholm

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A B S T R A C T
This paper investigates workplace accessibility in Stockholm through a workplace choice model within a space–time prism concept. We develop a workplace accessibility measure that incorporates individuals’ constraints in time, space, and resources. The accessibility measure is derived from an activity-based demand model formulated as a Markov decision process in a dynamic discrete choice framework, where space–time constraints affect the possibilities of individuals to engage in activities during spare time. Indeed, the results show that spare time accessibility is significantly linked to workplace accessibility. Applications of the results show how space–time constraints, such as access to a car or having children, affect benefits in terms of consumer surplus for relocating a large workplace (a hospital in our case), car dependency, and segregation.

1. Introduction

In general, people tend to avoid long travel times since it will decrease the time available for work and spare time activities. Having the possibility to participate in a wide range of activities or being able to reach different workplaces are central constituents of what is typically regarded as accessibility (El-Geneidy and Levinson, 2006, Miller, 1999, Levinson, 1998). In Sweden, as elsewhere, improving accessibility is one of the main transport policy objectives, see Proposition (2008), and particularly workplace accessibility, which is a determinant factor affecting unemployment, segregation, and inequality (Martens, 2012, Bastiaanssen et al., 2021). Workplace accessibility mainly influences low income and younger individuals with limited transportation options (Lau and Chiu, 2003). In order to have access to more employment opportunities, research has shown (forced) car ownership among low income households, which results in material deprivation and economic distress (Vermesch et al., 2021), and a more polluted local environment (Lucas, 2006). Workplace accessibility has traditionally been explained by factors such as travel time to work, and the number of workplaces that can be reached (Wilson, 1971). It is well known that spatial and temporal constraints of individuals affect location choices (Miller, 1999), and occupational size-variables influence workplace location choice (Inoa et al., 2015), thus both aspects should enter into measures of workplace accessibility.

The purpose of this paper is, first, to develop a model of workplace choice in the microeconomics consistent with the dynamic discrete choice framework of Karlström (2005), and Västberg et al. (2020) and, second, to apply it to investigate the effects on accessibility from non-marginal land use policy changes. We will use a concept of spare time accessibility, which can be analyzed

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across geographical space and socioeconomic groups, taking into account behavioral adaptations including scheduling, temporal, and physical constraints. We estimate a workplace location model based on the dynamic discrete choice framework that accounts for the full-day schedule-activity path possibilities, respecting the spatial and temporal constraints of individuals, and then demonstrate how the estimated model can be used to address a wide range of issues such as equity, segregation, car dependency, and social benefits of workplace relocation. In particular, we demonstrate how the proposed measure is amendable to calculating consumer surplus (making it useful to calculate social benefits) and useful to address equity. Gender differences give a rationale for equity analysis considering space–time constraints, particularly when the constraint involves childcare or out-of-home activities (see Kwan, 2000).

Inherent in the dynamic discrete choice framework is the derivation of state-dependent expected utility, which we here will interpret as an accessibility measure. In our framework, the expected utility is given by a recursive log-sum formula. In a more static framework, log-sum has a long tradition as an accessibility measure that predates the utility based framework, see e.g. Neuberger (1971). As an accessibility measure, the log-sum includes the relevant components of transport, land use, temporal, and individual constraints (Geurs and Van Wee, 2004). There have been several efforts to extend this concept of accessibility to a more dynamic framework. Dong et al. (2006) also use the expected maximum utility from an activity-based travel demand model as an accessibility measure, noting that it thus departs substantially from the more traditional, static, trip-based accessibility measures. This is echoed by Jonsson et al. (2014), who first developed the corresponding accessibility measure in the framework of a dynamic discrete choice. The proposed framework allows for a priori non-restricted activity and scheduling patterns, taking into account scheduling decisions by individuals while respecting the spatial-geographical constraints.

In this paper we will develop this measure further, using the concept of spare time accessibility and develop a workplace choice model integrated with an activity-based model Scaper of Västberg et al. (2020). Thus making workplace location endogenous is an important step to evaluate long-term changes of the integrated land use and transport system. Our workplace choice model is sensitive to policy changes, as it includes individuals' taste heterogeneity and is able to differentiate between sub-groups of the population, and is amendable for equity considerations across, e.g., geographical space and socioeconomic groups, (De Palma et al., 2007, Shiftan and Ben-Akiva, 2011). The methodology is also consistent with microeconomic theory and can be used on the benefit side of cost–benefit analysis (consumer surplus and willingness to pay) to address non-marginal changes of workplace locations in counterfactual policy evaluations.

We analyze the role of space–time constraints in a dynamic discrete choice based measure of workplace accessibility. We illustrate the influences of constraints through three different cases, one related to the relocation of a large hospital, the other related to spatial segregation of labor demand, and finally how individual-level space–time constraints, governed by e.g. car accessibility or mandatory activities such as bringing children home from daycare, influences workplace accessibility. This case is relevant from an equity point of view, particularly gender equity, since the majority of individuals with the extra space–time constraint are women.

In the following section, a brief literature review is provided. Later, the methodology of the workplace choice model and the accessibility measure that is used in this paper are covered. Then the data and the estimation results are provided, followed by some applications demonstrating how the accessibility changes as spatial and temporal constraints change.

2. Literature review

Accessibility can be seen as a measure of an individual’s freedom to participate in activities in the environment (Weibull, 1980). The concept of accessibility, constrained in a space–time prism was first introduced by Hägerstrand (1970). Mode of transport, time limits for working, and being at home are examples of such constraints. Explaining how individuals can reach locations within their time budget is possible through the space–time prism concept. Also, Weibull (1976) developed an axiomatic approach for estimating an attraction accessibility measure in general, which was relative to distance and attraction characteristics. Examples of attraction factors are the number of jobs, annual retail sales and population as Hansen (1959) mentions. Weibull (1976) used a general function, consistent with his axiomatic approach to include attraction's characteristics. Later, Miller (1991) used Geographic Information System (GIS) for deriving and manipulating space–time prism concepts and presented a generic GIS-based procedure for calculating accessibilities. Also, to capture the varying attractiveness of different opportunities, Miller (1999) calculated three attraction accessibility measures consistent with Weibull (1976) axiomatic framework. One attraction accessibility measure was consistent with the theory of random utility, and two others were measures of locational benefits.

According to Miller and Wu (2000), the three available approaches to measure accessibility are the space–time prism, attraction accessibility measures, and finally accessibility as a measure of the benefits from a choice set for an individual. The benefit measure calculation has two strategies, which are user benefit according to Williams (1976) and Ben-Akiva et al. (1985), and locational benefit measure developed by Wilson (1974). Miller and Wu (2000) later tried to operationalize the three attraction accessibility measures in GIS from the study performed by Miller (1999). The attraction accessibility measures weighted the attractiveness of opportunities against the travel cost required, and were interpreted as the potential interaction. Wu and Miller (2001) tried to overcome the static treatment of travel time of space–time prism by the development of dynamic space–time accessibility measure in networks with time-varying congestion. Miller (2007) argued that instead of location-based studies, individual-based perspective should be used to measure accessibility that examines an individual’s activities, their distribution of space and time, availability of resources to overcome spatial activities among activities and constrained activities. Ettema and Timmermans (2007) worked on an accessibility measure which accounts for: the ability of individuals to adjust their activities, uncertain perceived travel time, and the influence of travel information on accessibility. The accessibility measure in their study is the expected maximum utility of the
opportunities within the time geography concept by Miller (1999), where they investigated an activity chain with three destinations and activities.

On the other hand, Landau et al. (1982) used choice set models, for shopping destination choice, by using the space–time concept and argued that much of economic analysis should include scheduling behavior. According to Bowman and Ben-Akiva (2001), the most important elements of activity-based travel theory can be summarized in two basic ideas. First, the demand for travel is derived from the demand for activities (Bowman and Ben-Akiva, 2001) and second, humans face temporal-spatial constraints (Hägerstrand, 1970). Ben-Akiva and Bowman (1998) argued that trip-based travel demand models may fail to capture the interdependence of an individual’s trip decisions across trips in a tour, and across tours in the daily schedule. They suggested a hierarchy which conditions residential location on the daily pattern, and conditions the details of the activity schedule (i.e. tour destinations, modes and times of day) on the residential location. Dong et al. (2006) found that “activity-based accessibility” based on random utility theory, can capture the influence of both socio-demographic characteristics and multiple types of activity purposes on perceived accessibility. In a similar effort as ours to develop an accessibility measure in a dynamic context, Dong et al. (2006) also used the expected maximum utility from an activity-based travel demand model as an accessibility measure (Dong et al., 2006).

In this paper, we will build on Karlström (2005) and Västberg et al. (2020) to develop an accessibility measure derived from a dynamic discrete choice framework consistent with random utility (Rust, 1987; McFadden, 1978). In this framework, the sequential decision making of an individual in an uncertain environment is modeled as a finite horizon Markov Decision Process (MDP) for one-day activity (and scheduling pattern).

Later, Jonsson et al. (2014) applied the Bellman principle on the MDP from Karlström (2005) for an infinite horizon problem, to take into account all possible future activities of an individual. They interpreted the value function of the MDP, derived in a dynamic discrete choice setting, as an accessibility measure. A similar activity-based model was estimated by Västberg et al. (2020) for choices of daily activity-travel patterns which incorporates the space–time constraints in fixed activities and dependence on the previous activities.

Jonsson et al. (2014) explained that accessibility to more than one activity, in the form of log-sum is linked to microeconomic theory and trip-based demand models, and it can be used in applied cost–benefit analysis, consistent with behavioral models of travel demand. Their accessibility measure can be seen as a theoretical bridge between time geography and microeconomics.

Their approach allowed them to extend the log-sum accessibility measures of static discrete choice theory, into measures that are consistent with dynamic discrete choice theory. Their model framework allowed to study how the marginal value of time varies over the day.

In this paper we will develop the model further to allow for workplace choice to be endogenous, using the interpretation of Jonsson et al. (2014), whereby the value function of the MDP of Västberg et al. (2020) can be considered as an accessibility measure. This measure will be used as a latent variable in a workplace location choice model, generating a measure of workplace accessibility.

Before proceeding, it may be useful to point out some differences between our approach and the one in Dong et al. (2006), and similar activity-based modeling approaches. The primary difference is that our model is a dynamic discrete choice model, in which the individuals are modeled as taking decision sequentially in an uncertain environment, taking into account the history and the future. All feasible destinations and scheduling patterns are technically available without prior restrictions. In our model, the individual is only constrained in terms of transport, land use, and spatial-temporal constraints, including for instance mandatory activities defined in time or geographical space, or resource constraints, for instance, car availability. We do not use the concepts of primary/secondary tours or available activity patterns.

2.1. Application of the accessibility measure

While measures of accessibility are important tools for, e.g., selecting appropriate sites for new development, traffic management, and parking standards (Halden et al., 2000), it is also a potential indicator of how urban life is affected in terms of segregation, car dependency, and location costs. Besides, accessibility mapping is an effective tool to support smart growth planning as accessibility based planning may help reduce vehicle miles traveled and mitigate congestion (Li et al., 2011). Maps indicate the spatial inequalities in terms of accessibility to urban centers and transport nodes, and the impact of congestion on these inequalities (Vandenbulcke et al., 2009). In this paper, as an illustration of the versatile nature of our accessibility measure, we will provide three different illustrations related to (i) segregation, (ii) benefit (consumer surplus) of relocating a large workplace, which is a hospital in our case, and (iii) car dependency. We will here provide a brief overview of related literature, considering these three aspects in turn.

2.1.1. Car dependency

Automobile dependency is defined as high levels of per capita automobile travel, automobile oriented land use patterns and restricted transport alternatives (Litman and Laube, 2002). Lucas and Jones (2009) claimed that the term ‘car dependence’ is used in a wide spectrum of literature to explain car use behavior, and in their report, they discussed the difference between car-dependence and car-reliance. They also mentioned that car usage and car dependence are mistaken, which does not show choice for individuals. Car dependency implies that the preference for car-based travel is both due to habit and the personal intention.

Having no car on the other side is a transport disadvantage that could interact with social disadvantage directly or indirectly and lead to inaccessibility to essential goods and services, and even further to social exclusion (Lucas, 2012). The key connection between car dependency and social exclusion occurs through access. While car-owners may not have a problem for reaching to suburb or city center, with limited public transport for shopping, entertaining, and employment, this may be a problem for everyone
else (Wickham and Lohan, 1999). Social exclusion is defined as a lack or denial of access to the social relations, customs and activities in which the great majority of people in society engage (Bradshaw, 2000). Physical access to a wide range of opportunities, including employment, is among the contributing factors to social exclusion that Hine and Preston (2018) counts. There are clear relationships between low mobility, relative inaccessibility and social disadvantage (Pickup and Giuliano, 2005). However, the problems of car dependency can be clearly understood through its impact at the social level and through the process of social exclusion (Hassan, 2016). Preston and Rajé (2007) claimed that social exclusion is a lack of access to social opportunities and not due to a lack of those opportunities.

Steg (2005) studied different motives for car use. The motives are categorized as either instrumental (for instance speed, flexibility and convenience) or symbolic and affective motives (for instance sensation, power and superiority) and found that the extent of the different motives are related to the level of car use and commuter car was most strongly related to symbolic and affective motives, and not to instrumental motives.

Child-related travels are also more constrained in time and space compared to other household activities. Oakil et al. (2016b) showed that child-related activities are associated with commuting in rush hours. As Oakil et al. (2016a) discuss, this relative inflexibility may lead to higher car dependency and thus could explain the higher level of car ownership among families with children compared to singles and childless couples. They found that urbanization level has the strongest effect on car ownership among young couples, for whom the likelihood to own a car increases most strongly with decreasing urbanization level. Their results also suggest that families with children are much more car-dependent than singles and couples, because they have more complex daily travel needs.

2.1.2. Segregation

In Sweden, social segregation and unequal accessibility to services and the labor market are considered as major social problems (Legeby, 2010). For social segregation in society, interplay segregation that is focusing on urban life and the interplay among people in public space is argued to be as important as housing segregation. In qualitative studies of segregated suburbs in Sweden (Lilja, 2002), it is found that especially people who feel excluded from society at large, appreciate the opportunity to have an urban life to interact in. Accessibility to different workplaces shows where people are likely to spend time in a working day, and therefore it is a potential indicator of how urban life is affected (Legeby, 2010). Segregation levels have increased over recent decades in the main metropolitan areas in Sweden. In a study performed in 2018, Östh et al. (2018) showed that mobility reduces observed pattern of economic segregation at the residential level.

Korsu and Wenglenski (2010) performed an empirical study to investigate if more long-term unemployment is caused by living in high-poverty neighborhoods and/or neighborhoods with low job accessibility. According to them, in European cities the movement of jobs and population towards outlying suburbs, the deficiency of public transport for many suburban origin–destination pairs and high-poverty neighborhoods are all observable. They found out that job accessibility is one of the factors that affect long-term unemployment for low-skilled workers. One other finding is that poor job accessibility for low-skilled workers is mainly caused by lack of access to a car. Grengs (2001) conducted a study to investigate if the public transit counteract segregation of car-less households. The results suggested that transit service is compensating to some extent for the concentration of zero-vehicle households but not enough to achieve the equitable condition of randomness in accessibility.

As Kwan (2013) discussed, research on segregation has been conducted largely with a focus on people’s residential location. Yet, they also experience segregation in other spaces including their workplace and sites for social and recreational activities. Considering daily mobility of people helps to assess the segregation experience more accurately.

3. Methodology

To assess the implications of individual-level space–time constraints on accessibility to workplaces, we estimate a workplace location choice model which respects such constraints. Fig. 1 provides a methodological map illustrating the general idea of the implementation of our workplace accessibility measure.

From an individual’s perspective, there are many exogenous factors which could influence how constrained they are. Having access to a car may increase the possible action-radius, while having children at daycare may restrict it in the sense that one has to appear at the daycare before it closes. Similarly, flexibility and duration of working hours will have an effect on space–time constraints. Västberg et al. (2020) presented SCAPER, an activity-based demand model (ABM), which is designed to predict how space–time constraints influence daily activity-travel planning in a utility-maximization framework (see Section 3.1).

In this paper we argue that the expected maximum utility of a daily activity-travel pattern conditional on an individual’s space–time constraints is a good measure of spare time accessibility, to be defined in Section 3.1 below. Spare time accessibility provides a measure of an individual’s accessibility to different activities conditional on where they live and work, their available modes of transport, and any space–time constraints caused by mandatory activities. It will further account for travel costs between different locations, including commuting. Also, we argue that spare time accessibility affects workplace choice. When considering where to work an individual is likely to consider the possible restrictions this workplace choice will put on his/her spare time activities. We use the spare time accessibility ($A_{ij}^h$), given by ABM (Västberg et al., 2020), as a latent variable explaining workplace choice. In addition to the spare time accessibility, traditional size variables enter into the workplace choice through the number of available workplaces per sector and zone. In the end, workplace accessibility is calculated as the expected utility of the workplace choice, which in this case is given by the well-known log-sum formula (McFadden, 1978).
3.1. Spare time accessibility

In this section, we introduce the spare time accessibility measure based on the dynamic activity-based travel demand model Scaper of Västberg et al. (2020), and illustrate how it is calculated and how it is influenced by individuals’ space–time constraints. The spare time accessibility for each individual is calculated conditional on where they live and where they go to work. An individual living in zone $i$ and going to zone $j$ for work will have some spare time which can be used for transportation or attending different activities, the value of which can be captured through a spare time accessibility measure $A_{ij}$. In our case, the spare time accessibility measure is given by the expected maximum utility of an individual’s spare time activity-travel patterns conditional on work zone and home zone. This measure considers temporal and spatial constraints, socioeconomic characteristics of the individual, activity participation as well as travel mode and travel time. Typical space–time constraints are: mandatory fixed working hours, the required time for returning home, tending to children that may affect an individual’s mobility, since eventually schools or daycare centers close, and having access to car which provides clear space–time restrictions for an individual. All these types of restrictions are modeled in the spare time accessibility measure presented in this section.

To define our space time accessibility measure, we first give a short outline of the underlying activity and scheduling model as defined by Västberg et al. (2020). In the estimated model, individuals are assumed to maximize the utility stemming from their daily activities, conditional on being at home in the morning and evening, and working during the day. During the day, the individual may travel and engage in different activities and at the end of the day the individual may have engaged in a sequence of trips and activities, constituting a daily activity-travel pattern. In Fig. 2 possible paths are illustrated, and this particular individual is constrained in space and time by home, work and child locations at specific points in time. In addition to those constraints, the individual is also space–time constrained through mobility restrictions, he is not able to choose activities that he cannot reach within his available time budget.

In Scaper, the activity and scheduling decisions are made in the framework of a Markov decision process. Following a path throughout the day, the individual will at stage $k$ achieve an immediate utility $u(x_k, a) + c_k(a)$, which depends on action $a$ taken
and an action-specific random utility component (error) \( \varepsilon_k(a) \), and where \( x_k \) is a vector of state variables. The state variables \( x_k \) include time-of-day, location, purpose of previous action, time spent on current activity, previous mode of transportation, and activity history. The previous mode of transportation makes it possible to encode for instance car (or bike) availability depending on previous actions.

Thus, at each stage \( k \) the individual can choose from a number of actions, which includes activity, mode, and destination. The actions available at stage \( k \) is given by a state-dependent choice set \( C(x_k) = \{ a_{k1}, \ldots, a_{kJ} \} \) with \( J_k \) alternatives. The random utility component vector \( \varepsilon_k = [\varepsilon(a_{k1}), \ldots, \varepsilon(a_{kJ})] \) is assumed to be known by the individual at stage \( k \), but for future decision stages \( k \in \{ k+1, k+2, \ldots, K-1 \} \) only the distribution is known.

We are assuming that individuals are maximizing the utility stream throughout the day, and also that utilities across time steps are temporally additive separable, and no temporal discounting. Following a random utility maximization framework and using the Bellman’s equation, the individual therefore chooses the action that maximizes the sum of the immediate utility in the present stage \( k \) and the expected utility for all future stages (Rust, 1987; Västberg et al., 2020), and we denote

\[
U^{\text{max}}(x_k, \varepsilon_k) \overset{\text{def}}{=} \max_{a \in C(x_k)} \{ u(x_k, a) + \varepsilon_k(a) + E_{k+1}[U^{\text{max}}(x_{k+1}, \varepsilon_{k+1})] \}
\] (1)

where \( k = 0, \ldots, K-1 \) denotes the order of states that are traversed in a day, and \( E_{k+1} \) denotes the expectation over the \( J_{k+1} \)-dimensional vector \( \varepsilon_{k+1} \). The state transitions are defined by a state-transition rule \( Q(x_{k+1} | x_k, \hat{a}_k) \), and assumed to be deterministic, such that in a given state \( x_k \) and taking any action \( \hat{a}_k \in C(x_k) \), the next state \( x_{k+1} \) will be given uniquely and deterministically, see Västberg et al. (2020). The second term on the right hand side of (1) is also known as the continuation value, which in the final stage at \( K \) is deterministically given by \( U^{\text{max}}(x_K, \cdot) = \psi(x_K) \), where \( \psi(x_K) \) is exogenous. For further details, see Västberg et al. (2020).

In short, at stage \( k \), the individual observes the state \( x_k \) and the random utility component vector \( \varepsilon_k \) and chooses an action \( \hat{a}_k \in C(x_k) \) that maximizes the immediate utility in the current stage plus the expected utility for all future time periods, i.e.

\[
\hat{a}_k \overset{\text{def}}{=} \arg\max_{a \in C(x_k)} \{ u(x_k, a) + \varepsilon_k(a) + E_{k+1}[U^{\text{max}}(x_{k+1}, \varepsilon_{k+1})] \},
\] (2)

taking into account that future states may depend on the current action.

Note that the utility as defined in (1) depends on the vector of random utility terms \( \varepsilon_k \) at current stage \( k \), whereas the expectation is taken over random utility terms for all future stages. If we furthermore assume that the element in the random utility component vector \( \varepsilon_k \) are i.i.d Gumbel distributed with zero mean, the expectation of (1) before \( \varepsilon_k \) has been observed is given by the following recursive log-sum measure (Rust, 1987; Västberg et al., 2020):

\[
V(x_k) \overset{\text{def}}{=} E_{\varepsilon_k} [U^{\text{max}}(x_k, \varepsilon_k)] = \log \sum_{a \in C(x_k)} e^{u(x_k, a) + E_{k+1}[U^{\text{max}}(x_{k+1}, \varepsilon_{k+1})]}\]
(3)

The expected value function \( V(x_k) \) as defined in (3) can be recursively calculated for each state \( x_k \) for \( k = 0, 1, \ldots, K-1 \) by backward induction, starting from each possible final state \( x_K \). It should be noted that the expected value in (3) is qualitatively different than a nested logit model, as it captures the expected values of the future activity pattern recursively during the day.

In summary, referring to Fig. 2, we model the individual’s path throughout a day. Following the Bellman principle, we decompose the problem into a sequence of decisions, one at each time step, allowing for all feasible combinations of activity patterns and scheduling decisions, with a travel demand model (including trip decision, trip distribution, and modal split) in each time step. For further details on the \textsc{sCAPER} activity and scheduling model see Västberg et al. (2020).

Next, having thus arrived at the expected value function \( V(x_k) \) in (3), we are now ready to define our spare time accessibility measure. Note that the expected value function in (3) calculates the expected utility for an individual being in state \( x_k \), i.e. it depends on for example location, activity history, and also on characteristics of the individual, including home location and work location. As evident from Section 2, using expected utilities, including the log-sum measure as such, have in different contexts been used as an accessibility measure, including in nested logit models of activity-based travel demand models (Dong et al., 2006). In the context of our dynamic discrete choice model, Jonsson et al. (2014) argued that the above expected value function \( V(x_k) \) from the dynamic activity-based demand model that considers space–time constraints of individuals by introducing time to the equations, can be interpreted as an accessibility measure.

In the present paper this is also the view taken. Of particular interest is to calculate the expected value function in the first state \( x_0 \), in which the individual is by assumption at home. We will therefore define \textit{spare time accessibility} as the expected value for an individual \( n \) that is living in zone \( i \) and working at zone \( j \):

\[
A_{nij} \overset{\text{def}}{=} V(x_0)
\] (4)

which is the expected utility for an individual in the morning state \( x_0 \), which depends on home location, work location, activity and travel opportunities, as well as physical resources such as car availability and spatial or temporal constraints throughout the day.

The spare time accessibility measure \( A_{nij} \) as defined in (4) can be used to calculate the effect of applying a change on both individual-level constraints and on system level attributes such as travel times and costs. The spare time accessibility measure for an individual will depend on for instance, home location, work location, car availability, and temporal constraints (such as mandatory activities, opening hours of shops). We use this connection to analyze the effects of constraints of space, time, and resources on workplace accessibility.
Fig. 3. Workplace Choice. The individual considers workplace location, spare time activity patterns, occupation and actual workplace in workplace choice. The expected utility from activities is summarized through $A_{ij}$, which is used as a latent variable. In this developed nested logit model, the variables in the blue squares correspond to the upper nest while the gray squares shows the lower nest structures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Of particular interest for this paper is how workplace location will affect spare time accessibility. However, in the estimated model by Västberg et al. (2020), workplace is exogenous, and the associated accessibility measure in (4) is conditional on workplace $j$. Therefore, in the next subsection we turn to the development of a workplace location choice model in which the thus defined accessibility measure is used as a latent variable. The derived workplace location model will form the basis for investigation of accessibility measures to be subsequently applied in Section 5.

3.2. Workplace location choice

We assume that an individual’s choice of a specific workplace depends on: (1) the workplace location, which is defined by the zone where the workplace is located; (2) the occupation, where different types of jobs may be available to the individual; (3) characteristics of the specific workplace; and (4) spare time accessibility conditional on the workplace. This choice situation is illustrated in Fig. 3. As occupational and workplace choices are unobserved in our data, the model is aggregated to the workplace location level.

In a nested logit (NL) model, the structure is formed by grouping all the subsets of correlated alternatives in nests. Each nest competes with other available alternatives as a composite alternative. The information in the lower nests is introduced to the next higher nest $m$ by using the expected maximum utility (EMU), also known as the log-sum formula, which is calculated as

$$EMU_m = \log \sum_k e^{V_k/\lambda_m},$$

Where $V_k$ represents the utility of alternative $k$ in the nest. The composite utility in the next higher nest $m$ enters as

$$V_m = \lambda_m \cdot EMU_m.$$
where $\lambda$ is the structural parameter to be estimated. If $\lambda = 1$ then the NL model reduces to MNL (see, e.g., Ben-Akiva et al., 1985, McFadden, 1978).

We now explain how workplace accessibility is estimated, using spare time accessibility as an explanatory variable in a NL model. The spare time accessibility measure $A_{nj}$ obtained from Västberg et al. (2020) provides a measure that is conditional on home zone $i$, work zone $j$, and additional space–time constraints for an individual $n$. This measure is already described in Section 3.1 above.

The utility of the NL workplace location choice model, $v_{nij}$, represents the deterministic part of utility for an individual $n$ living in $i$ and choosing work location $j$ according to an NL model. It can be divided into two parts. First, the utility that an individual will get from the activity patterns in each zone that is calculated as follow:

$$v_{nij} = (\beta_A + \beta_A p_t) A_{nj}$$  \hspace{1cm} (7)

where $\lambda$ is the parameter for the spare time accessibility measure, $A_{nj}$. The spare time accessibility measure is also interacted with a dummy indicating if the individual is part time employed $p_t$ with a parameter $\beta_A p_t$. Second, the log-sum of different occupation types and number of workplaces in each zone is which is the composite utility from lower nests as illustrated in Fig. 3, which is:

$$v_{nij} = \lambda \log \sum_{o=1}^{O} e^{a_o / 1 + \log(N_{jo})},$$  \hspace{1cm} (8)

where $\lambda$ is the structural log-sum parameter of the nested logit model, and $a_o$ acts as occupational specific constants for different types of occupations. The log-sum represents the expected utility of choosing any of the workplaces available in zone $j$, where these workplaces belong to an occupational type ($o \in 1, \ldots, O$), and there are $N_{jo}$ such workplaces. Adding size variables in this manner can be seen as a consequence of aggregation of choice utilities (McFadden, 1978, Habibi et al., 2019), aggregation which is required in our case since only location choices are observed, while occupational and workplace choices are latent.\footnote{As pointed out by a referee, one other limitation of the current data set is that it does not allow for estimation of gender- or age-specific preferences for the occupations. Indeed, we believe that this would be part of an interesting line of investigation on gender equality in relation to labor economics, which we will return to in the last Section 6.}

The utility of the NL workplace location choice model, $v_{nij}$, is therefore given by:

$$v_{nij} = (\beta_A + \beta_A p_t) A_{nj} + \lambda \log \sum_{o=1}^{O} e^{a_o / 1 + \log(N_{jo})}.$$  \hspace{1cm} (9)

For the remainder of the paper we will drop the individual index $n$ in order to simplify the exposition. While $A_{nj}$ holds the spare time accessibility, conditional both on home and workplace location, we are interested in workplace accessibility which is conditional only on home location.

Such a workplace accessibility measure is provided by the expected maximum utility, $A_i$, of choosing a workplace location provided by the nested logit model defined in Eq. (9). Thus, in our case, the workplace accessibility for an individual living in zone $i$ is given by

$$A_i = \log \sum_{j=1}^{J} e^{v_{ij}}$$  \hspace{1cm} (10)

where $J$ is the number of workplace locations in our application.

Finally, the probability of observing a workplace location choice, given home zone $i$, is given by

$$P_{ij} = \frac{e^{v_{ij}}}{\sum_{k=1}^{J} e^{v_{ik}}}$$  \hspace{1cm} (11)

recalling that we have dropped the individual index $n$. The parameters of the model ($\alpha, \beta, \lambda$) are estimated using a maximum likelihood approach, where the likelihood function is formulated using the above probabilities. We now turn to a more detailed description of spare time accessibility.

Before continuing, and following a comment from a referee, we should also point out that in a structural modeling approach such as this, it would be useful to also address consistency of sequential estimation and related issues of omitted variables. For instance, in a (pure) nested logit framework, there are theoretical results of consistency using sequential estimation (although statistically inefficient). Clearly, these theoretical results are not directly transferable to our context and merit further investigations, but they are outside the scope of this paper.

### 3.3. Consumer surplus and willingness to pay

Relocating a workplace or facility makes a difference in the workplace accessibility that people experience. To evaluate such a change in accessibility a measure that is interpretable and comparable between individuals is needed. McFadden developed the idea to apply random utility models to transportation decisions and using them in cost–benefit analysis (McFadden et al., 1974, McFadden, 1974, 1981). According to McFadden (1998), when consumers are utility maximizers, an evaluation of a change can be achieved through the calculation of the consumer’s surplus (CS) attached to the change and this shows the consumer’s willingness to pay (WTP), and mean WTP is a measure of social value.

As pointed out by a referee, one other limitation of the current data set is that it does not allow for estimation of gender- or age-specific preferences for the occupations. Indeed, we believe that this would be part of an interesting line of investigation on gender equality in relation to labor economics, which we will return to in the last Section 6.
In models using a random utility maximization approach, according to Handy and Niemeier (1997) “the calibrated utility function can be viewed as the demand curve for a particular alternative in which a change in choice attributes, … results in a change in consumer surplus”. As an example of evaluating alternative scenarios, Handy and Niemeier (1997) used a utility-based measure of accessibility and used compensating variation, which is equal to CS in our case, to interpret changes in accessibility from different scenarios in monetized terms.

In the upcoming applications of workplace accessibility, we will use monetized measures of individual changes in utility. One reason for this is that the monetized measures are easier to communicate, the other is that we use them for the aggregation of results. As an example, we illustrate the monetary value, to the whole population of Stockholm, of changing the location of a large hospital. As is well-known the log-sum formula (10) can be applied for calculating the consumer surplus when the utility functions are linear in income, see Hanemann (1996) and McFadden (1998).

The consumer surplus for an individual living in zone $i$ is given by

$$\text{CS}_i = \frac{1}{c} [A_i^1 - A_i^0],$$

still suppressing the individual index $n$. Here $A_i^k$ is the workplace accessibility for an individual living in zone $i$ is defined in Eq. (10), while superindices $k = \{0, 1\}$ indicates the utility before and after a change, respectively. This measure also reflects the individuals willingness to pay (WTP) for such a change. $c$ is the estimated travel cost parameter from Västberg et al. (2020) that reflects the individual’s marginal utility of income, which is assumed to be constant. Dagsvik and Karlström (2005) and McFadden (1998) discussed cases in the presence of income effects, see also De Palma and Kilani (2011). For aggregate predictions, we will perform in-sample predictions for each individual sampled in our data. Since the individuals are sampled using stratification, we utilize the corresponding stratification weights $w_n$ in aggregate predictions in order to achieve representability. The average welfare change over the population, e.g. for relocating a facility or workplace, is then calculated as follows:

$$\overline{\text{CS}}_A = \frac{1}{N} \sum_{n=1}^{N} w_n \text{CS}_{i_n},$$

where we have reintroduced the individual index $n$, to highlight that the stratification weights and consumer surplus are provided at the individual-level. In the following section, we will present the data and estimated models.

4. Data and estimation results

In this section we provide a description of the data, followed by the estimation results for a nested logit model that shows the effects of spare time accessibility and size variables on workplace choice. An extended model is provided in the appendix that shows the effect of spare time accessibility for different groups of households, also including interactions between some of the main variables. All models in this paper were estimated using MATLAB R2018b.

4.1. Data

The data used in this study is the same data set used for the estimation of the activity-based travel demand model presented by Västberg et al. (2020), which provides the spare time accessibility presented in Section 3.1. We use two data sets, one of which is the Stockholm travel survey from 2004, which includes full-day travel diaries. The other data set is SAMS-based data from Statistics Sweden, with information containing the number of workplaces per occupational type and zone.

Summary statistics of the sampled individuals from the travel survey is provided in Table 1. The data is limited to people who work on weekdays. It contains 2954 individuals who worked no sooner than 6:00 am, no later than 8:00 pm, did not take a break for more than 2 h, and returned home before 11:00 pm. People who were at a business trip rather than at their work location were removed from the data.

While the number of observations in each zone in limited, we take the same zones as ABM (Västberg et al., 2020) rather than aggregating, since the spare time accessibility measure that enters workplace location choice model is based on that model, and it should also be noted that we do not estimate any location specific constants. The workplace location choice model was estimated using data including socioeconomic characteristics of the individuals, where they live, where they work, and the number of workplaces in each zone for each employment type. Most of the sample population lives and work in zones near the city center. The city is divided into 1240 zones and a majority of the zones contain only a few observations. In addition to the raw data, the spare time accessibility, $A_{ij}$ is calculated in accordance with the Scaper model provided by Västberg et al. (2020) and is used as a latent variable in the workplace location choice model. The spare time accessibility is calculated for all the sampled individuals from their home zone to all possible work zones in Stockholm city to provide $A_{ij}$.

3 The representative individual approach is also closely related, see e.g. Anderson et al. (1988) and Verboven (1996). For further discussion on this duality, and its relation to income effect, see Karlström (2014).

4 Small Areas for Market Statistics.

5 A reviewer suggested that sampling would be a useful approach. Indeed, while allowing for all 1240 zones in the choice set is useful, doing so for all different activities at all the time-steps is also computationally costly. However, consistently estimating and implementing the model using sample is not trivial, and a matter for on-going research. For instance (Saleem et al., 2018) studied the effect of sampling in the context of a similar model.
Table 1
Summary statistics for sampled individuals.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>gender</td>
<td></td>
</tr>
<tr>
<td>male</td>
<td>1267</td>
</tr>
<tr>
<td>female</td>
<td>1687</td>
</tr>
<tr>
<td>age</td>
<td></td>
</tr>
<tr>
<td>20 &gt;</td>
<td>43</td>
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<td>21–40</td>
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<td>&gt;80</td>
<td>1</td>
</tr>
<tr>
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</tr>
<tr>
<td>(1) single adult</td>
<td>611</td>
</tr>
<tr>
<td>(2) 2/more adults without children</td>
<td>1278</td>
</tr>
<tr>
<td>(3) 2/more adults with youth(^a)</td>
<td>185</td>
</tr>
<tr>
<td>(4) single adult with children</td>
<td>82</td>
</tr>
<tr>
<td>(5) 2/more adults with children</td>
<td>798</td>
</tr>
<tr>
<td># of working people in the household</td>
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<tr>
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<td>693</td>
</tr>
<tr>
<td>2</td>
<td>1897</td>
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<tr>
<td>3</td>
<td>294</td>
</tr>
<tr>
<td>4</td>
<td>64</td>
</tr>
<tr>
<td>5</td>
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<td>mode to work</td>
<td></td>
</tr>
<tr>
<td>walk</td>
<td>264</td>
</tr>
<tr>
<td>bike</td>
<td>290</td>
</tr>
<tr>
<td>car</td>
<td>1054</td>
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<tr>
<td>public transport</td>
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</tr>
<tr>
<td>mode from work</td>
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<td>walk</td>
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<tr>
<td>bike</td>
<td>281</td>
</tr>
<tr>
<td>car</td>
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<tr>
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<td>cars in the household</td>
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<tr>
<td>1</td>
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<td>2</td>
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<td>full time</td>
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<tr>
<td>part time</td>
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<tr>
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<tr>
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<td>450</td>
</tr>
<tr>
<td>(5) 25001 – 40000 kr</td>
<td>704</td>
</tr>
<tr>
<td>(6) 40001 – 55000 kr</td>
<td>780</td>
</tr>
<tr>
<td>(7) 55001 – 70000 kr</td>
<td>540</td>
</tr>
<tr>
<td>(8) more than 70000 kr</td>
<td>435</td>
</tr>
<tr>
<td>Total</td>
<td>2954</td>
</tr>
</tbody>
</table>

\(^a\)Age of youth is between 12–17 years old.

4.2. Estimation results

In this part the estimation result of a nested logit workplace location choice model is provided, to show how spare time accessibility affects workplace choice. The estimated model will capture how likely people are to choose a workplace location given the spare time accessibility it admits, considering their mobility restrictions, affected by for example home and work zones, and working hours. The model, illustrated in Fig. 3, is estimated using a maximum likelihood approach based on the probabilities of individuals’ workplace location choices as provided by Eq. (9)–Eq. (11). The estimated model, see Table 2, includes the spare time accessibility measure $A_{ij}$ and its interaction with a dummy variable indicating part time employment. Additionally, the model contains the size attributes for different types of occupations with the corresponding occupational specific constants, and a log-sum parameter.

As seen in Table 2, spare time accessibility has a significant\(^6\) and positive impact on workplace choice. The effect is significantly higher for part time working individuals, which suggests that the flexibility which follows by less working hours increases the effect of spare time accessibility on workplace choices. The part time working group, consists of 84% women. In the part time working group 28% have one more space–time constraint of picking up children from day care, while only 8% of full time workers have this constraint. For both full time and part time working groups that have to pick up the children, 88% have access to car. Also, for

\(^6\) At the 5% level, tested through $|T\text{-value}| > 1.96.$


the part time working group with the extra pick-up constraint 93% of the sample are women, while in the full time working group with the extra constraint, 52% are women. Seemingly, the higher share of individuals with extra constraint in the part time working group suggests higher value for the spare time accessibility. This is inline with finding of Kwan (2000) that women, employed part time, face more constraints from out-of-home activities and childcare responsibilities. The occupational specific constant is only significantly different from zero for Education. Yet, it is customary to keep these constants in the model even when insignificant, since they assure that aggregate in-sample predictions of the model will generate proportions of people choosing occupational types which are consistent with the total number of workplaces for each type. Also, the constant $a_t$ is normalized to zero, since not all occupational constants can be identified in a NL model. The log-sum parameter $\lambda$ is significantly different from both zero and one. The motivation for testing the log-sum parameter against one is that it represents a test of the nested logit specification. If $\lambda = 1$, the nested model would simplify to a conventional multinomial logit model, which the T-test against 1 rejects (see Table 1, $T = 11.76$).

The result of a more comprehensive nested logit model is presented in Table 3 in Appendix. This model estimates the role of the spare time accessibility measure for different types of individuals, but maintain the same structure as the model described above. In the applications of Section 5, we use the result of the estimated nested logit model in Table 3 to illustrate how individual-level constraints affects workplace accessibility.

5. Applications

In this section, we use the estimated workplace location choice model to illustrate how individual-level constraints may affect workplace choice and workplace accessibility. The model is applied in three different examples related to: workplace relocation benefits, potential segregation on the labor market, and the interdependence between individual space–time constraints and car dependency. By having the socioeconomic characteristics of individuals and space–time constraining variables included in the same measure of accessibility, it is possible to provide a versatile analysis. The maps presented in this section has been generated using QGIS 3.2.2.

5.1. Workplace relocation benefits

In the following part we illustrate how it is possible to calculate benefits, in monetary terms, of moving a workplace to other zones in the city. This is achieved by calculating the individual’s consumer surplus from having workplaces relocated and the consumer surplus is calculated in terms of our workplace accessibility measure (10). Here, we analyze changes of welfare due to changes in location of a large hospital, the Karolinska hospital, in the southern part of Stockholm, with 7073 workplaces. Also, we discuss how workplace accessibility for all individuals in the sample changes, and how large the benefits of relocating this hospital is in monetary terms.

In this counterfactual analysis, we relocate the workplaces provided by the Karolinska hospital to each other zone in Stockholm, and call each change in location of the hospital a scenario. People in the sample will experience a different workplace accessibility in each scenario. To calculate the consumer surplus and workplace accessibility, the formulas explained in Sections 3.2 and 3.3 are used. In the base scenario, without any relocation, $CS$ and $Ai$ is calculated using the actual number of workplaces reported in data. In the counterfactual scenarios, where the workplaces of the Karolinska hospital are relocated, $CS$ and $Ai$ are recalculated under the new conditions. We then assign the average consumer surplus (Eq. (13)) of each scenario to the zone where the workplaces were moved to, and thereby we have the average consumer surplus for all the 1240 zones in Stockholm county.

Fig. 4 shows consumer surplus maps for all relocation scenarios in Stockholm. According to Fig. 4, people in the sample are willing to pay up to 0.21 SEK per person per day to move the hospital to the city center. The per capita $CS$ measures how much the per capita workplace accessibility will change by moving Karolinska hospital to any zone. The workplace choice model is estimated on a working sample of individuals, that means $CS$ mainly represents the potential workers. While $CS$ reflects the welfare measure of the working population from moving Karolinska hospital to each zone, acceptability of each alternative is not investigated here.
People with and without access to car will experience different workplace accessibility and therefore will benefit differently from the relocation of the hospital. Therefore we also calculate the consumer surplus for the sample when there is a car constraint, i.e. when car is removed from the transport mode set in the accessibility calculation. That is, we will illustrate how the average consumer surplus changes if people did not have access to car.

Fig. 5 shows the difference in average consumer surplus between the cases where there is no car constraint and when there is. As shown in Fig. 5, in the city center the difference is negative which shows that, when loosing access to the car alternative people would experience larger (positive) welfare changes of moving the hospital to the center as compared to the situation when they did have car access. In addition to the central locations being attractive when the car alternative is removed, the difference in consumer surplus indicates a radial structure from the city center, with red and blue areas extending from the center and outwards. We speculate that these streaks of welfare differences are largely driven by the more localized accessibility along public transport lines which people would experience if the car alternative was removed. They would be confined to move within the public transport system, e.g., using commuter trains, thus valuing workplace relocations close to the public transport system higher.

The result provided here is partially aligned with Olsand and Thosen (Olsand and Thorsen, 2008) finding, that an isotropic and ring-like CBD gradient shows the urban attraction, since it is traveling distance rather than the direction that matters. From the results presented, we can claim that the coverage of the public transport lines matter as well.

5.2. Car dependency

Using the accessibility measure for different sub-groups, we can address equity aspects. In this section, we will address the impact of accessibility due to adding or removing a mandatory pick-up activity for individuals with availability to car, as compared to those without car. We have in mind picking up children at school/kindergarten, that puts a temporal and spatial constraint on individuals’ space–time prisms.

By knowing space–time constraints that individuals face, we check if car users with one additional constraint, having to pick up their children from daycare, are willing to pay more to use their car. This translates into analyzing how car dependency affects workplace accessibility for those with and without the constraint of picking up children from daycare. For this purpose, we divide car users into two groups, one is the group that has to pickup their child and the other is with no pickup. It is then possible to check which group is affected more if they lose their access to the car. Fig. 6 shows the consumer surplus,\(^7\) for the two groups.

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\(^7\) Since we are assuming constant marginal utility of money, in this case this consumer surplus is also equivalent to willingness-to-pay (WTP).
The vertical axis is the empirical CDF (cumulative distribution function). As shown in Fig. 6 the tail of the plot for the group with pickup is fatter which means more individuals in this group are willing to pay higher amounts to keep their car access. Also, the average consumer surplus in this group is higher compared to the group with no pickup. This result confirms that individuals with stricter time-space constraints are willing to pay more to maintain their spare time and workplace accessibility.

From a gender equity point of view, it should be noted that mandatory pick-up activities are not gender neutral. As stated earlier in Section 4.2, the majority of individuals that have to pick up children are women. In a study focused on gender rigidity of space–time constraints, Schwanen et al. (2008) explained that the context (when, where and for how long) of the activity matters in the fixity level of individuals and it seems to be systematically different for men and women.

Also, the result of car dependency example illustrates how the workplace accessibility measure is sensitive to marginal value of time of car when a new space–time constraint is introduced. While the value of time (here consumer surplus or willingness to pay) has been extensively studied by including different variables such as income effects, travel time, and travel cost (see for example Börjesson and Eliasson, 2014, Ramjerdi and Lindqvist Dillén, 2007), introducing the space–time constraints is specific to this work.

5.3. Segregation

In this part we want to investigate if high and low income people are likely to experience workplace segregation, based on where they are likely to work according to the workplace location choice model. For the purpose of illustrating segregation, we divide the sample to two groups of people with high (group 6,7,8) and low (group 1,2,3,4,5) income. We calculate the average demand for the high income people for different workplace locations using the workplace location choice model. We have 1755 individuals with high income. The average demands for the high income group and all individuals are calculated as

\[
\bar{P}_{j,hi} = \frac{1}{N_{hi}} \sum_{n \in hi} w_n P_{nj}
\]

\[
\bar{P}_j = \frac{1}{N_{tot}} \sum_{n} w_n P_{nj}
\]

respectively, where \(N_{hi} = 1755\) and \(N_{tot} = 2954\). Fig. 7 shows the ratio of the average workplace demand for high income people to all people. High income people are more likely to choose a workplace location in the city center and northern part of the city, while the low income people are more likely to choose a workplace in the southern and south-west part. The difference in the
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Fig. 6. Consumer surplus (Willingness to pay) for access to car, individuals that have to pick up their children from daycare are more likely to have a higher consumer surplus.

demand can be used as an intuitive indicator of where the high and low income people are likely to work. It also shows that people are prone to experience social segregation as mentioned in Legeby (2010). Also, Östh et al. (2018) showed that wealth tends to concentrate in the central areas of the city and according to Gould (2007) this may be because of the spatial distribution of jobs where higher wage jobs are more clustered in the central parts of the urban area. In another study (Clark and Burt, 1980) showed that when the distance between workplace and home increases, there is a marked tendency to move closer to workplace. While we do not claim that labor market segregation is necessarily driven by individual-level constraints, any residential segregation appearing between housing areas, will almost certainly be connected to segregation between different workplace locations, housing segregation is mediated through individual space–time constraints into workplace segregation and vice versa.

6. Concluding comments

In this paper we elaborate on the concept of a spare time accessibility measure, focusing on individuals’ spatial and temporal constraints. The spare time accessibility measure is used as a latent variable affecting workplace location choice. The spare time accessibility measure embeds socioeconomic variables of individuals, their participation in activities as well as transportation patterns. We argued that this form of spare time accessibility would predict workplace location choices, and it does turn out to be a significant factor in our estimation of the workplace location choice model.

By integrating workplace location choice into the underlying ABM, we achieve an elaborate measure of workplace accessibility, where the role of individual-level constraints affecting mobility can be investigated. We show how individuals lose or gain interest in different workplace locations if they are more or less constrained in space and/or time. For instance, individuals who have access to a car have a more extensive range of options for choosing their workplace and have higher accessibility in general, and we show that without the car workplace accessibility changes, and they will presumably be more limited to the workplaces along the public transport lines.

Furthermore, the county of Stockholm experience north-south segregation on the labor market according to our estimated workplace location choice model. High income people have a higher likelihood to choose a workplace located centrally or to the north of the center, and we argue that while segregation is not necessarily caused by individual-level constraints, e.g. access to car or non-work fixed activities, such constraints may mediate segregation in one domain to another.

The developed measure of accessibility enables us to look at equity in new dimensions, for instance, we show how accessibility is dependent on car availability in relation to new space–time constraints that involves childcare activities. The finding quantifies the significant differences in accessibility facing men and women, given the unequal distribution of childcare activities across gender.
Fig. 7. Average demand ratio, Average demand for high income group divided by average demand $\bar{P}_{j,h}$, $P_j$ for all regions $j$. Red indicates that a high income person is more likely than the average person to choose the zone as his/her workplace location. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

These results may provide a contribution to guide, for instance, school bus policies. Similarly, the framework provides information on incentives for carpool and coordination services.

Several policy insights can be derived from this study explicitly and implicitly. For instance, car dependence is significantly impacted by household characteristics such as having young children, which creates additional time-space constraints. Thus, unless public transport access is significantly improved, reducing car dependence for work trips may not be a simple task, since the car compensates for the additional time-space constraints. Also, high-income individuals tend to choose workplaces in the northern part of Stockholm, potentially contributing to social segregation. In this context, land-use policies are one set of measures that may be informed by the present analysis, providing quantitative and spatial insights. Furthermore, workplace choice and allocation may also depend on occupation type. Specifically, workplaces that integrate individuals from different income groups could benefit more from a central location, due to better public transport access, and more specifically highlight locations with such a relative advantage. Finally, we quantify the inequality of workplace accessibility between men and women. Although transport and urban infrastructure are the same on a nominal level, their impact on accessibility is not gender-neutral. Thus, there is a potential for an integrated policy approach that may go beyond land use and transportation.

Finally, we note that in the model presented in this paper, we consider some choices as exogenous. As prominent examples, both residential location and car ownership (and availability) are considered exogenous. In reality, these are endogenous choices. As pointed out by one of the referees, endogeneity issues may affect parameter estimates. Ideally, these choices should be modeled in a theoretically consistent framework (e.g. Van Ommeren, 2018). Although this research program is quite challenging, there are some important research questions that may be important from a societal point of view. For instance, on a gender differentiated (or segregated) labor market, accounting for gender- and age-specific occupations, the gender differences in accessibility may be further amplified in the context of outcomes on a (spatial and gender segregated) labor market. Even temporary differences on wage-ladder differences across gender and other segments may have amplified effects on life-time income. Therefore, for further research, it would be interesting to quantify how the gender inequality in space–time accessibility is translated into gender inequality in terms of life-time labor market outcomes. However, this is left for future research.

See, e.g., Picard et al. (2018) for a recent study and approach.

An ongoing research that uses Scaper investigates ‘mobility patterns stratified by socioeconomic groups as an effect of the Covid-19 pandemic’, where changes in spatial segregation is also being studied.

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8 See, e.g., Picard et al. (2018) for a recent study and approach.

9 An ongoing research that uses Scaper investigates ‘mobility patterns stratified by socioeconomic groups as an effect of the Covid-19 pandemic’, where changes in spatial segregation is also being studied.
### Table 3
Accessibility parameters for all the groups in the sample.

<table>
<thead>
<tr>
<th>Variables (upper level)</th>
<th>Estimate</th>
<th>Ste</th>
<th>T-value</th>
</tr>
</thead>
<tbody>
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<td>$A_{ij}$ work type</td>
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<td></td>
<td></td>
</tr>
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<td>hh = 1 pickup = 0</td>
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<td>0.028</td>
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**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Appendix. Extended workplace choice model**

See Table 3.

**References**


Williams, H.C., 1976. Travel demand models, duality relations and user benefit analysis. J. Reg. Sci. 16 (2), 147–166.
