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REPRESENTING ACCESSIBILITY: EVIDENCE FROM VEHICLE OWNERSHIP
CHOICES AND PROPERTY VALUATIONS IN SINGAPORE

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ABSTRACT

This paper compares the relative performance of different measures of accessibility in relevant models. Specifically, we formulate three measures of accessibility: gravity-based accessibility, an aggregate measure of potential; trip-based accessibility, a disaggregate, utility-based measure of the value of travel alternatives; and, activity-based accessibility, a theoretically richer disaggregate utility-based measure of the value of alternative activities (including travel). We use these accessibility measures as explanatory variables in household vehicle ownership models and real estate market price models, comparing the explanatory power of each accessibility measure in each model as expressed by the confidence in the coefficient estimates and captured by the models’ goodness-of-fit statistics. We find that trip-based accessibility best represents preferences for accessibility in both vehicle ownership decisions and property valuations. This supports the theoretical value of disaggregate, utility-based accessibility measures over aggregate, potential-based measures. The fact that trip-based measures perform better than activity-based accessibility measures underscores several empirical and technical limitations. Finally, we note that accurately representing accessibility preferences requires congruence between the granularity of the accessibility measure and that of the explained behaviour. This emphasizes the importance of understanding that which accessibility measures actually capture and ensuring that they align with the analysis purpose.

Keywords: Accessibility measures, Vehicle ownership, Property valuation,
INTRODUCTION
Accessibility has attracted increasing interest as transportation and planning professionals have shifted their attention to the interactions between the transportation system and the larger urban system. Its importance and usefulness as an urban performance measure have been demonstrated widely. Glaeser noted that “all of the benefits of cities come ultimately from reduced transport costs for goods, people and ideas” (1). Although Glaeser did not use the term accessibility, his quote mirrors the accessibility concept in emphasizing the interaction between the transportation system (reduced transport costs) and the activity and land use systems (goods, people and ideas), as opposed to one or the other in isolation. The benefits Glaeser refers to can take many different forms. Investments in transportation infrastructure are often seen as a means of generating economic development. However, for project evaluation these benefits have traditionally been measured in travel time savings. Accessibility offers a more nuanced perspective aligned with the transportation as a derived demand paradigm. Specifically, accessibility captures how the transportation and land use systems interact to generate opportunities for individuals (e.g., access to employment and other urban amenities).

Essentially, accessibility is the raison d’être of an urban system. In practice, however, it remains relatively abstruse. Even professionals within the fields of transportation and urban planning are not always clear – or at least not in agreement – about what it encompasses or how it should be measured. Numerous increasingly sophisticated and complex measures of accessibility have been proposed, but how well can we operationalize them? Do they improve our abilities to predict relevant behaviors in the system? This paper examines how accessibility performs in predicting household vehicle ownership choices and estimating residential property valuations. Specifically, we explore the appropriateness, advantages, and limitations of three different accessibility measures – gravity-based, trip-based, and activity-based – in representing household and market preferences in models of these long-term choices. This study is part of our recent work in developing meaningful accessibility measures that capture the interaction between the day-to-day performance of the transportation system and people’s long-term choices.

BACKGROUND
Since the 1950’s, scholars have proposed various definitions of accessibility, leading to a wide range of interpretations and measures. Geurs and van Wee (2) and Bhat et al. (3), among others, provide comprehensive reviews. Here we focus on two types of accessibility measures: measures of potential and measures of utility. Potential measures originate from Hansen’s definitions of accessibility: “the potential of opportunities for interaction” (4). These measures add up the destinations of a certain type, e.g. employment opportunities, that can reasonably be reached considering travel impedance. Reasonable is generally defined by assuming an upper bound on distance, travel time, or generalized travel cost. The resulting accessibility measure is commonly known as cumulative opportunities accessibility. Alternatively, distant destinations can be assigned a lower weight to reflect the inconvenience of reaching them. This is the idea behind gravity-based accessibility, aptly named for its similarity to Newton’s law of gravitation. The weights should be determined by empirically estimating an impedance function that penalizes travel. Measures of potential are usually defined for a specific location, such as a person’s home, and travel impedance is thus considered from that location. They can also be estimated for specific trip types, modes, groups of individuals, etc., depending on data availability.

The attractiveness of “utility-based” accessibility measures come from their direct link to individual utility (welfare) as estimated from relevant choices (e.g., destinations, modes).
Utility-derived accessibility measures come from discrete choice models, widely applied in transportation system analyses (e.g., to predict a consumer’s choice from among different travel modes). Utility-based accessibility measures can reflect individual preferences, be measured for the individual (based on the individual’s actual choice) and are directly linked to traditional measures of consumer surplus. Ben-Akiva and Lerman (6) explicitly link the disaggregate discrete choice modeling framework to the accessibility concept, enabling a direct relationship to individual choice based on that individual’s choice set. Specifically, they offer a definition of accessibility as “simply the utility of the choice situation to the individual”: the expected maximum utility (EMU) of all choices in a choice situation. In the context of travel and activities, these choices include mode, destination, and activity scheduling choices and the decision-maker selects, from a set of alternatives, the choice providing the highest utility. Accessibility measured in this way ostensibly captures user preferences. The distinction between potential and utility measures is not clear-cut. They should be considered ends of a spectrum rather than labels for discrete bins. For example, gravity-based accessibility measures, if empirically estimated, begin to account for people’s preferences, although it is fundamentally a measure of potential.

In light of the numerous definitions and measures, we must acknowledge that: first, accessibility is fundamentally a construct and therefore does not have one true interpretation; and, second, any measure of accessibility has its own advantages and limitations vis-à-vis representation of preferences, data requirements, communicability, theoretical appeal, etc. For example in a study of highway toll impacts in Portland, Oregon, Dong et al. (7) used activity-based accessibility to measure benefits. Activity-based accessibility is a measure of utility determined by calculating the EMU of an activity schedule choice that has been formulated in a nested logit structure (including activity scheduling, mode choice, destination choice, etc.). Although somewhat esoteric, the sophistication allows for capturing preference heterogeneity, determining market segment-specific distributions of accessibility impacts, and accounting for the fact that individuals can change the time of day of activity participation and/or the actual activities performed. The trade-off, however, is that utility-based measures, such as activity-based accessibility, are very demanding in terms of data, and they may appear opaque – like black-box measures – to laypeople (8). Conversely, the relative simplicity of aggregate measures, such as cumulative opportunities accessibility, lends itself well for analyses in data-poor environments, e.g. He et al. (9), and for stakeholder engagement, e.g. Stewart and Zegras (10).

Many researchers have explored the role of accessibility in vehicle ownership and residential location choices. For vehicle ownership, improved accessibility by alternative modes is linked with lower vehicle ownership rates. This finding is consistent – at least in direction – across different contexts and different measures of accessibility and model structures, including: in the San Francisco Bay Area, using measures of potential in ordinary least-squares (OLS) regressions (11); in Santiago de Chile, using measures of potential in discrete choice models (12); in Sacramento County using measures of potential in structural equation models (SEM) (13); in the Tel Aviv metropolitan area using measures of utility in discrete choice models (14). Similarly, several studies have demonstrated that accessibility is an important explanatory factor for the desirability of a property or residential location. Both measures of potential (15, 16) and measures of utility (17, 18) have been shown to be positively correlated with the attractiveness of locations. Together, these studies clearly establish that accessibility plays a role in people’s long-term decisions. However, these studies’ differences in contexts and – by extension – underlying datasets used, do not make it clear which are the “best” measures.
We conduct our study in the context of Singapore. The primary datasets used to estimate our models are the 2012 Household Interview Travel Survey (HITS) and real estate transaction records from 2001 and 2017. Additionally, the trip-based and activity-based accessibility measures are calculated from models estimated in the activity scheduling module of SimMobility, an integrated agent-based microsimulation framework (19).

METHODS, MEASURES, AND MODELS
How well do different accessibility measures represent household and market preferences for accessibility as estimated in models? To answer this question, we estimate models which include accessibility as a key explanatory variable. Accessibility measures with more explanatory power can be interpreted to be better representations of the role of accessibility in influencing relevant choices. The analysis framework is presented schematically in Figure 1, which illustrates two measures of accessibility, $A^i$ and $A^j$, and a model, $M$. The model is estimated with each accessibility measure separately, and then the outputs are compared to evaluate the explanatory power of each measure. Explanatory variables other than accessibility are kept constant regardless of the accessibility measure used, in an attempt to satisfy the *all else equal* assumption. Some accessibility measures will be more correlated with the non-accessibility variables, thus arguably putting them at a disadvantage vis-à-vis model goodness-of-fit. However, this simply implies that the goodness-of-fit criterion evaluates explanatory power beyond that of the non-accessibility variables.

**FIGURE 1 Analysis framework**

The confidence in the coefficient estimates indicate how consistently and accurately the accessibility measure reflects a notion of accessibility as reflected in people’s choices. This confidence is expressed by the corresponding t-statistic and its statistical significance level. Examining the overall goodness-of-fit of the models reveals how large a role a particular operationalized notion of accessibility plays in the context of the explained behaviour/variable, all else equal. Here we consider $\bar{R}^2$ for linear regression models and $\bar{\rho}^2$ for discrete choice models as well as relative model likelihoods calculated using Akaike’s information criterion (AIC). The relatively simple measures, $\bar{R}^2$ and $\bar{\rho}^2$, are often criticised for inadequately capturing goodness-of-fit and prediction error. Thus, we supplement these with AIC, which is an estimator of how much information is lost in a model relative to other models estimated on the same
dataset (20). As such, it is useful for ranking models but cannot capture their absolute quality. For our purpose, information loss can be interpreted as failure to capture accessibility as it is perceived in people’s decision making processes. For a model with $k$ parameters and log-likelihood $L$, equation (1) shows how AIC is determined.

$$AIC = 2k - 2L$$

For a set of estimated models, the model with the lowest AIC value is preferred. Additionally, the relative probability that a model $M$ is the best-fitting model in the set of estimated models is proportional to the term $\exp(-\Delta_M/2)$, where $\Delta_M$ is the difference between model $M$’s AIC and the AIC of the best-fitting estimated model (21). For ease of interpretability, this can be normalized and expressed as so-called Akaike weights as shown in equation (2). For a set of estimated models $r \in R$ the probability that a given model $M$ in this set is the best-fitting model is equal to $w_M$.

$$w_M = \frac{\exp(-\Delta_M/2)}{\sum_r \exp(-\Delta_r/2)}$$

This method for comparing goodness-of-fit is not very common for linear and logistic regressions. Typically, we would simply use likelihood ratio tests for model selection. However, our models are not nested, i.e. the parameters of one model are never entirely a subset of another due to the different accessibility measures, and therefore the standard likelihood ratio test is not applicable. We considered composite likelihood ratio tests, for which we would estimate a composite model with the accessibility measures of both models we wish to compare. We could then conduct likelihood ratio tests between this model and each of the two models with only one accessibility measure since they would then be nested versions of the composite model. However, this test can be inconclusive if sample sizes are very large and the explanatory variables that differ between the two models, i.e. accessibility measures in our case, capture different underlying phenomena. We applied the composite likelihood ratio test to our models but they were generally inconclusive.

**Accessibility Measures**

**Gravity-based Accessibility**

Gravity-based accessibility is an aggregate measure of potential that summarizes the opportunities for interaction and travel impedance of accessing them from a given location, e.g. a person’s home. In this study, we measure gravity-based accessibility at the zonal level to match the granularity of the underlying travel and opportunities datasets. Gravity-based accessibility for a zone $i$ is given by:

$$A_i^G = \sum_j d_j \cdot f(c_{ij})$$
where: $d_j$ is the number of destinations in zone $j$ and $f(c_{ij})$ is the travel impedance function between zones $i$ and $j$. We consider three destination types with corresponding units of measurement:

- **Work**, per 1000 jobs;
- **Shopping**, per 1000 sq. metres of retail and food services; and
- **Other**, per amenity establishment.

These destination types were chosen to match the trip purpose types captured in the activity-based accessibility measure derived from the SimMobility activity scheduling module. The impedance function $f(c_{ij})$ can be formulated in a number of different ways. We use the negative exponential formulation presented in equation (4).

$$f(c_{ij}) = e^{-\lambda c_{ij}} \quad (4)$$

c_{ij} \text{ is the travel impedance measured by generalized cost of travel and } \lambda \text{ is a coefficient that determines the rate of decay. To estimate } \lambda, \text{ we use revealed trip-making behaviour from the 2012 HITS as a proxy for how the value of an opportunity decays with increasing travel impedance from a person’s home location. Generalized travel costs are determined using inter-zonal travel times and costs and their respective coefficients estimated in the mode-destination choice models in SimMobility.}

**Trip-based Accessibility**

Trip-based accessibility is a disaggregate utility measure calculated as the EMU of mode and mode-destination choice models. It captures preference heterogeneity across market segments through the parameters of these choice models. For a logit model, the EMU of a choice situation with alternatives $j \in J$ is:

$$EMU = \ln \left( \sum_j e^{V_j} \right) \quad (5),$$

where $V_j$ is the systematic utility for alternative $j$ as estimated in the mode or mode-destination choice model. We consider the same trip purposes as we did for gravity-based accessibility, namely work, shopping and other. For work, the EMU of a work mode choice model is used if the individual indicated that she works at a fixed location. Otherwise, we use the EMU of a work mode-destination choice model, which models the mode and destination choices for work jointly. For shopping and other trips, we always use the EMUs of their respective mode-destination models since their destinations are generally not fixed. Both mode and joint mode-destination choice models were modelled using multinomial logit structures. These models were estimated as part of SimMobility’s daily scheduling module.

**Activity-based Accessibility**

In theory, activity-based accessibility reflects the EMU of an entire day schedule of travel and activities as opposed to simply a mode or mode-destination choice. This requires that activity schedules be modelled in a nested structure, such that the top-level choice encompasses the consumer surplus of every sub-choice in the activity schedule. The EMU can similarly be
expressed by equation (5) where $V_J$ represents the systematic utility of day schedule choices including the EMU of sub-level choices. However, in practice, expressing the complexity of activity schedules in terms of choice models – let alone structuring them in nests – necessarily requires some assumptions. The best approach is far from obvious. The scheduling module in SimMobility proposes one such structure shown in Figure 2. The arrows show the EMU of lower-level choice situations that appear as explanatory variables in an upper-level model. Other models in the scheduling module, including time-of-day and stop generation models, which are not connected to the top-level choice through EMUs are not shown.

**FIGURE 2 SimMobility activity schedule model nesting structure**

The mode and mode-destination activity choice models are the same as those used to determine trip-based accessibility. The EMU of these models appear as explanatory variables in the *Tours* and *Stops* models where they were found to be statistically significant through estimation. The *Tours* model is a multinomial logit model where each alternative consists of possible tour combinations represented by four purpose-specific binary dummy variables. A “1” indicates that at least one tour of that purpose was completed during the modelled day, while a “0” indicates that no tour of that purpose was completed. The four purposes are work, shopping, other, and education. The tour purposes are the same ones considered for all three accessibility measures with the addition of education. However, note that no education mode/mode-destination EMU is represented in the upper-level choices. Hence, accessibility to education was not considered for the trip-based and gravity-based accessibility measures. The *Stops* model is very similar; it is also a multinomial logit model that consists of the same four purpose-specific binary dummies and ten choice alternatives. However, a “1” in the purpose-specific dummy means that a stop of this type is possible as part of the person’s tours. In other words, whether or not an activity of this type was conducted is decided in a different model, a so-called stop-generation model, where this stop type becomes part of the choice set if the purpose-specific dummy of the *Stops* model is “1”.

Finally, the *Day Pattern* model is a binary logit model representing the choice between staying at home for the modelled day and participating in out-of-home activities.

Although the parameters in these models are specific to SimMobility in Singapore, the model structure is neither unique nor irreproducible. We can draw a parallel to the impedance function used in the gravity-based accessibility measure. The rate of decay parameters are specific to our dataset and the Singapore context. However, the functional form of the impedance
function can be used and validated with other datasets in different study contexts

Models

Vehicle Ownership Model

The government in Singapore uses a licensing system for controlling the supply of motorized vehicles. Prior to purchasing a vehicle, Singaporeans must acquire a Certificate of Entitlement (COE) through an auction held by the Land Transport Authority (LTA). Different COE categories allow the certificate holder to own different vehicle types, e.g. cars, goods vehicles, or motorcycles. Furthermore, an off-peak car scheme exists, allowing vehicle owners to pay reduced registration fees and road taxes if they limit their vehicle use to off-peak hours and weekends.

The vehicle ownership choice model is a disaggregate household-level model that predicts the number and type of vehicles each household owns based on its socio-demographic and locational attributes. The choice is modelled using a multinomial logit model structure with six choice alternatives (with revealed choice probabilities in brackets):

1. No motorized vehicles (57.0%);
2. One or more motorcycles only (4.7%);
3. Off-peak car with or without motorcycles (1.9%);
4. Normal car only (31.1%);
5. One normal car with one or more motorcycles (1.0%); and
6. More than one normal car with or without motorcycles and with or without off-peak cars (4.3%).

The utility of household $h$ for choosing vehicle ownership alternative $z$ is given by:

$$U_{hz} = V_{hz} + \varepsilon$$

(6),

$$V_{hz} = \beta_z + \sum_k \eta_k P_{kzh} + \sum_m \pi_{mz} H_{mh} + \sum_n \lambda_{nz} L_{nzh}$$

(7),

where $U_{hz}$ is the total utility, $V_{hz}$ is the systematic utility, and $\varepsilon$ is the Gumbel-distributed error term. $P_{kzh}$ and $L_{nzh}$ are alternative-specific attributes, while $H_{mh}$ are generic. Conversely, $\pi_{mz}$, and $\lambda_{nz}$ are alternative-specific coefficients, while $\eta_k$ are generic. The probability of choosing $z$ from the choice set $J$ is then:

$$P(z) = \frac{e^{V_z}}{\sum_j e^{V_j}}$$

(8).

As an explanatory variable in a vehicle ownership choice model, accessibility captures the relative benefit with respect to improved mobility and access to opportunities of private vehicles. Each choice alternative offers a different level of accessibility. The difference between these informs the vehicle ownership choice. In other words, if the estimated accessibility difference between owning a car and not owning a car is small, there is little reason to own one from an accessibility perspective. Finally, vehicle ownership is a household-level decision. However, we
represent a household’s accessibility by that of the household’s highest income earner. While this is of course a simplification, models estimated with the accessibility of all the household members by role suggest that it is a reasonable approximation. This does not affect the gravity-based measure, since it is insensitive to personal attributes. Other explanatory variables in the model include: income, occupation, household composition, ethnicity, and availability of transit services nearby.

Real Estate Hedonic Price Model

The real estate hedonic price model predicts the log(market price) of properties based on their attributes. The market price $P_i$ for property $i$ is modelled with a linear regression model as:

$$\ln(P_i) = \alpha + \sum_m \beta_m H_{mi} + \epsilon$$

(9),

where $\alpha$ and $\beta_m$ are parameters to be estimated, $H_{mi}$ are property-specific attributes, and $\epsilon$ is a normal-distributed error term. We estimated separate models for private and Housing and Development Board (HDB) units due to the regulation in the HDB market. HDB units are government-subsidized public housing units, in which more than 80% of Singaporeans live. However, buyers of HDB units must satisfy a set eligibility conditions vis-à-vis residency status, household status, income, etc. and the units are usually associated with minimum occupation periods.

Since market price should reflect the value that the market as a whole places on a unit, we consider the average accessibility across every household in the population were they to live in the location of the unit as an explanatory variable. Average accessibility reflects the broadness of appeal of a location and by extension the competition for that location. In our model of market prices, we would expect this to be positively correlated with the dependent variable. Again, this aggregation does not affect the gravity-based measure because it is already aggregate. Other explanatory variables in the models include: area, tenure status, availability of amenities, availability of transit services nearby, age of the property, and the time of the transaction.

RESULTS AND DISCUSSION

For each model and accessibility measure we tried different model specifications. For example, we tested generic and alternative-specific coefficients for accessibility, and we examined the correlation between the accessibility measures to avoid collinearity issues in the model estimation. Through a series of likelihood ratio tests we arrived at the final model specifications presented here. Although potentially interesting, we have omitted the estimates of non-accessibility variables in this paper for brevity.

Vehicle Ownership Model

We estimate the vehicle ownership model with each of the three accessibility measures, i.e. three separate models, each with one measure of accessibility. The estimated coefficients for the accessibility measures are presented in Table 1 and the goodness-of-fit measures are presented in Table 2.

The results show that the confidence in accessibility coefficients generally increase with increasing sophistication in the accessibility measure. In particular, only 5/18 coefficients for the
gravity-based accessibility measures are statistically significant with at least 95% confidence. Conversely, this fraction is 12/18 for trip-based measures and 6/6 for activity-based measures. The inferiority of the gravity-based interpretation for the purpose of modelling vehicle ownership can largely be attributed to its inflexibility due to its aggregate nature. In particular, it only differentiates between owning a motorized vehicle versus not owning a motorized vehicle. As expected, coefficients for accessibility to work are always positive and appear to be the primary determinant in terms of accessibility vis-à-vis vehicle ownership decisions. Coefficients for accessibility to other amenities are also positive with at least 90% confidence that the coefficient is different from 0. For accessibility to shopping destinations, the coefficients are consistently negative. Although very tenuous, this finding is surprising since interpreting accessibility to shopping as undesirable is counterintuitive. The prevalence of malls in Singapore does encourage more local shopping behaviour, which could explain the low estimate confidence. The apparent undesirability of accessibility to shopping may be an artefact of how we capture shopping destinations, i.e. by area, a variable that interacts with the size of retail establishments in desirable locations.

Unfortunately, a direct comparison of coefficient magnitudes is not meaningful since the different accessibility measures are expressed in different units. Instead we examine the effect size of each accessibility measure by the overall model goodness-of-fit, which serves as a reasonable alternative since all other variables remain unchanged across the models. The $\bar{\rho}^2$ suggests that the model estimated with trip-based accessibility yields the best model fit. This finding is verified by the relative model likelihoods; the Akaike weight indicates that of the three models estimated we can be 100% sure (to at least three significant digits) that the model estimated with trip-based accessibility lost the least information. In other words, the trip-based accessibility measures best represent accessibility in households’ vehicle ownership choices.
TABLE 1 Coefficient estimates for accessibility measures in the vehicle ownership models

| Variable   | 1: No vehicle | 2: 1+ Motorcycle only | 3: 1 Off-peak car w/ or w/o motorcycle | 4: 1 Normal car only | 5: 1 Normal car w/ motorcycle | 6: 2+ Normal car w/ or w/o motorcycle |
|------------|---------------|-----------------------|----------------------------------------|----------------------|-------------------------------|---------------------------------------|
|            | $\beta$ | $t$ | $\beta$ | $t$ | $\beta$ | $t$ | $\beta$ | $t$ | $\beta$ | $t$ | $\beta$ | $t$ |
| GBA_work   | 2.03 | ** 2.75 | -0.21 | -0.24 | 0.65 | 1.12 | 0.39 | 0.38 | 1.36 | 1.74 | . |
| GBA_shop   | -6.50 | -2.18 | -2.86 | -1.37 | -3.77 | -1.39 | -1.66 | -0.99 | -1.86 | -0.57 | -1.05 | -0.49 |
| GBA_othr   | 0.38 | 1.60 | -0.12 | -1.20 | 0.40 | 2.54 | * 0.17 | 2.49 | * -0.04 | -0.20 | 0.07 | 0.57 |
| TBA_work   | 0.18 | 15.21 | *** 0.31 | 6.78 | *** 0.45 | 6.39 | *** 0.17 | 19.40 | *** 0.25 | 7.50 | *** 0.24 | 12.78 | *** |
| TBA_shop   | -0.05 | -0.27 | -0.11 | -0.65 | -0.64 | -3.02 | ** -0.26 | -1.47 | -0.66 | -2.66 | ** -0.37 | -1.86 | . |
| TBA_othr   | -0.05 | -0.36 | 0.76 | 8.65 | *** 0.60 | 5.35 | *** -0.09 | -0.82 | 0.86 | 7.03 | *** 0.37 | 3.10 | ** |
| ABA        | 2.34 | 19.09 | *** 2.79 | 18.45 | *** 2.44 | 13.15 | *** 2.07 | 17.31 | *** 2.43 | 11.33 | *** 2.02 | 14.12 | *** |

Significance codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 ’ 1

TABLE 2 Goodness-of-fit of the vehicle ownership models

| Accessibility measure | Relative likelihood (w) | $\bar{\rho}^2$ |
|-----------------------|-------------------------|----------------|
| Gravity-based         | 0%                      | 0.191          |
| Trip-based            | 100%                    | 0.254          |
| Activity-based        | 0%                      | 0.208          |
Real Estate Hedonic Price Model

We also estimate real estate hedonic price models with the three measures of accessibility. The estimated coefficients for these are presented in Table 3 and the goodness-of-fit measures can be found in Table 4.

TABLE 3 Coefficient estimates for accessibility measures in the hedonic price models

| Variable   | HDB β  | HDB t  | Private β | Private t |
|------------|--------|--------|-----------|-----------|
| GBA_work   | 0.01   | 29.80  | ***       | 0.07      |
| GBA_shop   | 0.01   | 6.76   | ***       | -0.08     |
| GBA_other  | 0.41   | 187.24 | ***       | 0.04      |
| TBA_work   | 0.27   | 98.56  | ***       | 0.56      |
| TBA_shop   | 0.08   | 60.77  | ***       | 0.20      |
| TBA_other  | -0.05  | -20.74 | ***       | -0.91     |
| ABA        | 5.29   | 305.70 | ***       | 5.67      |

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

TABLE 4 Goodness-of-fit of the hedonic price models

| Accessibility measure | HDB Relative likelihood (w) | HDB $R^2$          | Private Relative likelihood (w) | Private $R^2$ |
|-----------------------|-----------------------------|---------------------|---------------------------------|---------------|
| Gravity-based         | 0%                          | 0.855               | 0%                              | 0.765         |
| Trip-based            | 100%                        | 0.881               | 100%                            | 0.817         |
| Activity-based        | 0%                          | 0.876               | 0%                              | 0.769         |

All the estimates are statistically significantly different from 0 with at least 99.9% confidence. The t-statistics are extremely high because we have large datasets for real estate transactions, specifically 108,044 HDB and 338,956 private unit transactions. Additionally, a large number of data points are very similar, e.g. similar units in the same condo sold at the same price. That said, this fact does not diminish the validity of the results; we can say with very high confidence that accessibility is an explanatory factor in the transaction price of real estate. While we cannot compare the magnitude of coefficients of different accessibility, we can compare the models for HDB and private units that have been estimated with the same accessibility measures. We observe that the coefficients for private units are generally larger in magnitude. This suggests that the price of private units is more sensitive to accessibility, which seems intuitive. There are still a number of unexpected negative coefficients, namely those for $GBA_{shop}$ (private) and $TBA_{other}$ (HDB and private). Both of these can likely be attributed to spatial correlations in land use as we discussed for the vehicle ownership model. Furthermore, it should be noted that $TBA_{other}$ does not explicitly capture destinations other than those already captured by $TBA_{work}$ and $TBA_{shop}$. Rather its destination component relies primarily on zonal population, employment, and area. Although all three accessibility measures yield statistically significant coefficients, the models estimated with trip-based accessibility again produce the best fitting model. For both HDB and private units, the trip-based accessibility measure loses the least
information of the three measures based on the relative likelihood. Thus it best represents accessibility in real estate prices.

Discussion
For both the vehicle ownership model and the hedonic price model it appears that trip-based accessibility is superior for representing accessibility preferences. The implication of these results can be summarized as follows: (1) disaggregation, which allows us to capture heterogeneity in taste preferences across different market segments, is important in representing accessibility in relevant choices; (2) although measures of potential are useful as performance indicators, people and market behaviour are better explained by utility-based measures, which capture experienced benefit; and (3) accessibility is generally perceived in the context of a specific location, as opposed to in the context of activity schedules. This last observation is not surprising for the hedonic price model, since we expect accessibility to capture locational benefits. However, it is somewhat unexpected that people seemingly pay less attention to their activity patterns in vehicle ownership decisions. That said, the result may also be due to the particularities of the activity-based models estimated in this specific case. Furthermore, it is important that we recognize the uniqueness of the Singaporean context. In particular, the heavy regulation of land and vehicles almost certainly affects the valuation of accessibility in the housing market and people’s vehicle ownership preferences. As such, the model coefficients would likely be quite different were they estimated for a different city. However, our findings vis-à-vis the different ways of representing accessibility and their advantages and limitations apply generally.

A single measure that comprehensively encapsulates the benefits that an individual derives from the transportation-land use system is attractive. However, the mediocre performance of activity-based accessibility – the most theoretically sophisticated measure – suggests that we should not be blinded by this promise. Instead it would be prudent to carefully consider what it actually measures and why the results differ from a priori expectations. At least three categories of limitations and potential issues exist: technical, empirical, and theoretical. The technical limitations generally stem from the discrepancy between what activity-based accessibility should capture and what it actually captures with our proposed formulation. For example, in practice the measure only captures household and social interactions implicitly. Additionally, it has very limited sensitivity to non-anchor activities in tours and time-of-day effects, hence it does not accurately represent the benefits of more complex travel-activity behaviour, e.g. trip-chaining. Alternative formulations of activity-based accessibility that address these shortcomings would likely represent people’s accessibility preferences more accurately. Of course, the technical limitations are often related to the empirical ones, since the estimated model parameters will only be sensitive to behaviour captured by the data. Specifically, the HITS survey only captures a single day of activity for each person, while in reality people schedule most activities on a longer time scale, e.g. grocery shopping every few days or once per week. On average, the activity frequencies are correct, however we cannot capture the details of individuals’ scheduling process, e.g. interactions and substitutability between different activity types. Finally, it is important to consider the theoretical underpinning for using activity-based accessibility as an explanatory factor in people’s behaviour. Even if we accurately capture all the benefits an individual derives from the transportation-land use system, this may not be the basis for her decision-making. People conceivably use much simpler criteria, such as travel time from work, in their decision-making.

In practice, researchers and analysts may not have the luxury of choosing between
accessibility measures due to data limitations. Additionally, the ease of interpretation of simpler measures can be a deciding advantage if communicating accessibility outputs, particularly to laypeople, is pivotal. For such scenarios, the more pertinent takeaway is that the accessibility concept encompasses different meanings. When we use it, we must understand what it actually measures and this should align with the purpose for which we use it. Our results show that the granularity of the accessibility measure should at least match that of the modeled decision-maker. The use of an aggregate measure of potential was less useful for explaining households’ vehicle ownership choices. On the other hand, it was more useful for modelling the market price of properties. In other words, aggregate measures of potential, such as cumulative opportunities or gravity-based accessibility, are useful to describe the transportation-land use system and possibly even for explaining macro-level behaviour, however we should be very cautious in using them to explain disaggregate decisions.

CONCLUSION AND FUTURE DIRECTIONS

We examined how well gravity-based, trip-based, and activity-based accessibility measures performed in predicting people’s behaviors and related outcomes (market prices) in the context of Singapore. To compare the measures, we estimated household vehicle ownership models and real estate hedonic price models. We found trip-based accessibility to be more accurate relative to the other two measures for these purposes. The gravity-based measure performed least well. We largely attribute that to its aggregate nature, which limits its ability to capture heterogeneity in taste preferences. The activity-based accessibility measure performed better than the gravity-based measure but not as well as the trip-based measure. Although the use of activity-based measures has great theoretical promise, our proposed formulation was not able to fully capture the benefits of the interaction between activity schedules and trip-based accessibility delivered by the mode-destination choice models. This is an area where improvements could have a large impact, especially by ensuring that the structure of the underlying activity scheduling model captures what we expect activity-based accessibility should capture. Another area for future research involves the scaling of activity-based measures. Fully realizing their potential benefits requires that they be expressed in real units, e.g. dollars or minutes. Expressed as such, we can determine the benefits of the transportation land use system consistently, which is necessary for project evaluation. Additionally, we can compare accessibility across different contexts and time points, which has otherwise been a challenge in accessibility analyses.

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REFERENCES

1. Glaeser, E.L. (1998). Are Cities Dying? *Journal of Economic Perspectives, 12*(2), 139-160.

2. Geurs, K.T., & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography, 12*(2), 127-140. [https://doi.org/10.1016/j.jtrangeo.2003.10.005](https://doi.org/10.1016/j.jtrangeo.2003.10.005)

3. Bhat, C.R., Handy, S.L., Kockelman, K., Mahmassani, H., Chen, Q., & Weston, L. (2000). Development of an urban accessibility index: Literature review. Retrieved from [http://ctr.utexas.edu/wp-content/uploads/pubs/4938_1.pdf](http://ctr.utexas.edu/wp-content/uploads/pubs/4938_1.pdf)

4. Hansen, W.G. (1959). How Accessibility Shapes Land Use. *Journal of the American Institute of Planners, 25*(2), 73–76. [https://doi.org/10.1080/01944365908978307](https://doi.org/10.1080/01944365908978307)

5. Hägerstrand, T. (1970). What about people in regional science? Papers in Regional Science, 24(1), 7-24.

6. Ben-Akiva, M., & Lerman, S. (1979). *Disaggregate Travel and Mobility-Choice Models and Measures of Accessibility*. In Behavioural Travel Modelling (654-679).

7. Dong, X., Ben-Akiva, M.E., Bowman, J.L., & Walker, J.L. (2006). Moving from trip-based to activity-based measures of accessibility. *Transportation Research Part A: Policy and Practice, 40*(2), 163-180. [https://doi.org/10.1016/j.tra.2005.05.002](https://doi.org/10.1016/j.tra.2005.05.002)

8. Beria, P., & Grimaldi, R. (2014). Cost Benefit Analysis to assess urban mobility plans. Consumers’ surplus calculation and integration with transport models.

9. He, H., Quirós, T.P., Lozano-Gracia, N., Avner, P., Augusto Zagatti, G., Bengtsson, L., & Gonzalez, M. (2018). Accessibility-based assessment of transit improvements in data-poor environments: case study of Port-au-Prince, Haiti. Presented at the TRB Annual Meeting.

10. Stewart, A.F., & Zegras, P.C. (2016). CoAXs: A Collaborative Accessibility-based Stakeholder Engagement System for communicating transport impacts. Research in Transportation Economics, 59, 423-433. [https://doi.org/10.1016/j.retrec.2016.07.016](https://doi.org/10.1016/j.retrec.2016.07.016)

11. Kockelman, K. (1996). Travel behavior as a function of accessibility, land use mixing, and land use balance: Evidence from the San Francisco Bay Area. UC Berkeley. Retrieved from [https://pdfs.semanticscholar.org/097b/f2d032a2dfa3a1b0ddaee78acf68ad29ec48.pdf](https://pdfs.semanticscholar.org/097b/f2d032a2dfa3a1b0ddaee78acf68ad29ec48.pdf)

12. Zegras, C. (2010). The Built Environment and Motor Vehicle Ownership and Use: Evidence from Santiago de Chile. *Urban Studies, 47*(8), 1793-1817. [https://doi.org/10.1177/0042098009356125](https://doi.org/10.1177/0042098009356125)

13. Gao, S., Mokhtarian, P.L., & Johnston, R.A. (2008). Exploring the connections among job accessibility, employment, income, and auto ownership using structural equation modeling. *The Annals of Regional Science, 42*(2), 341-356. [https://doi.org/10.1007/s00168-007-0154-2](https://doi.org/10.1007/s00168-007-0154-2)
14. Shiftan, Y. (2011). The Use of Activity-Based Accessibility Measures in Land Use and Other Long Term Life Style Models. Imperial College London. Retrieved from https://workspace.imperial.ac.uk/cts/Public/Seminars/2011/sem20111028.pdf
15. Srour, I., Kockelman, K., & Dunn, T. (2002). Accessibility Indices: A Connection to Residential Land Prices and Location Choices. Transportation Research Record: Journal of the Transportation Research Board, 1805, 25-34.
16. Lee, B.H.Y., Waddell, P., Wang, L., & Pendyala, R.M. (2010). Reexamining the Influence of Work and Nonwork Accessibility on Residential Location Choices with a Microanalytic Framework. Environment and Planning A, 42(4), 913-930. https://doi.org/10.1068/a4291
17. Zondag, B., & Pieters, M. (2005). Influence of accessibility on residential location choice. Transportation Research Record: Journal of the Transportation Research Board, (1902), 63-70.
18. Ben-Akiva, M., & Bowman, J.L. (1998). Integration of an Activity-based Model System and a Residential Location Model. Urban Studies, 35(7), 1131-1153.
19. Adnan, M., Pereira, F., Azevedo, C.M.L., Basak, K., Lovric, M., Feliu, S.R., Zhu, Y., Ferreira, J., Zegras, C., Ben-Akiva, M. (2015). SimMobility: A Multi-Scale Integrated Agent-based Simulation Platform. Presented at the TRB Annual Meeting.
20. Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. 2nd International Symposium on Information Theory, 1973.
21. Burnham, K.P., & Anderson, D.R. (2003). Model selection and multimodel inference: a practical information-theoretic approach.